

LamRA: Large Multimodal Model as Your Advanced Retrieval Assistant

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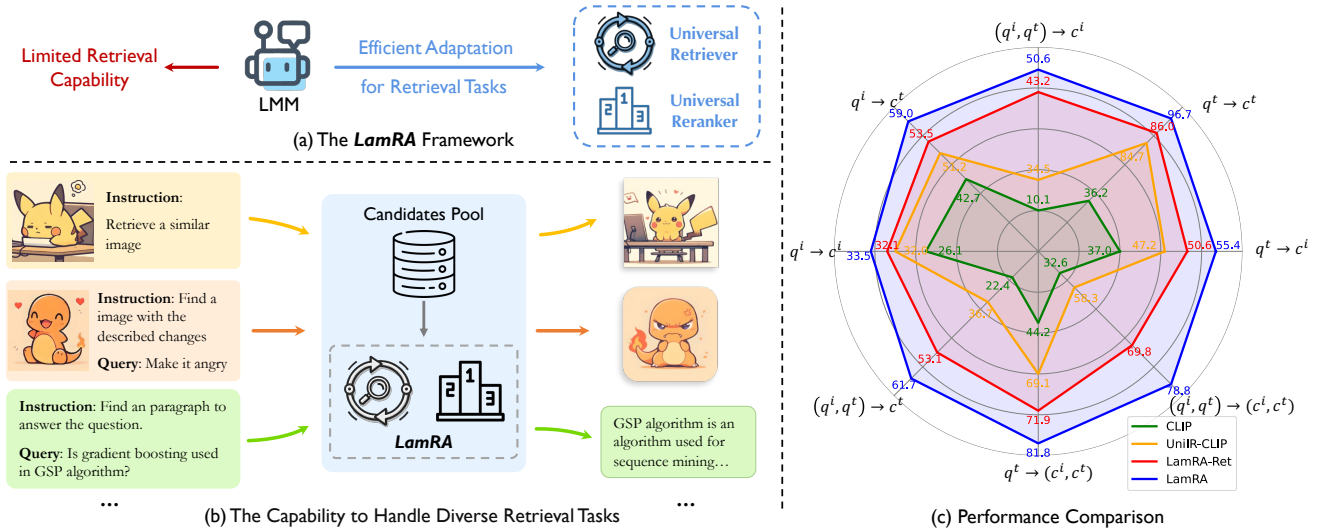


Figure 1. The **LamRA** framework empowers Large Multimodal Models with advanced retrieval and reranking capabilities. (a) LamRA enhances LMMs with universal retrieval and reranking capabilities by inserting lightweight LoRA modules into the LMMs. (b) Examples of varied retrieval tasks demonstrate LamRA’s capability to handle diverse retrieval tasks. (c) Performance comparison on the M-BEIR test set shows LamRA’s superior performance across a wide range of retrieval tasks. For instance, $q^t \rightarrow c^i$ represents text-to-image retrieval.

Abstract

With the rapid advancement of multimodal information retrieval, increasingly complex retrieval tasks have emerged. Existing methods predominantly rely on task-specific fine-tuning of vision-language models, often those trained with image-text contrastive learning. In this paper, we explore the possibility of re-purposing generative Large Multimodal Models (LMMs) for retrieval. This approach enables unifying all retrieval tasks under the same formulation and, more importantly, allows for extrapolation towards unseen retrieval tasks without additional training. Our contributions can be summarised in the following aspects: (i) We introduce **LamRA**, a versatile framework designed to empower LMMs with sophisticated retrieval

and reranking capabilities. (ii) For retrieval, we adopt a two-stage training strategy comprising language-only pre-training and multimodal instruction tuning to progressively enhance LMM’s retrieval performance. (iii) For reranking, we employ joint training of both pointwise and listwise reranking, offering two distinct ways to further boost the retrieval performance. (iv) Extensive experiments underscore the efficacy of our method in handling more than ten retrieval tasks, demonstrating robust performance in both supervised and zero-shot settings, including scenarios involving previously unseen retrieval tasks. Project page: <https://code-kunkun.github.io/LamRA/>.

1. Introduction

Recently, the field of multimodal information retrieval has been significantly advanced by the remarkable success of Vision-Language Models (VLMs). For instance, CLIP [42]

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and ALIGN [15], which are trained through contrastive learning [38] on large-scale image-text pairs, have demonstrated surprisingly impressive generalizability on cross-modal retrieval. However, as the landscape of information retrieval evolves, more challenging tasks have emerged, including composed image retrieval [34, 53], long-text image retrieval [59], and image/question to multimodal document retrieval [8, 36]. Existing methods [33, 55, 56] employ task-specific fine-tuning to adapt VLMs to these specialized tasks, which remains cumbersome and laborious.

In parallel, recent advancements in Large Multimodal Models (LMMs) [22, 23, 47] have spurred a growing trend toward leveraging LMMs for a diverse range of vision-language tasks. For instance, LISA [21] uses LMMs for segmentation tasks [63], while LLaVA [32] applies them to general Visual Question Answering (VQA). The success of LMMs in these domains can be attributed to two key factors: (i) the use of language as an interface between machines and humans, which naturally facilitates interaction across multiple tasks; and (ii) the training of Large Language Models (LLMs) on extensive text corpora, which has substantially improved their comprehension of natural language and, crucially, enriched their understanding of real-world knowledge. In this paper, we aim to extend this success by addressing a broad range of retrieval and reranking challenges within the scope of LMMs. This approach enables the unification of all retrieval tasks under the same formulation and allows for extrapolation to unseen retrieval tasks without the need for additional training.

We introduce a framework that enhances LMMs with universal retrieval and reranking capabilities, by simply inserting lightweight LoRA modules into LMMs, termed as **LamRA**. For quick retrieval, we adopt a two-stage training strategy to progressively improve the model’s retrieval performance. Specifically, the first stage involves text-only pre-training, to enable the LMM to output embeddings in response to summarization prompts. The second stage involves instruction-tuning, where we fine-tune the model on diverse datasets across various retrieval tasks. For reranking, we train an additional LoRA module on the LMM, to handle multiple images or lengthy texts. Using hard sample mining from the quick retrieval model, we conduct joint training for both pointwise and listwise reranking, enabling flexible support for single or multiple candidate inputs, further boosting the overall performance significantly.

To validate the effectiveness of our method, we conduct extensive experiments across more than 10 distinct retrieval scenarios, including text-to-image, text-image-to-image, and text-image-to-text-image retrieval, *etc.* The robust performance indicates that our method can handle both simple and complex retrieval tasks effectively. Furthermore, we examine the model’s task-level generalization by training on a subset of retrieval tasks and evaluating on previ-

ously unseen tasks. Remarkably, our method demonstrates strong generalization abilities, effectively performing on held-out tasks without prior exposure, underscoring its potential for transferability to unseen retrieval challenges.

To summarise, in this paper, we make the following contribution: (i) We introduce **LamRA**, a versatile framework designed to empower LMMs with sophisticated retrieval and reranking capabilities. (ii) To enable efficient retrieval, we propose LamRA-Ret, which adopts a two-stage training strategy comprising language-only pre-training and multimodal instruction tuning to progressively enhance the model’s retrieval capability. (iii) For reranking, we present LamRA-Rank, which supports both pointwise and listwise reranking to further boost the retrieval performance. (iv) Through extensive experiments, we demonstrate the effectiveness of our method in both supervised and zero-shot settings, achieving robust performance even on previously unseen retrieval tasks. Consequently, our method performs on par with or significantly surpasses existing state-of-the-art (SOTA) models across more than ten retrieval tasks.

2. Related Work

Multimodal Information Retrieval. Traditional multimodal information retrieval has often been limited to cross-modal retrieval settings, with evaluation benchmarks typically restricted to datasets like MSCOCO [29] and Flickr30K [41]. As the field progresses, more complex retrieval tasks have emerged, including composed image retrieval [2, 34, 46, 53], long-text-to-image retrieval [59], and image/question-to-multimodal document retrieval [8, 13], among others. As discussed in [8, 36, 59], these tasks present substantial challenges for VLMs. Current approaches [1, 3, 37, 55] often address this by fine-tuning models on individual tasks, yet developing universal multimodal embeddings capable of handling these various tasks simultaneously remains a significant challenge.

Multimodal Representation Learning. The challenge of developing robust multimodal representation remains a foundational question in multimodal learning. Pioneering models such as CLIP [42] and ALIGN [15] have explored this by employing a dual-encoder architecture to learn effective representations through contrastive learning [38] on large-scale image-text pairs. However, given that dual-encoder networks like CLIP aim to enhance the alignment between the image and text, they encounter challenges when dealing with interleaved image-text inputs. Moreover, the text encoder learned in this way shows a limited understanding of complex text [12], suggesting the traditional dual-encoder models may require further refinement.

Numerous studies have pursued further exploration to achieve more universal multimodal representation. For instance, UniIR [52] introduces a benchmark comprising eight distinct retrieval tasks, demonstrating that CLIP, when

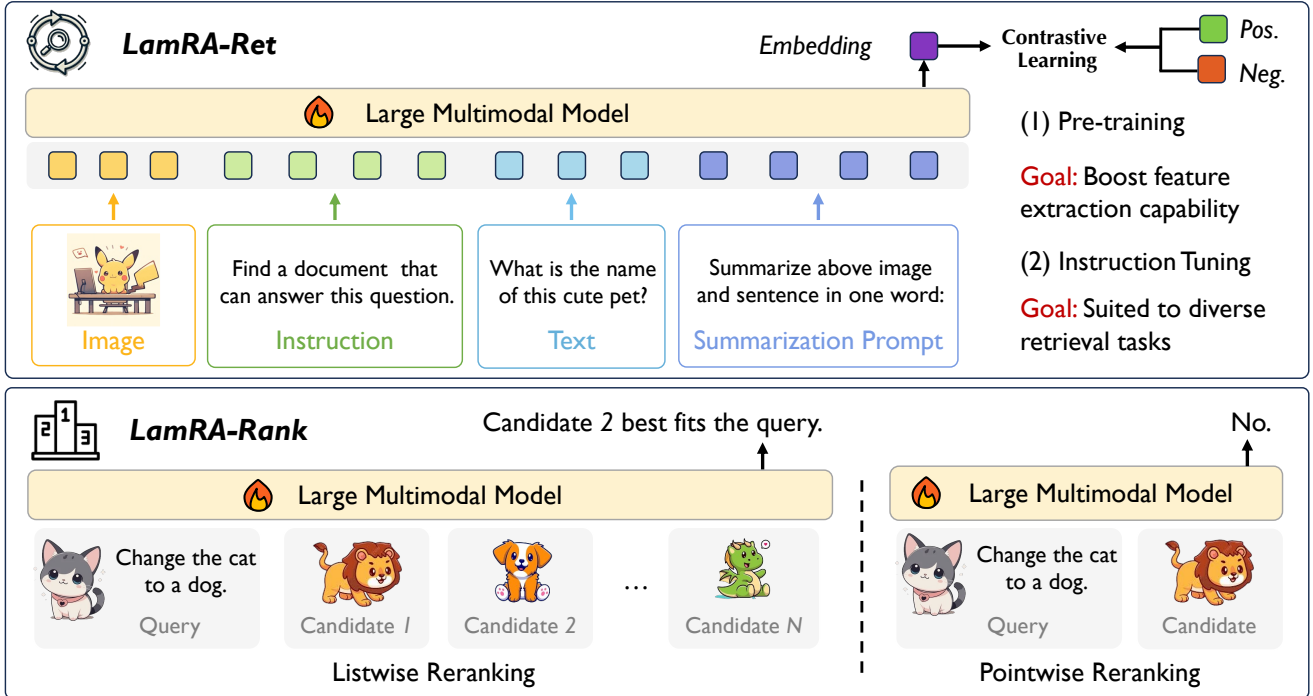


Figure 2. **Overview of the proposed LamRA framework.** LamRA consists of two components: LamRA-Ret and LamRA-Rank. The top section illustrates LamRA-Ret, encompassing both the pre-training and instruction-tuning stages, where contrastive learning is employed to enhance the retrieval capability of LMMs. The pre-training stage aims to improve the feature extraction capabilities through text-to-text retrieval, while the instruction tuning stage adapts the LMMs to various retrieval tasks by fine-tuning on diverse tasks with task-specific instructions. The bottom section depicts the joint training process of LamRA-Rank, which integrates both pointwise and listwise reranking.

trained on this benchmark, achieves enhanced generality and adaptability across various retrieval tasks. E5-V [18] leverages Large Multimodal Models (LMMs), using carefully designed prompts to map images and text into a shared language hidden space. Through fine-tuning on text pairs [11], E5-V demonstrates remarkable zero-shot retrieval capabilities. However, these methods demonstrate limited effectiveness on certain complex retrieval tasks. In this paper, we explore the potential of LMM as a universal retriever and reranker to address these challenges.

Large Multimodal Model. With recent advancements in Large Language Models (LLMs) [4, 10, 16], recent research has focused on Large Multimodal Models (LMMs) to align visual and textual modalities through visual instruction tuning. In particular, there is a growing trend toward using LMMs to tackle a wide range of vision-language tasks [43, 60, 63]. For instance, LISA [21] applies LMMs to segmentation tasks, DetGPT [40] utilizes LMMs for object detection, and VisionLLM [48] addresses various vision-centric tasks using LMMs. Nevertheless, relatively few studies have explored the potential of LMMs in universal retrieval tasks, which is our focus in this paper, where we propose a framework LamRA, that adapts LMMs with lightweight LoRAs for advanced retrieval and reranking, significantly enhancing their performance in various retrieval

tasks. We notice a few concurrent studies [19, 28] also explore the use of LMMs for universal retrieval, and we hope that further research will continue to advance this field.

3. Method

This section starts by formulating our considered problem in Section 3.1; then we elaborate on the architecture and feature extraction process in Section 3.2; and describe the training details to equip the LMMs with retrieval capability in Section 3.3; then, we present the approach to endow the LMMs with universal reranking abilities in Section 3.4, aiming to further boost retrieval performance; lastly, we detail the inference pipeline of our method in Section 3.5.

3.1. Problem Formulation

We address the challenge of universal retrieval and reranking with a generative model. Specifically, for one specific query (q), which can be an image, text, or an interleaved image-text format, and a retrieval set of N candidates $\Omega = \{c_1, c_2, \dots, c_N\}$ where each c_i comprises images, text, or interleaved formats, we first extract the embeddings for both the query and all candidates with LMMs, and rank all candidates in Ω based on the relevance, *i.e.*, cosine similarity between the query and candidate embeddings. This initial retrieval process yields the top- K can-

didates, represented as $\mathcal{C}_1 = \Phi_{\text{ret}}(q, \Omega)$. Subsequently, we refine this subset through a reranking process to produce the final ranked output, denoted as $\mathcal{C}_2 = \Phi_{\text{rerank}}(q, \mathcal{C}_1)$. Here, \mathcal{C}_2 represents the final reordered set of candidates.

In the following section, we provide details on extracting features for queries and candidates of arbitrary format.

3.2. Architecture & Feature Extraction

Generally speaking, the architecture of Large Multimodal Models (LMMs) typically consists of three main components: a vision encoder, a vision projector, and a language model. To compute the embedding with a generative model, we adopt a similar approach as [17, 18], using an Explicit One-word Limitation (EOL). Specifically, we use the following prompts: (i) for image-only input, we use: `<image> Summarize above image in one word: <emb>`; (ii) for text-only input, we use: `<text> Summarize above sentence in one word: <emb>`; (iii) for mixed image-text input, we utilize: `<image1><text1>...<imagei><textj> Summarize above image and sentence in one word: <emb>`. where `<image>` and `<text>` denote placeholders for the input image and sentence, respectively. For any combination of images and text inputs, the LMM uses the vision encoder and vision projector to map images into language space, which are then processed alongside the text by the large language model. We use the last hidden state immediately preceding the `<emb>` token as the representation of the input.

3.3. Training for Retrieval

In this section, we describe a two-stage training scheme, to advance the retrieval capabilities of LMMs. The first stage involves language-only pre-training to output improved embeddings. The second stage, instruction tuning, further adapts the LMMs to diverse retrieval tasks.

Stage-I: Adapting LMMs for Retrieval Tasks. LMMs were trained for generative tasks, *e.g.*, next-token prediction, which limits their ability for retrieval, as evidenced by the performance metrics in Table 2, *i.e.*, directly employing Qwen2-VL-7B [47] for retrieval tasks results in inferior performance. To address this issue, we start by adapting LMMs for text-to-text retrieval by training LoRA modules on the Natural Language Inference (NLI) dataset [11], consisting pairs of text samples that are ideal to enhance LMMs for retrieval. For further discussion on the selection of pre-training datasets, please refer to Appendix A.

Stage-II: Instruction Tuning for Universal Retrieval. To further enhance the retrieval capabilities of the LMMs across various multimodal retrieval tasks, we train on M-BEIR, which comprises 8 retrieval tasks with 10 datasets, as curated by [52], including image-to-image retrieval, composed image retrieval, and image/question-to-multimodal-

document retrieval, among others. For different retrieval tasks, we incorporate task-specific instructions tailored for each retrieval type. For example, to complete an image-to-image retrieval task, the instruction can be “*retrieval a similar image.*” For further details regarding the instructions and M-BEIR datasets, please refer to Appendix C.

Training Objective. We employ contrastive learning with the InfoNCE loss [38] for both language-only pre-training and instruction tuning stages. Specifically, given a batch size of B , the embeddings of n -th query q_n should be positioned close to the embeddings of its positive target c_n and far away from other negative instances, formulated as:

$$\mathcal{L}_{\text{ret}} = -\frac{1}{B} \sum_{n=1}^B \log \left[\frac{\exp[\kappa(\text{LMM}(q_n), \text{LMM}(c_n)) / \tau]}{\sum_{m=1}^B \exp[\kappa(\text{LMM}(q_n), \text{LMM}(c_m)) / \tau]} \right]$$

where τ refers to the temperature parameter, and $\kappa(\cdot, \cdot)$ denotes the cosine similarity. Additionally, $\text{LMM}(\cdot)$ represents the feature extraction process with LMMs, as mentioned in Section 3.2. The model after both pre-training and instruction tuning is referred as **LamRA-Ret**.

3.4. Training for Reranking

Here, we exploit the flexibility of LMMs to process multiple images or long texts and train a lightweight LoRA module to adapt them for reranking. As a result, we propose **LamRA-Rank**, which supports inputs of single or multiple candidates from the outputs of LamRA-Ret, to further improve the retrieval performance.

Collecting Training Data for Reranking. Here, we employ the LamRA-Ret model trained in Section 3.3 as the initial retriever, and train the reranking model on its top 100 retrieved candidates and use them as hard negatives. This approach enables LamRA-Rank to acquire a more nuanced understanding and improve its ranking performance.

Joint Training for Pointwise and Listwise Reranking. Given that the LMMs can accept flexible inputs, we explore joint training for both pointwise and listwise reranking.

In the case of pointwise reranking, for any query (q), we randomly select a negative candidate (c_{neg}) from the top 100 candidates and instruct the LamRA-Rank to output YES for the ground truth (c_{pos}) and NO for the negative candidate. Cross-entropy loss is employed as the loss function, expressed as $\mathcal{L}_{\text{point}} = \mathcal{L}_{\text{ce}}(\text{YES}, \text{Reranker}(q, c_{\text{pos}})) + \mathcal{L}_{\text{ce}}(\text{NO}, \text{Reranker}(q, c_{\text{neg}}))$, where $\text{Reranker}(\cdot, \cdot)$ represents the autoregressive output process of LamRA-Rank.

In contrast, for listwise reranking, we randomly select M negative samples (c_1, c_2, \dots, c_M) from the top 100 candidates, where M is a randomly determined integer between 2 and 5. We then randomly insert the ground truth (c_{pos}) at any position and prompt the LamRA-Rank to directly output the position number of the

ground truth. This process can be formulated as $\mathcal{L}_{\text{list}} = \mathcal{L}_{\text{ce}}(\text{GT-POSITION}, \text{Reranker}(q, c_{\text{pos}}, c_1, c_2, \dots, c_M))$.

The final loss is a weighted sum: $\mathcal{L}_{\text{rank}} = \mathcal{L}_{\text{point}} + \mathcal{L}_{\text{list}}$.

3.5. Inference Pipeline

At the inference stage, we employ LamRA-Ret for the initial retrieval phase (Φ_{ret}) and LamRA-Rank for the subsequent reranking (Φ_{rank}). Given a query (q) and a candidate set (Ω), LamRA-Ret is first utilized to compute an embedding similarity score (S_{ret}) for each candidate based on cosine similarity. Subsequently, the candidates are sorted to obtain the top- K candidate set (\mathcal{C}_1). For the reranking process, we offer two options: pointwise reranking and listwise reranking. In the case of pointwise reranking, the query and each of the top- K candidates are sequentially input into the LMM, performing K inference operations and assigning a reranking score (S_{rank}) to each candidate. This reranking score comes from the probability of the LMMs outputting YES for each candidate. Conversely, for listwise reranking, the query and the top- K candidates are simultaneously fed into LamRA-Rank, which directly output the serial number of the most relevant candidate. More discussion on these two methods can be found in Section 4.3. In the final step, the embedding similarity score from LamRA-Ret and the reranking score from LamRA-Rank are aggregated into a weighted sum to get the final score: $S = \alpha \times S_{\text{ret}} + (1 - \alpha) \times S_{\text{rank}}$, where α is a weight hyperparameter. This final score is then used to generate the reordered candidate set (\mathcal{C}_2). We refer to the combined framework of LamRA-Ret and LamRA-Rank as **LamRA**.

4. Experiments

4.1. Experimental Setup

Datasets and Metrics. We utilize the NLI dataset [11] for pre-training and the M-BEIR [52] dataset for instruction tuning. The M-BEIR dataset encompasses eight retrieval tasks across 10 retrieval datasets, comprising a total of 1.1M training samples. As shown in Table 1, to evaluate the versatility of LamRA across various retrieval tasks, we conduct assessments on the M-BEIR test set. Furthermore, we investigate LamRA’s generalization ability on other previously unseen datasets, including ShareGPT4V [59], CIRCO [2], and Visual Dialog [9], among others. We adhere to the standard evaluation metrics established for each dataset. For the retrieval tasks, we utilize Recall@K as the evaluation metric, and for the image-text matching task, we employ Accuracy as the evaluation metric.

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 it on all 8 tasks in the M-BEIR benchmark and evaluate its performance on the test sets. For the baseline in this set-

Benchmark	Zero-shot	# Queries	# Candidates
M-BEIR [52]	✗	190K	5.6M
ShareGPT4V [59]	✓	1K	1K
Urban-1K [59]	✓	1K	1K
Flickr30K [41]	✓	1K	5K
CIRCO [2]	✓	800	120K
GeneCIS [46]	✓	8K	10 ~ 15
Visual Storytelling [14]	✓	5K	8K
Visual Dialog [9]	✓	2K	2K
Multi-round FashionIQ [57]	✓	2.4K	6.2K
CC-Neg [44]	✓	40K	2
Sugar-Crepe [12]	✓	7.5K	2

Table 1. **Summary of the evaluation benchmarks.** # Queries represents the number of test queries, and # Candidates denotes the number of test candidates per query.

ting, we follow UniIR [52], comparing with several strong VLMs, such as CLIP, SigLIP, and BLIP2, to assess their zero-shot performance. In the supervised setting, we compare our method with fully fine-tuned versions of UniIR-BLIP and UniIR-CLIP. (ii) To evaluate the generalization ability on previously **unseen retrieval datasets**, we perform zero-shot experiments on 10 datasets not encountered during training. In this case, the baseline includes a selection of universal retrievers, such as E5-V, MagicLens, and EVA-CLIP-18B. (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.

Implementation Details. Our framework is implemented in Pytorch and leverages the Qwen2-VL-7B [47] by default. In the pretraining stage for retrieval, we conduct experiments on 8 A100 GPUs with a batch size of 576 and a learning rate of 4×10^{-4} , training for two epochs. During the instruction tuning stage, we train on 16 A100 GPUs with a batch size of 960 and a learning rate of 1×10^{-4} for one epoch. For the rerank training stage, we train for one epoch on 16 A100 GPUs, employing a batch size of 64 and a learning rate of 2×10^{-5} . Throughout all experiments, the parameters on the vision side remain fixed, while the LLM is fine-tuned using LoRA. LamRA-Rank adopts the pointwise reranking by default. During the M-BEIR evaluation, experiments are conducted in the local pool, with LamRA-Rank reranking the top-50 results. For experiments on unseen datasets, reranking is applied to the top-10 results. The weight hyperparameter α is set to a default value of 0.5.

4.2. Experimental Results

Versatility Across Various Retrieval Tasks. As demonstrated in Table 2, our model is capable of handling retrieval tasks across various input formats. We can draw the following observations: (i) Our approach significantly

Methods	$q^t \rightarrow c^i$			$q^t \rightarrow c^t$			$q^t \rightarrow (c^i, c^t)$			$q^i \rightarrow c^t$			$q^i \rightarrow c^i$			$(q^i, q^t) \rightarrow c^t$			$(q^i, q^t) \rightarrow c^i$			$(q^i, q^t) \rightarrow (c^i, c^t)$			Avg.	
	VN		COCO	F200K		WebQA	EDIS	WebQA	VN	COCO	F200K	NIGHTS	OVEN	InfoS	FIQ	CIRR	OVEN	InfoS	OVEN	InfoS	OVEN	InfoS	OVEN	InfoS		
	R@5	R@5	R@10	R@5	R@5	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	R@5	R@5	R@5	R@5	R@5	R@5		
<i>Zero-shot</i>																										
CLIP-L [42]	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 [58]	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 [24]	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 [25]	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									
Qwen2-VL-7B [47]	9.3	55.1	5.0	42.0	26.2	9.4	5.4	46.6	4.0	21.3	21.4	22.5	4.3	16.3	43.6	36.2	23.0									
<i>Supervised - Dual Encoder</i>																										
UniIR-BLIP _{FF} [52]	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} [52]	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									
<i>Supervised - LMMs</i>																										
LamRA-Ret	41.6	81.5	28.7	86.0	62.6	81.2	39.6	90.6	30.4	32.1	54.1	52.1	33.2	53.1	76.2	63.3	56.6									
LamRA	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									

Table 2. **Comparison with up-to-date state-of-the-arts on M-BEIR test set.** The first row indicates the retrieval task type: q^t for text queries, q^i for image queries, c^t for text candidates, and c^i for image candidates. Abbreviations used include VN for VisualNews, F200K for Fashion200K, InfoS for InfoSeek, and FIQ for FashionIQ. Evaluation standards follow UniIR, with FashionIQ and Fashion200K using Recall@10, while all other evaluations employ Recall@5. The best (resp. second-best) numbers are in red (resp. blue).

outperforms the dual-encoder paradigm method, UniIR-CLIP, in both multimodal and pure text retrieval tasks. For instance, in text-image-to-text retrieval on the InfoSeek dataset, our method LamRA-Ret, achieves an improvement of 24.2 points over UniIR-CLIP in Recall@5. Similarly, in composed image retrieval on the CIRR dataset, our method exceeds UniIR-CLIP by 8.5 points in Recall@5. (ii) In simpler retrieval tasks, such as cross-modal retrieval, the performance of LamRA-Ret is either comparable to or slightly higher than that of UniIR-CLIP. (iii) Furthermore, LamRA (with reranking) achieves additional performance gains across all retrieval tasks, with an average improvement of 7.1 points over 16 M-BEIR retrieval tasks. (iv) Notably, Qwen2-VL-7B achieves an average zero-shot score of only 23.0 on the M-BEIR benchmark, which increases to 63.7 after applying our framework. This highlights the effectiveness of our proposed LMMs framework in enhancing general retrieval and reranking performance.

Advanced Generalization Capability on Unseen Dataset.

To validate the strong generalization capability of our method, we conduct extensive experiments across 10 unseen datasets. As illustrated in Table 4, we can make the following observations: (i) Our method demonstrates excellent generalization across various unseen datasets, with performance either significantly exceeding or comparable to other strong baseline methods. (ii) Notably, our method performs exceptionally well in scenarios where dual-encoder approaches tend to underperform. For instance, in the image-to-long-text retrieval task on the Urban-1K dataset, our LamRA-Ret achieves over a 10-point improvement compared to other methods. Similarly, in tasks such as dialog-to-image retrieval and multi-round composed image retrieval, our method also yields substantial performance gains. (iii) In Image-Text Matching tasks, LMMs-

Methods	$q^i \rightarrow c^i$		$(q^i, q^t) \rightarrow c^t$		$(q^i, q^t) \rightarrow (c^i, c^t)$		Avg.
	NIGHTS	OVEN	InfoS	OVEN	InfoS	R@5	
<i>Supervised</i>							
UniIR-BLIP _{FF} [52]	33.0	41.0	22.4	55.8	33.0	37.0	
UniIR-CLIP _{SF} [52]	32.0	45.5	27.9	67.6	48.9	44.4	
<i>Zero-shot</i>							
LamRA-Ret*	27.2	44.7	44.0	62.8	49.5	45.6	
LamRA*	29.2	46.9	54.2	65.1	59.1	50.9	

Table 3. **Held-out task generalization experiments on M-BEIR.** * means that the training is carried out on the remaining five tasks, with no exposure to these three held-out tasks.

based methods outperform those using the dual-encoder paradigm. We attribute this improvement primarily to the LMM’s exceptional ability to comprehend complex text.

Exceptional Generalization on Unseen Retrieval Task.

As outlined in Section 4.1, we train our model on five tasks and evaluate it on excluded tasks to assess its generalization on these previously unseen tasks. As demonstrated in Table 3, our approach shows impressive performance on unseen retrieval tasks. Notably, when compared to supervised methods such as UniIR-CLIP, our method achieves competitive or even superior zero-shot results in more complex tasks, such as text-image-to-text retrieval task on the InfoSeek benchmark, our method exceeds UniIR-CLIP by 26.3 points in Recall@5. This remarkable generalization ability suggests that our method can extrapolate to unseen retrieval tasks without additional training and may hold significant practical applicability across a broader range of scenarios.

4.3. Ablation Study & Analysis

In this section, we conduct experiments to further investigate the effect of our proposal, for example, the two-stage

Methods	$q^t \rightarrow c^i$			$q^i \rightarrow c^t$			$(q^i, q^t) \rightarrow c^i$		$q^{\text{dialog}} \rightarrow c^i$		$(q^i \oplus q^t) \rightarrow c^i$		ITM	
	Share4V	Urban*	Flickr	Share4V	Urban*	Flickr	CIRCO*	GeneCIS*	VisD*	VIST	MT-FIQ*	CC-Neg	Sugar-Crepe*	
	R@1	R@1	R@1	R@1	R@1	R@1	MAP@5	R@1	R@1	R@1	R@5	Acc.	Acc.	
CLIP-L [42]	84.0	52.8	67.3	81.8	68.7	87.2	4.0	13.3	23.7	0.6	17.7	66.7	73.0	
Long-CLIP-L [59]	95.6	86.1	76.1	95.8	82.7	89.3	5.7	16.3	37.9	1.1	18.5	76.3	80.9	
UniIR-CLIP [52]	85.8	75.0	78.7	84.1	78.4	94.2	12.5	16.8	26.8	0.6	39.4	79.9	80.3	
E5-V [18]	86.7	84.0	79.5	84.0	82.4	88.2	24.8	18.5	54.6	10.0	19.2	83.2	84.7	
MagicLens-L [61]	85.5	59.3	72.5	60.9	24.2	84.6	29.6	16.3	28.0	3.3	22.6	62.7	75.9	
EVA-CLIP-8B [45]	91.2	77.8	80.8	93.1	80.4	95.6	6.0	13.1	23.2	1.2	22.1	59.4	81.7	
EVA-CLIP-18B [45]	92.1	81.7	83.3	94.0	83.3	96.7	6.1	13.6	24.7	1.0	21.9	63.8	83.1	
LamRA-Ret	93.3	95.1	82.8	88.1	94.3	92.7	33.2	18.9	62.8	23.1	60.9	79.6	85.8	
LamRA	97.9	98.8	88.1	96.5	98.0	97.6	42.8	24.8	70.9	28.6	63.9	85.9	93.5	

Table 4. **Comparison with up-to-date state-of-the-arts on unseen dataset.** The first row indicates the retrieval task type: q^t for text queries, q^i for image queries, q^{dialog} for dialog queries, $(q^i \oplus q^t)$ for multi-interleaved image-text queries, c^t for text candidates, c^i for image candidates, and ITM for the Image-Text Matching task. Abbreviations used include Share4V for ShareGPT4V, Urban for Urban-1k, VIST for Visual Storytelling, VisD for Visual Dialog, and MT-FIQ for Multi-round FashionIQ. * indicates that the images in these datasets are sourced from COCO or FashionIQ. However, due to significant differences in their captions or query formats, we still classify these datasets as unseen. We adhere to the standard evaluation metrics specific to each dataset. The best (resp. second-best) numbers are in red (resp. blue). For more details about these datasets, please refer to Appendix D.

training for LamRA-Ret, the scaling trends of LamRA, *etc.* **Effectiveness of Two-stage Training.** According to the results presented in Table 5, both the pre-training and the instruction tuning stages significantly impact retrieval performance. Specifically, omitting the pre-training stage results in an average performance decline of three points on the M-BEIR benchmark. Similarly, the absence of the instruction tuning stage yields suboptimal results, as the model struggles with some complex multimodal retrieval tasks. Collectively, these stages together enable a progressive enhancement in the retrieval performance of the LMMs.

Pre-training	Instruction tuning	Avg.
✗	✗	23.0 (-33.6)
✓	✗	36.2 (-20.4)
✗	✓	53.6 (-3.0)
✓	✓	56.6

Table 5. **Effect of the two-stage training.** Avg. refers to the average recall performance across the M-BEIR test set.

Scaling Trends of LamRA. As shown in Table 6, to investigate the scaling effect associated with LamRA, we conduct experiments on LMMs of different sizes, specifically Qwen2-VL-2B and Qwen2-VL-7B. The results indicate that as the model size scales, performance improves correspondingly. Currently, due to the computational limitations, we are able to conduct experiments solely on the 2B and 7B models; however, our findings suggest that larger and more powerful LMMs potentially yield even superior results within our framework, thereby laying the groundwork for further exploration in this area.

Discussion on Pointwise and Listwise Rerank Methods. As outlined in Section 3.4, LamRA-Rank is designed to perform both pointwise and listwise reranking. We investigate

LMMs	LamRA-Ret	LamRA-Rank	Avg.
Qwen2-VL-2B [47]	✓	✗	51.6
	✓	✓	58.3
Qwen2-VL-7B [47]	✓	✗	56.6
	✓	✓	63.7

Table 6. **Scaling Trends of LamRA.** Experimental results on the M-BEIR test set across various model sizes.

Task	LamRA-Ret		LamRA-Rank(P)		LamRA-Rank(L)	
	R@1	R@1	Time	R@1	Time	
$q^t \rightarrow c^t$	58.2	75.9	0.020s	75.9	0.010s	
$(q^i, q^t) \rightarrow c^i$	18.5	24.5	0.071s	24.3	0.067s	
$(q^i, q^t) \rightarrow c^t$	30.1	37.3	0.047s	36.6	0.017s	
$(q^i, q^t) \rightarrow (c^i, c^t)$	33.4	39.9	0.084s	39.5	0.085s	

Table 7. **Comparison of Recall@1 performance and inference costs between pointwise (LamRA-Rank(P)) and listwise (LamRA-Rank(L)) reranking on M-BEIR.** Reranking is applied to the top-5 results. Time denotes the per-query inference time cost measured on eight A100 GPUs with a batch size of 32.

these two distinct reranking methods on the M-BEIR test set, with the results presented in Table 7. Both methods demonstrate a significant improvement in retrieval performance. Although pointwise reranking generally incurs a higher computational overhead than listwise reranking, the latter is constrained by the LLM’s context length, which limits the number of candidates it can process. Consequently, each reranking method offers distinct advantages and can be flexibly applied in different contexts based on specific application requirements.

Extending to Video Retrieval. As shown in Table 8, we evaluate our method on the MSR-VTT [54] and MSVD [5] datasets in a zero-shot setting for the text-to-video retrieval

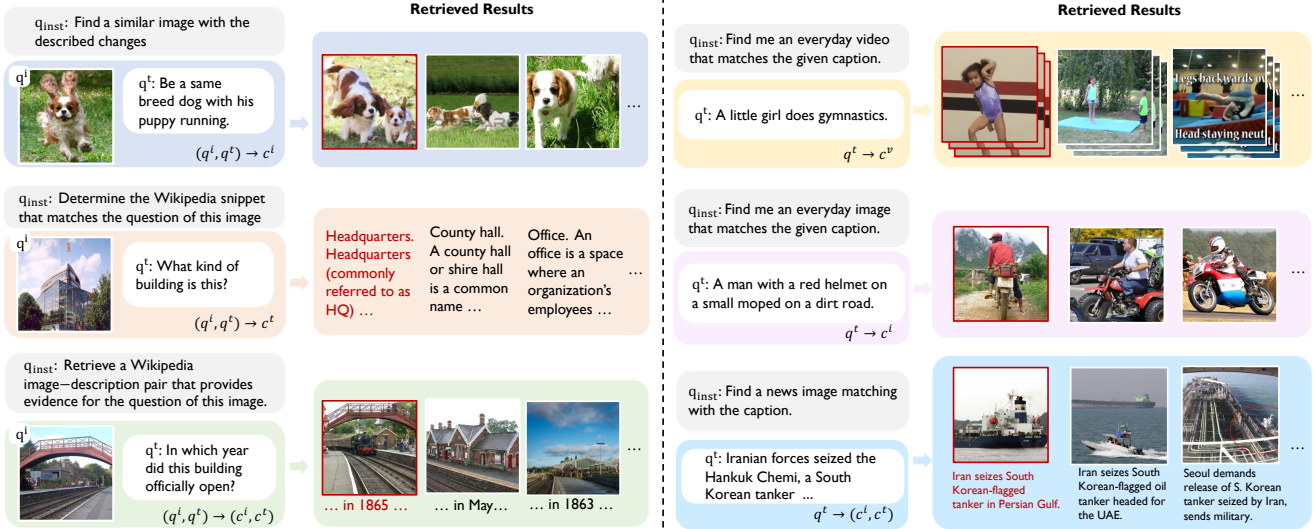


Figure 3. **Qualitative examples.** We show the results of our method across six different retrieval tasks, with the ground truth indicated by a red box and red text. Here, q^t for text queries, q^i for image queries, c^t for text candidates, c^i for image candidates, and c^v for video candidates. For more qualitative examples, please refer to Appendix H.

task. The results demonstrate that our approach exhibits competitive performance. For instance, on the MSR-VTT dataset, our method outperforms InternVideo [49] by 4.7 points in Recall@1. Similarly, on the MSVD dataset, we achieve an improvement of 2.5 points over UMT-L [26] in Recall@1. Notably, our method has not been exposed to any video data during the fine-tuning stage, indicating that it preserves Qwen2-VL’s inherent video understanding capability. Although our approach currently falls short of the performance achieved by the state-of-the-art InternVideo2 [51], we intend to address this gap by exploring the integration of video data in future research.

Method	MSR-VTT			MSVD		
	R@1	R@5	R@10	R@1	R@5	R@10
InternVideo [49]	40.0	65.3	74.1	43.4	69.9	79.1
ViCLIP [50]	42.4	-	-	49.1	-	-
UMT-L [26]	42.6	64.4	73.1	49.9	77.7	85.3
InternVideo2 _{s2} -6B [51]	55.9	78.3	85.1	59.3	84.4	89.6
LamRA	44.7	68.6	78.6	52.4	79.8	87.0

Table 8. **Zero-shot text-to-video retrieval performance.**

Discussion on Inference Cost. One potential drawback of applying LMMs to retrieval and reranking tasks is the high inference costs. Nevertheless, various strategies can be employed in practical applications to mitigate this issue. For instance, pre-extracting features for the candidate pool in advance or deploying our method in scenarios with low query-per-second requirements can significantly reduce inference costs. Moreover, several recent studies [20] focus on improving the inference speed of LMMs. We believe that leveraging LMMs for retrieval and reranking holds promis-

ing potential for future applications.

4.4. Qualitative Results.

In Figure 3, we present the qualitative results across six retrieval tasks. In the top left panel, we demonstrate our method’s effectiveness in handling the composed image retrieval task, where the query requires retrieving an image of a dog of the same breed as shown in the reference image, along with its puppy running. Our method captures this complex intent, successfully retrieving the target image. In the third row of the first column, we showcase our method’s performance on the text-image-to-text-image retrieval task, where it not only retrieves a Wikipedia snippet for the query but also identifies an image similar to the query image. For more qualitative examples, please refer to Appendix H.

5. Conclusion

In this paper, we have explored a novel paradigm for applying LMMs to address a broad range of retrieval tasks. By simply inserting lightweight LoRA modules, Our proposed universal framework, LamRA, endows LMMs with robust retrieval and reranking capabilities. Specifically, for efficient retrieval, we introduced LamRA-Ret, which adopts a two-stage training strategy to progressively enhance retrieval performance. For reranking, we presented LamRA-Rank, which supports both pointwise and listwise reranking to further optimize results. Comprehensive quantitative and qualitative comparisons across more than ten diverse retrieval tasks underscore the versatility and effectiveness of our method. We anticipate that our framework will provide valuable insights into the multimodal information retrieval field and inspire further research in this area.

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LamRA: Large Multimodal Model as Your Advanced Retrieval Assistant

Supplementary Material

A. Analysis of Pre-training Dataset Selection

As outlined in Section 3.3 of the main paper, the LamRA-Ret undergoes a two-stage training process to enhance retrieval performance incrementally. These stages consist of the language-only pre-training phase and the multimodal instruction-tuning phase. In this section, we conduct our pre-training experiments using various types of datasets, which can be categorized into the following groups: (i) datasets containing only image data, (ii) datasets comprising solely text data, (iii) datasets consisting of image-text pairs, and (iv) a combination of pure text data and image-text pair datasets. We utilize MSCOCO and Flickr30K as our evaluation benchmark for the pre-training stage.

Image-only Dataset. To construct suitable training data, we utilize the Region-based 100K dataset within UltraEdit [62], a region-based image editing dataset. The reference image is employed as the query, the reference image with appropriate data enhancements serves as the positive sample, and the edited image is used as the hard negative sample.

Language-only Dataset. We employ the NLI dataset introduced in [11], which comprises a series of triplets: (query text, positive text, and hard negative text). The dataset contains 275K samples. In our experiments, we observe that excluding the hard negative text yields improved results. Consequently, in the default experimental setting, we use only the query text and positive text while treating other samples within the same batch as negative samples.

Image-Text Pairs Dataset. We use the ShareGPT4V dataset [7], which comprises paired images and long texts, with an initial size of 100K samples. After excluding the COCO images, the final dataset size is reduced to 52K samples.

Combined Dataset. We construct our combined dataset using a combination of the language-only and image-text pairs data.

Results Analysis. The experimental results, as presented in Table 9, reveal the following observations: (i) Across different types of pertaining data, the retrieval performance consistently improves. (ii) Performance fluctuates depending on the data type, with language-only pertaining data yielding the best results. (iii) Simply combining different types of pretraining data can unexpectedly degrade performance. Based on these findings, we ultimately opt for the language-only pretraining approach.

Dataset Type	Image Retrieval						Text Retrieval					
	Flickr30K			COCO			Flickr30K			COCO		
	R@1	R@5	R@10	R@1	R@5	R@10	R@1	R@5	R@10	R@1	R@5	R@10
No Training	52.4	78.9	86.0	26.4	50.9	62.9	54.7	80.8	88.3	32.3	55.3	66.6
Image-only	71.3	92.0	95.2	38.9	66.2	76.6	79.3	94.0	97.3	58.0	80.0	88.0
Language-only	80.8	95.3	97.2	53.3	77.0	84.8	91.2	99.0	99.5	67.5	87.1	92.6
Image-Text Pairs	72.5	90.7	94.4	46.0	71.1	79.9	88.4	97.5	99.0	65.3	85.4	91.3
Combined	74.1	92.5	95.8	47.2	71.8	80.4	83.9	96.0	98.4	55.1	78.9	86.3

Table 9. Performance across various Pre-training Dataset.

B. More Implementation Details

Supplement of Feature Extraction. As discussed in Section 3.2 of the main paper, the `<emb>` token is a newly introduced word added to the vocabulary, primarily serving as a placeholder. Essentially, we can use an arbitrary token to replace it, since the embedding we use is derived from the hidden state corresponding to the position preceding this token.

Supplement of Listwise Reranking Method. As discussed in Section 3.4 of the main paper, the pointwise reranking method assigns a score to each candidate based on the probability of the LMMs outputting YES for that candidate. Similarly, the listwise reranking method adopts a similar approach, assigning a reranking score to each candidate according to the probability of the LMM outputting a specific serial number.

Supplement of Baseline Methods. We utilize the official checkpoints of each baseline model for evaluation. We directly report the results of datasets that have already been evaluated in the corresponding papers. Note that, the Coca version of MagicLens [61] has not yet been open-sourced, therefore, we use its CLIP version for our experiments.

C. Details about M-BEIR Dataset

We present the details for the M-BEIR benchmark and the corresponding instruction in Table 10 and Table 12, respectively. 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 [52] paper.

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

Table 10. Summary of the M-BEIR benchmarks.

D. Details about Unseen Dataset

Here, we present the details of the Unseen Dataset in Table 11. 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 captions in Urban1K consist of extended captions generated by GPT-4V [39], while 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.

Dataset	Image Source	Task	Query Format	Candidate Format
ShareGPT4V	SA-1B	$q^t \rightarrow c^i$ $q^i \rightarrow c^t$	<long text> <image>	<image> <long text>
Urban-1K	MSCOCO	$q^t \rightarrow c^i$ $q^i \rightarrow c^t$	<long text> <image>	<image> <long text>
Flickr30K	Flickr	$q^t \rightarrow c^i$ $q^i \rightarrow c^t$	<short text> <image>	<image> <short text>
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	$q^{\text{dialog}} \rightarrow c^i$	<Q ₁ ><A ₁ >...<Q _j ><A _j >	<image>
Visual Storytelling	Flickr	$(q^i \oplus q^t) \rightarrow c^i$	<text ₁ ><image ₁ >...<text _j >	<image>
MT-FIQ	FashionIQ	$(q^i \oplus q^t) \rightarrow c^i$	<image ₁ ><relative caption ₁ >... <image _j ><relative caption _j >	<image>
CC-Neg	CC3M	ITM	<image>	<text>
Sugar-Crepe	MSCOCO	ITM	<image>	<text>

Table 11. Summary of the Unseen Dataset.

Task	Dataset	Instruction
$q^t \rightarrow c^i$	VisualNews	Identify the news-related image in line with the described event. Display an image that best captures the following caption from the news. Based on the caption, provide the most fitting image for the news story. I want you to retrieve an image of this news caption.
	MSCOCO	Find me an everyday image that matches the given caption. Identify the image showcasing the described everyday scene. I want to retrieve an image of this daily life description. Show me an image that best captures the following common scene description.
	Fashion200K	Based on the following fashion description, retrieve the best matching image. Match the provided description to the correct fashion item photo. Identify the fashion image that aligns with the described product. You need to identify the image that corresponds to the fashion product description provided.
$q^t \rightarrow c^t$	WebQA	Retrieve passages from Wikipedia that provide answers to the following question. You have to find a Wikipedia paragraph that provides the answer to the question. I want to find an answer to the question. Can you find some snippets that provide evidence from Wikipedia? I'm looking for a Wikipedia snippet that answers this question.
$q^t \rightarrow (c^i, c^t)$	EDIS	Find a news image that matches the provided caption. Identify the news photo for the given caption. Can you pair this news caption with the right image? I'm looking for an image that aligns with this news caption.
	WebQA	Find a Wikipedia image that answers this question. Provide with me an image from Wikipedia to answer this question. I want to know the answer to this question. Please find the related Wikipedia image for me. You need to retrieve an evidence image from Wikipedia to address this question.
$q^i \rightarrow c^t$	VisualNews	Find a caption for the news in the given photo. Based on the shown image, retrieve an appropriate news caption. Provide a news-related caption for the displayed image. I want to know the caption for this news image.
	MSCOCO	Find an image caption describing the following everyday image. Retrieve the caption for the displayed day-to-day image. Can you find a caption talking about this daily life image? I want to locate the caption that best describes this everyday scene image.
	Fashion200K	Find a product description for the fashion item in the image. Based on the displayed image, retrieve the corresponding fashion description. Can you retrieve the description for the fashion item in the image? I want to find a matching description for the fashion item in this image.
$q^i \rightarrow c^i$	NIGHTS	Find a day-to-day image that looks similar to the provided image. Which everyday image is the most similar to the reference image? Find a daily life image that is identical to the given one. You need to identify the common scene image that aligns most with this reference image.
$(q^i, q^t) \rightarrow c^t$	OVEN	Retrieve a Wikipedia paragraph that provides an answer to the given query about the image. Determine the Wikipedia snippet that identifies the visual entity in the image. I want to find a paragraph from Wikipedia that answers my question about this image. You have to find a Wikipedia segment that identifies this image's subject.
	InfoSeek	Retrieve a Wikipedia paragraph that provides an answer to the given query about the image. Determine the Wikipedia snippet that matches the question of this image. I want to find a paragraph from Wikipedia that answers my question about this image. You have to find a Wikipedia segment that answers the question about the displayed image.
$(q^i, q^t) \rightarrow c^i$	FashionIQ	Find a fashion image that aligns with the reference image and style note. With the reference image and modification instructions, find the described fashion look. Given the reference image and design hint, identify the matching fashion image. I'm looking for a similar fashion product image with the described style changes.
	CIRR	Retrieve a day-to-day image that aligns with the modification instructions of the provided image. Pull up a common scene image like this one, but with the modifications I asked for. Can you help me find a daily image that meets the modification from the given image? I'm looking for a similar everyday image with the described changes.
$(q^i, q^t) \rightarrow (c^i, c^t)$	OVEN	Retrieve a Wikipedia image-description pair that provides evidence for the question of this image. Determine the Wikipedia image-snippet pair that clarifies the entity in this picture. I want to find an image and subject description from Wikipedia that answers my question about this image. I want to know the subject in the photo. Can you provide the relevant Wikipedia section and image?
	InfoSeek	Retrieve a Wikipedia image-description pair that provides evidence for the question of this image. Determine the Wikipedia image-snippet pair that matches my question about this image. I want to find an image and subject description from Wikipedia that answers my question about this image. I want to address the query about this picture. Please pull up a relevant Wikipedia section and image.

Table 12. Summary of the M-BEIR instructions.

E. Additional Experimental Results

E.1. Experimental Results on the M-BEIR in Global Pool Setting

The M-BEIR benchmark can be evaluated in two distinct settings: the global pool and the local pool. The key difference between these settings lies in the composition of the candidate pool, which is either constructed from all datasets collectively or restricted to the specific dataset currently under evaluation. In the main paper, we report results using the **local pool setting**. This section provides supplementary evaluation results based on the **global pool setting**.

The experimental results are presented in Table 13. Our method also demonstrates exceptional performance under the global pool setting, achieving an average of 12.5 points higher than UniIR-CLIP.

Methods	$q^t \rightarrow c^i$			$q^t \rightarrow c^t$			$q^t \rightarrow (c^i, c^t)$			$q^i \rightarrow c^t$			$q^i \rightarrow c^i$			$(q^i, q^t) \rightarrow c^t$			$(q^i, q^t) \rightarrow c^i$			$(q^i, q^t) \rightarrow (c^i, c^t)$			Avg.
	VN		COCO	F200K		WebQA	EDIS	WebQA	VN	COCO	F200K	NIGHTS	OVEN	InfoS	FIQ	CIRR	OVEN	InfoS	OVEN	InfoS	OVEN	InfoS	Avg.		
	R@5	R@5	R@10	R@5	R@5	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	R@5	R@5	R@5	R@5	R@5		
<i>Supervised - Dual Encoder</i>																									
UniIR-BLIP _{FF} [52]	23.0	75.6	25.4	79.5	50.3	79.7	21.1	88.8	27.6	33.0	38.7	19.7	28.5	51.4	57.8	27.7	45.5								
UniIR-CLIP _{SF} [52]	42.6	77.9	17.8	84.7	59.4	78.8	42.8	92.3	17.9	32.0	39.2	24.0	24.3	43.9	60.2	44.6	48.9								
<i>Supervised - LMMs</i>																									
LamRA-Ret	41.3	75.4	28.7	85.8	62.5	81.0	39.3	90.4	30.4	32.1	48.4	48.7	33.1	50.5	70.0	60.0	54.9								
LamRA	46.9	78.0	32.5	96.5	74.4	87.1	47.6	92.4	36.6	34.2	54.0	58.7	37.4	59.7	72.6	74.0	61.4								

Table 13. **Comparison with up-to-date state-of-the-arts on M-BEIR test set in global pool setting.** The first row indicates the retrieval task type: q^t for text queries, q^i for image queries, c^t for text candidates, and c^i for image candidates. Abbreviations used include VN for VisualNews, F200K for Fashion200K, InfoS for InfoSeek, and FIQ for FashionIQ. Evaluation standards follow UniIR, with FashionIQ and Fashion200K using Recall@10, while all other evaluations employ Recall@5.

E.2. Qwen2-VL Vs. Qwen2.5-VL

In Table 14 and Table 15, we present a comparative analysis of the performance between Qwen2-VL and Qwen2.5-VL. It is evident that our framework demonstrates commendable performance across both models, thereby underscoring the versatility and generalizability of our proposed framework.

E.3. Detailed Experimental Results on the Pointwise and Listwise Reranking

As shown in Table 16, we present a comprehensive comparison of LamRA-Rank’s pointwise and listwise reranking methods across a range of tasks. Both approaches demonstrate enhanced performance in various applications. However, with respect to inference time, the listwise reranking method does not consistently outperform the pointwise approach, particularly when the candidate set includes images. This discrepancy arises because current LMMs often require hundreds of tokens to represent a single image, significantly increasing the context length during listwise reranking. The extended context can adversely affect inference speed. Ongoing research [6, 27] is actively investigating methods to reduce the number of visual tokens required. We anticipate that, as LMMs continue evolving, the use of LMMs for listwise reranking will become an increasingly prevalent approach.

Methods	$q^t \rightarrow c^i$			$q^t \rightarrow c^t$			$q^t \rightarrow (c^i, c^t)$			$q^i \rightarrow c^t$			$q^i \rightarrow c^i$		$(q^i, q^t) \rightarrow c^t$		$(q^i, q^t) \rightarrow c^i$		$(q^i, q^t) \rightarrow (c^i, c^t)$		Avg.
	VN	COCO	F200K	WebQA	EDIS	WebQA	VN	COCO	F200K	NIGHTS	OVEN	InfoS	FIQ	CIRR	OVEN	InfoS	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	R@5				
<i>Qwen2-VL-7B</i>																					
LamRA-Ret	41.6	81.5	28.7	86.0	62.6	81.2	39.6	90.6	30.4	32.1	54.1	52.1	33.2	53.1	76.2	63.3	56.6				
LamRA	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				
<i>Qwen2.5-VL-7B</i>																					
LamRA-Ret	38.5	81.1	24.0	85.8	59.5	81.1	36.3	91.2	23.2	30.9	58.4	57.3	32.0	52.3	79.7	65.1	56.0				
LamRA	45.9	85.2	27.3	96.2	73.0	87.8	45.4	92.8	27.1	33.6	61.6	68.6	36.2	63.5	80.9	79.9	62.8				

Table 14. Performance comparison between Qwen2-VL and Qwen2.5-VL on the M-BEIR test set.

Methods	$q^t \rightarrow c^i$			$q^i \rightarrow c^t$			$(q^i, q^t) \rightarrow c^i$		$q^{\text{dialog}} \rightarrow c^i$	$(q^i \oplus q^t) \rightarrow c^i$		ITM	
	Share4V	Urban*	Flickr	Share4V	Urban*	Flickr	CIRCO*	GeneCIS*	VisD*	VIST	MT-FIQ*	CC-Neg	Sugar-Crepe*
	R@1	R@1	R@1	R@1	R@1	R@1	MAP@5	R@1	R@1	R@1	R@5	Acc.	Acc.
<i>Qwen2-VL-7B</i>													
LamRA-Ret	93.3	95.1	82.8	88.1	94.3	92.7	33.2	18.9	62.8	23.1	60.9	79.6	85.8
LamRA	97.9	98.8	88.1	96.5	98.0	97.6	42.8	24.8	70.9	28.6	63.9	85.9	93.5
<i>Qwen2.5-VL-7B</i>													
LamRA-Ret	93.8	95.6	82.7	92.9	96.0	93.3	34.4	19.2	64.1	22.8	60.7	78.0	86.4
LamRA	97.5	99.1	88.6	97.4	98.3	96.7	43.0	23.6	73.5	30.0	62.2	79.5	92.8

Table 15. Performance comparison between Qwen2-VL and Qwen2.5-VL on unseen dataset.

Task	LamRA-Ret	LamRA-Rank(P)		LamRA-Rank(L)	
	R@1	R@1	Time	R@1	Time
$q^t \rightarrow c^i$	29.7	33.2	0.041s	33.1	0.057s
$q^t \rightarrow c^t$	58.2	75.9	0.020s	75.9	0.010s
$q^t \rightarrow (c^i, c^t)$	41.7	50.9	0.044s	50.5	0.099s
$q^i \rightarrow c^t$	34.0	38.5	0.043s	37.9	0.012s
$(q^i, q^t) \rightarrow c^i$	18.5	24.5	0.071s	24.3	0.067s
$q^i \rightarrow c^i$	8.4	10.0	0.046s	8.5	0.048s
$(q^i, q^t) \rightarrow c^t$	30.1	37.3	0.047s	36.6	0.017s
$(q^i, q^t) \rightarrow (c^i, c^t)$	33.4	39.9	0.084s	39.5	0.085s

Table 16. Detailed Comparison of Recall@1 performance and inference costs between pointwise (LamRA-Rank(P)) and listwise (LamRA-Rank(L)) reranking methods on M-BEIR. Reranking is applied to the top-5 results. Time denotes the per-query inference time cost measured on eight A100 GPUs with a batch size of 32.

F. Exploration of RAG Applications

According to the analysis in Section 4.2 of the main paper, the LMM demonstrates significant potential to serve as a universal retriever. This raises an important question: *Can the retrieval and generative capabilities be integrated within the same LMM?*

We have conducted experiments on three Knowledge-based Visual Question Answering (KVQA) tasks. KVQA requires to first retrieve the relevant documents, then answer the associated questions with the retrieved information. Specifically, we train the retrieval and VQA tasks simultaneously using LoRA during the training process. The experimental results, presented in Table 17, indicate that the retrieval performance of our method on the three datasets surpasses the current SOTA. Furthermore, the accuracy of answering questions based on the retrieved documents is comparable to or exceeds the current SOTA. These findings demonstrate the feasibility of integrating retrieval and generative capabilities within a single LMM, which we consider a promising direction for future work.

Method	OKVQA [35]	Infoseek [8]	E-VQA [36]
<i>Retrieval (PR@5)</i>			
PreFLMR [31]	70.9	62.1	73.7
Ours	89.0	73.4	75.0
<i>VQA (ACC.)</i>			
RA-VQAv2 w/ PreFLMR [30]	61.9	30.7	54.5
Ours	64.3	28.8	56.2

Table 17. Comparison with state-of-the-art (SOTA) Methods on KVQA tasks.

G. Limitations & Future Work

While our method has demonstrated superior performance over existing models, there remain several limitations that can be further improved. (i) The current implementation of LamRA necessitates training separate sets of LoRA parameters for the retrieval and reranking tasks. In the future, we may explore strategies for jointly training these two tasks simultaneously or consider integrating retrieval training into the SFT stage. (ii) Due to constraints in context length and computation resources, the listwise reranking method of LamRA-Rank currently supports input from 2-5 candidates. Investigating strategies to enable support for a larger number of candidates is an important area for future research. (iii) The current model sizes are restricted to 2B and 7B parameters. Further exploration of LMMs for multimodal information retrieval holds significant potential for improvement. (iv) The current model may exhibit sensitivity to instructions, where variations in instructions can lead to certain fluctuations in performance. Training a model that is more robust to variations in instructions is a promising direction for future research.

H. More Qualitative Results

H.1. Successful Cases

In this section, we show additional examples of successful retrieval. As illustrated in Figure 4 through 12, our method effectively handles a diverse range of retrieval tasks.

H.2. Failure Cases

We present several failure cases in Figure 13. As observed, some failures are attributable to false-negative candidates, while others stem from inherently challenging queries that lead to retrieval failures, as exemplified in the last row.

Query Cues

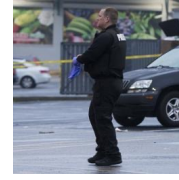
Instruction: I want you to retrieve an image of this news caption.

An officer checks a trash can near a transit stop a from police headquarters.

$$q^t \rightarrow c^i$$



Retrieved Results



...

Instruction: Find me an everyday image that matches the given caption.

A motorcycle sits parked across from a herd of livestock.

$$q^t \rightarrow c^i$$



...

Instruction: Match the provided description to the correct fashion item photo.

Brown studded zipped jacket.

$$q^t \rightarrow c^i$$



...

Figure 4. Qualitative examples on text-to-image retrieval task, where the red box marks the ground truth.

Query Cues

Instruction: Retrieve passages from Wikipedia that provide answer to the question.

What species of fruit bat is found in locations that are further south ...

$$q^t \rightarrow c^t$$



Veldkamp's dwarf epauletted fruit bat is a species of bat in the ...

Retrieved Results

Wahlberg's epauletted fruit bat is a species of megabat ...

Roost trees may be shared with other species, though roosting ...

...

Instruction: You have to find a Wikipedia that provide answer to the question.

Which bird is more likely to survive in a higher altitude ...

$$q^t \rightarrow c^t$$



The rufous-sided broadbill is a species of bird in the family ...

The rufous-sided broadbill ... Its natural habitat is subtropical ...

The rufous-sided warbling finch is a species of bird in the family ...

...

Instruction: I am looking for a Wikipedia snippet that answer this question.

Which occurred first, the last ever Daily Show hosted by Jon Stewart, or the retirement ...

$$q^t \rightarrow c^t$$



Joseph S. Benigno is an American sports radio personality. He was a ...

On February 10, 2015, Stewart announced that he would be ...

When Jon Stewart became the program's host in 1999 ...

...

Figure 5. Qualitative examples on text-to-text retrieval task, where the red text marks the ground truth.

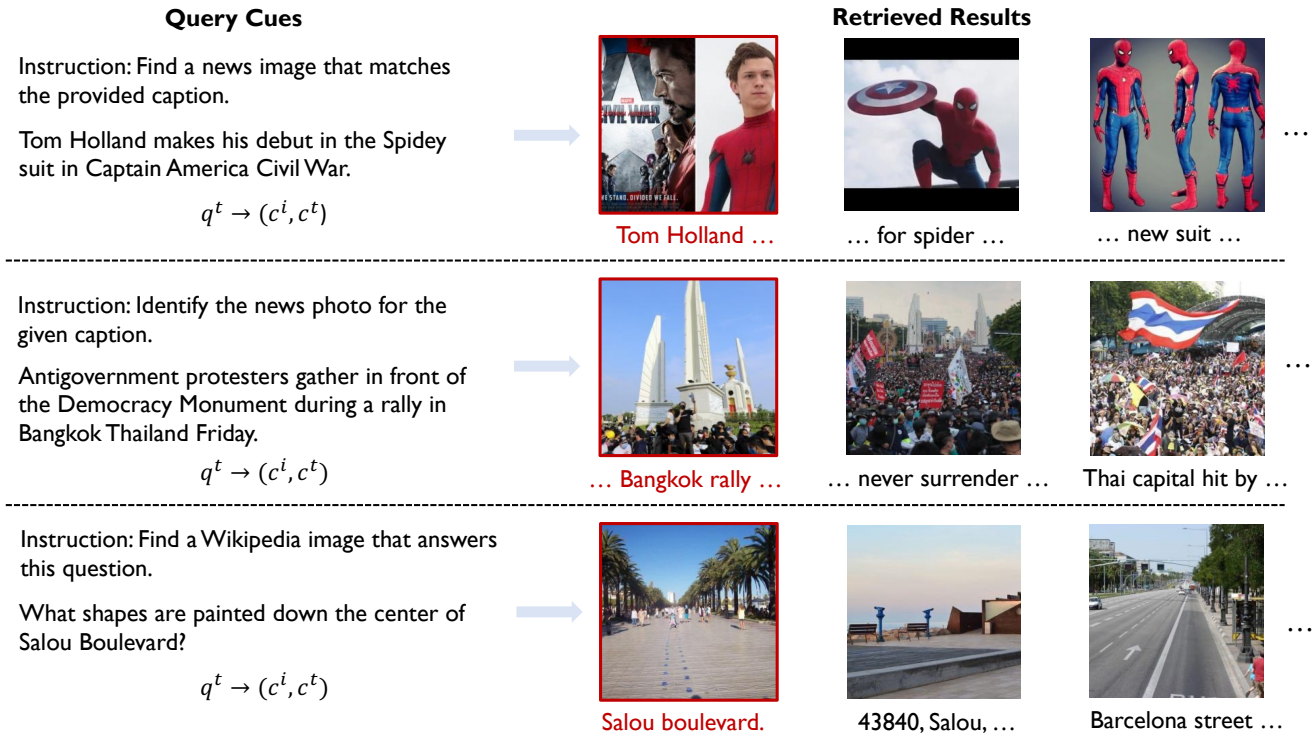


Figure 6. Qualitative examples on text-to-text-image retrieval task, with the ground truth indicated by a red box and red text.

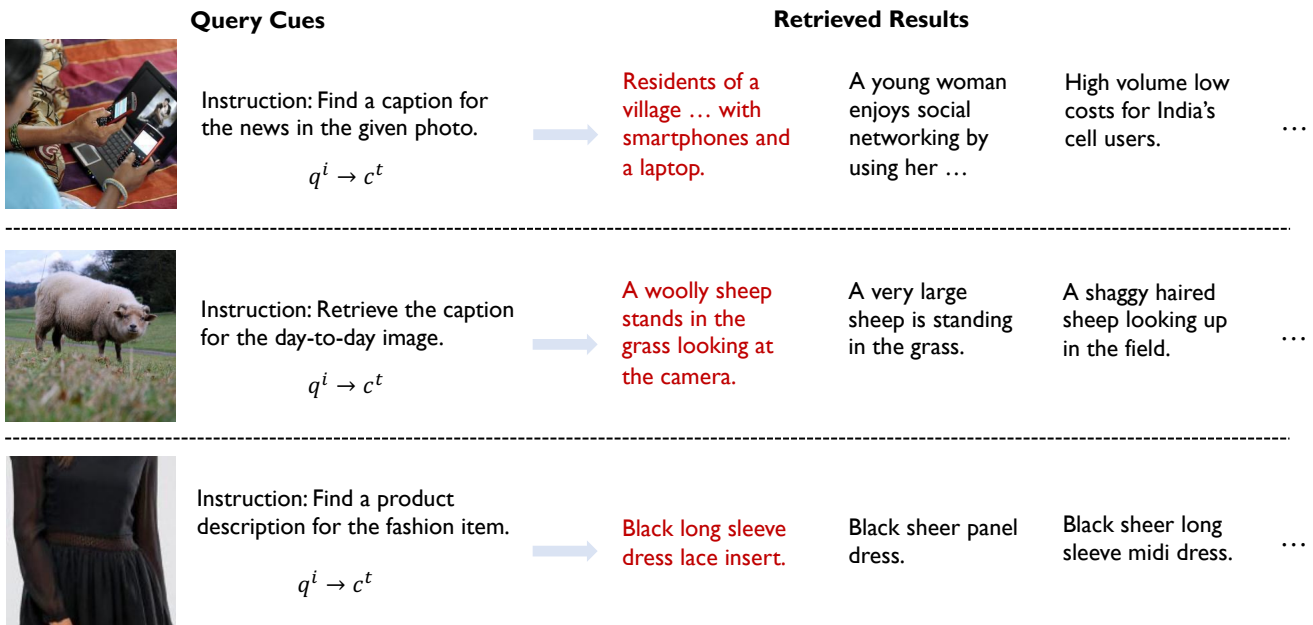


Figure 7. Qualitative examples on image-to-text retrieval task, where the red text marks the ground truth.

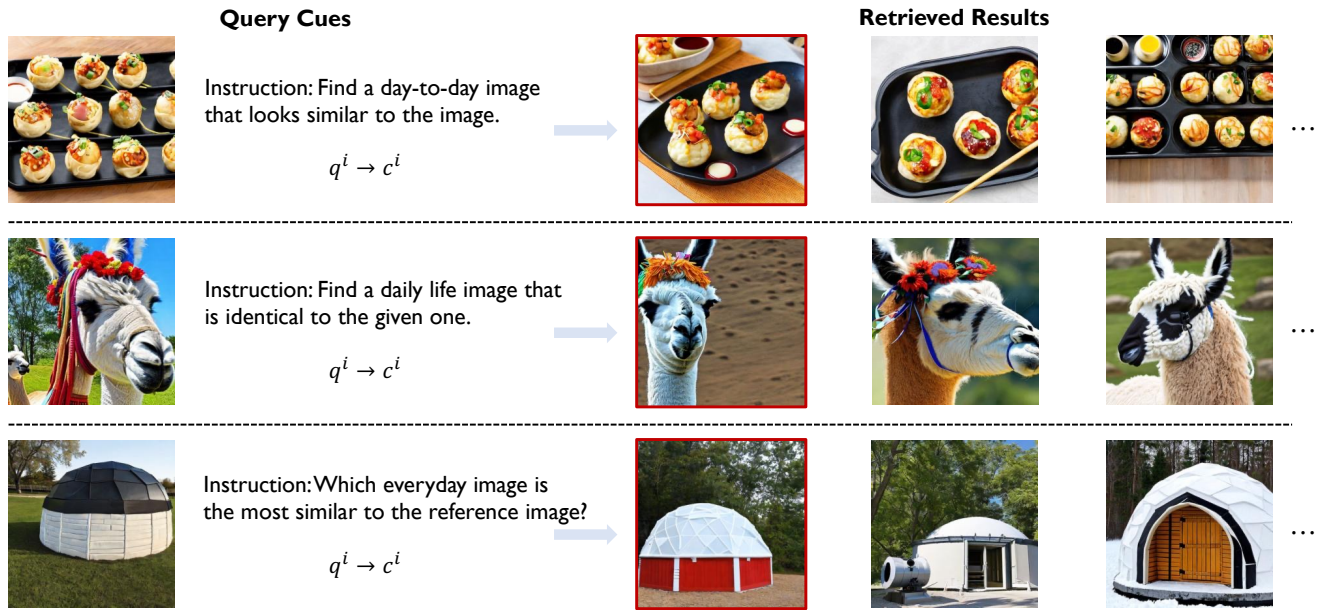


Figure 8. Qualitative examples on image-to-image retrieval task, where the red box marks the ground truth.

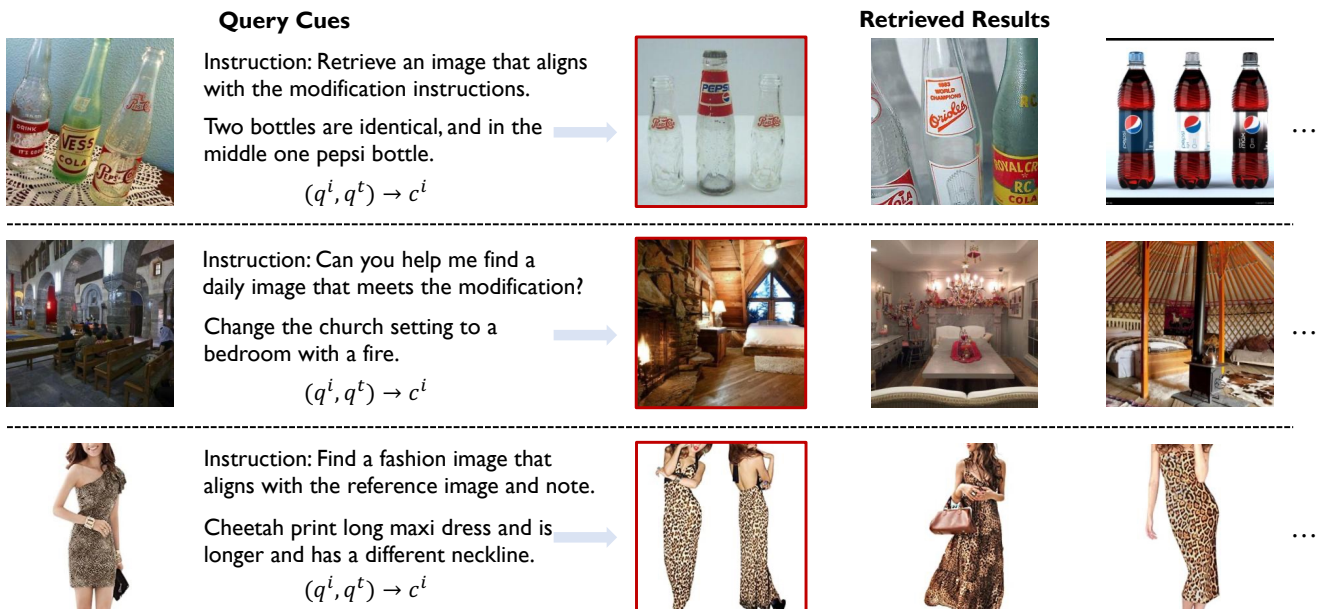


Figure 9. Qualitative examples on text-image-to-image retrieval task, where the red box marks the ground truth.




Query Cues		Retrieved Results	
	<p>Instruction: Retrieve a Wikipedia snippet that provides an answer to the query.</p> <p>What kind of plant is this? $(q^i, q^t) \rightarrow c^t$</p>	<p>Festuca. Festuca is a genus of flowering plants belonging to ...</p>	<p>Ornamental grass are grown as ornamental plants. Ornamental ...</p> <p>Festuca pallens, the blue fescue, is a species of grass. ...</p>
	<p>Instruction: Determine the Wikipedia snippet that identifies the visual entity.</p> <p>What kind of food is this? $(q^i, q^t) \rightarrow c^t$</p>	<p>Pumpkin seed. A pumpkin seed, also known in North America as ...</p>	<p>Sunflower seed. The sunflower seed is the seed of the sunflower ...</p> <p>List of culinary nuts. A culinary nut is a dry, edible fruit or seed ...</p>
	<p>Instruction: You have to find a Wikipedia segment that answers the question.</p> <p>Which city or region does this building locate in? $(q^i, q^t) \rightarrow c^t$</p>	<p>Guarda Cathedral. In Guarda Cathedral was finished around 1540. Around ...</p>	<p>Viseu Cathedral. Santos Pacheco, who was also responsible for ...</p> <p>Castle of Braganca. The ports of the Princess quarters, pretending to ...</p>

Figure 10. Qualitative examples on text-image-to-text retrieval task, where the red text marks the ground truth.












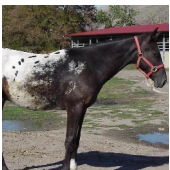
Query Cues		Retrieved Results		
	<p>Instruction: Retrieve a Wikipedia image-description pair that provides evidence ...</p> <p>Which category of food is shown in the image? $(q^i, q^t) \rightarrow (c^i, c^t)$</p>			
		Pina colada is a cocktail ...	Eggnog ...	Bombardino ...
	<p>Instruction: Determine the Wikipedia image-snippet pair that clarifies ...</p> <p>What is this building called? $(q^i, q^t) \rightarrow (c^i, c^t)$</p>			
		Stonehenge ...	Stones of Stennes...	Killin Stone Circle ...
	<p>Instruction: I want to find an image and subject description that answers ...</p> <p>What is shown in the photo? $(q^i, q^t) \rightarrow (c^i, c^t)$</p>			
		Mustang ...	Marismeño ...	Nez Perce Horse ...

Figure 11. Qualitative examples on text-image-to-text-image retrieval task, with the ground truth indicated by a red box and red text.

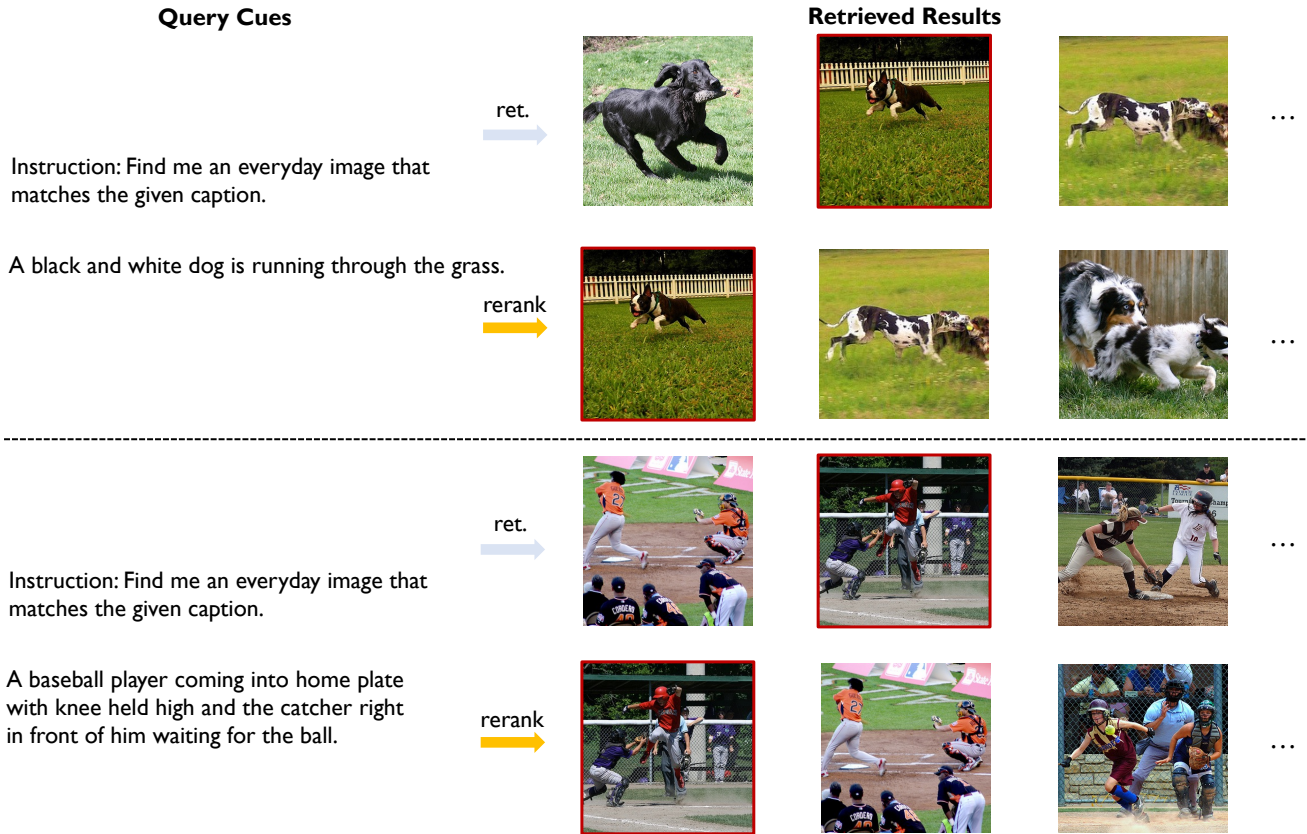


Figure 12. Some examples of retrieval followed by reranking are provided, with the red box indicating the ground truth.

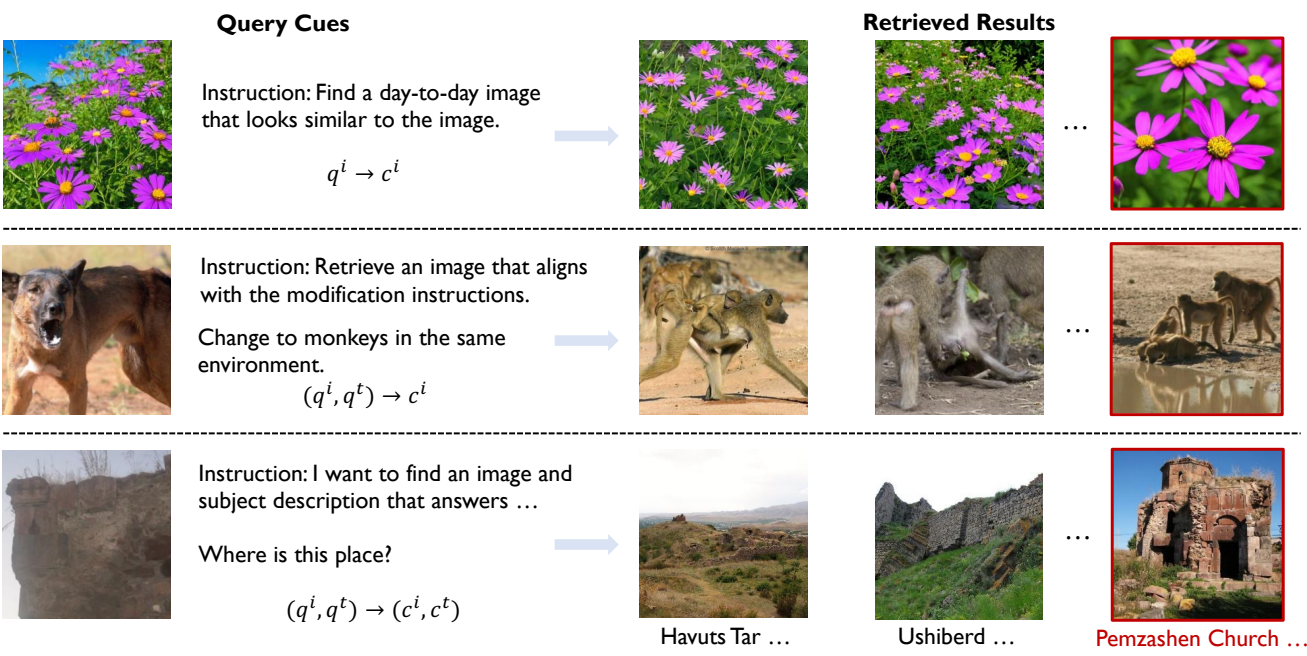


Figure 13. Some failure cases.