UNIVERSAL MULTIMODAL RETRIEVAL WITH MULTIMODAL LLMS

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ABSTRACT

State-of-the-art retrieval models typically address a straightforward search scenario, where retrieval tasks are fixed (e.g., finding a passage to answer a specific question) and only a single modality is supported for both queries and retrieved results. This paper introduces techniques for advancing information retrieval with multimodal large language models (MLLMs), enabling a broader search scenario, termed universal multimodal retrieval, where multiple modalities and diverse retrieval tasks are accommodated. To this end, we first study fine-tuning an MLLM as a bi-encoder retriever on 10 datasets with 16 retrieval tasks. Our empirical results show that the fine-tuned MLLM retriever is capable of understanding challenging queries, composed of both text and image, but underperforms a smaller CLIP retriever in cross-modal retrieval tasks due to *modality bias* from MLLMs. To address the issue, we propose modality-aware hard negative mining to mitigate the *modality bias* exhibited by MLLM retrievers. Second, we propose to continually fine-tune the universal multimodal retriever to enhance its text retrieval capability while maintaining multimodal retrieval capability. As a result, our model, UniEmb, achieves state-of-the-art performance on the multimodal retrieval benchmark M-BEIR, which spans multiple domains and tasks, while also surpassing the state-of-the-art text retrieval model, NV-Embed-v1, on MTEB retrieval benchmark. Finally, we explore to prompt the off-the-shelf MLLMs as the zero-shot reranker to refine the ranking of the candidates from the multimodal retriever. We find that through prompt-and-reranking, MLLMs can further improve multimodal retrieval when the user queries (e.g., text-image composed queries) are more complex and challenging to understand. These findings also pave the way to advance universal multimodal retrieval in the future.

1 INTRODUCTION

Information retrieval is crucial for a variety of downstream tasks, such as question answering (Kwiatkowski et al., 2019), fact-checking (Wachsmuth et al., 2018b), and retrieval-augmented generation (Lewis et al., 2020). Existing state-of-the-art retrievers often focus on narrow scenarios. For example, LLM-based retrievers (Wang et al., 2023b; Lee et al., 2024; Meng et al., 2024) are limited to text-to-text retrieval tasks, where both the query and the retrieved results are text-only. Recent work on multimodal retrieval (Zhang et al., 2024; Jiang et al., 2024) focuses on specific tasks and assumes a homogeneous document format. However, in real-world applications, documents and queries often consist of diverse formats or modalities, such as text, images, and interleaved text and images. To advance information retrieval and support broader search scenarios, this work explores the use of multimodal LLMs (MLLMs; Liu et al., 2023a; 2024; Dai et al., 2024) for universal multimodal retrieval, accommodating diverse user-instructed tasks with multimodal queries and documents, as illustrated in Figure 1.

We first explore to fine-tune MLLM-based bi-encoder retrievers with instructions as a guide (Asai et al., 2023) on 16 multimodal retrieval tasks from M-BIER (Wei et al., 2023). We find that MLLM-based retrievers significantly outperform CLIP-based retrievers in the challenging tasks, where interleaved text–image queries are given, such as visual question answering and composed image retrieval (tasks 3 and 7 in Figure 1). However, MLLM-based retrievers underperform in cross-modal retrieval tasks due to the *modality bias* from MLLMs. That is, given a text-based query with the instruction to retrieve an image (e.g., task 9 in Figure 1), an MLLM-based retriever tends to

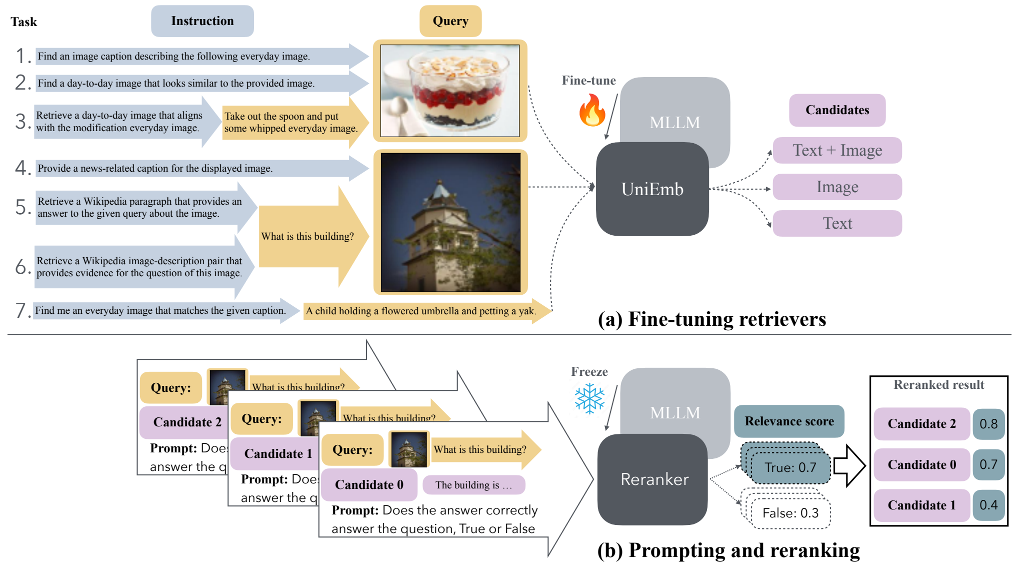

Figure 1: Illustration of universal multimodal retrieval in (a), where each task consists of a task-specific instruction and query. Both queries and candidate documents are in heterogeneous formats (i.e., text, image or interleaved text–image). In this work, we explore (a) fine-tuning MLLM-based universal multimodal retrievers and (b) prompting pre-trained MLLMs for zero-shot reranking upon retrieved candidates. In this work, we adopt LLaVa-Next (Liu et al., 2024) as our MLLM backbone.

retrieve a relevant text-only rather than documents with images, especially when we improve the MLLM-based retriever's text retrieval capability. To address the issue, we propose modality-aware hard negative mining in Section 4.1.1 and continual text-to-text retrieval fine-tuning in Section 4.1.2. Our final retriever, coined UniEmb, is the first state-of-the-art universal multimodal retriever while maintaining competitive text-to-text retrieval performance across diverse tasks.

Finally, we explore to prompt MLLMs as zero-shot rerankers. Surprisingly, we find that the zero-shot MLLM-based rerankers can further boost retrieval accuracy in the tasks, where user queries are interleaved text–image and more challenging to understand. For example, in the composed image retrieval dataset, CIRCO (Baldrati et al., 2023), the zero-shot reranker is able to refine the ranked lists and significantly boosts the accuracy (mAP@5) over 7 points from the existing state-of-the-art composed-image retriever (Zhang et al., 2024) and our universal multimodal retrievers. This finding indicates that there is still room for improvement in such challenging tasks in order to tackle universal multimodal retrieval. Also, knowledge distillation from zero-shot or few-shot MLLM-based rerankers to retrievers is a promising direction.

We summarize our contributions as follows: *i)* We present a study on applying MLLMs to universal multimodal retrieval. *ii)* We are the first to build MLLM-based universal multimodal retrievers. Notably, our UniEmb, initialized from the existing best-performing text retriever (NV-Embed-v1; Lee et al., 2024), not only achieves state-of-the-art results in universal multimodal retrieval benchmark, M-BEIR (Wei et al., 2023), but also surpasses NV-Embed-v1 in text-to-text retrieval tasks on MTEB. *iii)* We explore prompting MLLMs as zero-shot rerankers in various multimodal retrieval tasks. Surprisingly, we find that zero-shot MLLM-based rerankers are able to boost the ranking accuracy upon strong retrievers in challenging tasks involved interleaved text–image queries.

We organize the rest of the paper as follows. We discuss related work in § 2. We introduce the definition of universal multimodal retrieval in § 3 and present the proposed method in § 4. We report experiment results in § 5 and conclude the paper in § 6.

2 Related Work

Instruction-Aware Dense Representation Learning. Asai et al. (2023) is the first work to identify the implicit search intent behind each retrieval task and propose to fine-tune a retriever to learn diverse retrieval tasks with hand written task instructions. Su et al. (2023) and existing state-of-the-art LLM-based text embedding models (Wang et al., 2023a; Meng et al., 2024; Lee et al., 2024) adopt this approach to broader tasks beyond text retrieval, such as text classification and clustering. Recently, Wei et al. (2023) propose a universal multimodal retrieval dataset, M-BEIR, and find that instruction-aware dense retrieval fine-tuning is crucial to tackle universal multimodal retrieval.

Vision-Language Models for Multimodal Retrieval. With the advance of pre-trained vision-language models (Radford et al., 2021; Li et al., 2022), research focus shifts from single-modal (Bajaj et al., 2016; Fu et al., 2023) to cross-modal (Lin et al., 2014; Han et al., 2017; Liu et al., 2021a) or more complex multimodal retrieval tasks (Liu et al., 2021b; Wu et al., 2021; Baldrati et al., 2023). However, the aforementioned tasks assume homogeneous modality for queries and documents, limiting its application. Liu et al. (2023c) take one step further to tackle the retrieval scenario involving candidate pool with heterogeneous modalities but still limit to single retrieval task.

Wei et al. (2023) extend the study to a more general scenario, where retrievers are required to deal with queries, candidate pool in heterogeneous modalities and diverse retrieval tasks. However, the study is limited to CLIP-based retrievers and ignores important text-to-text retrieval tasks, such as fact checking (Wachsmuth et al., 2018b) and entity retrieval (Hasibi et al., 2017). While Koukounas et al. (2024) aim to fine-tune a CLIP-based retriever with both strong text-to-text and multimodal retrieval capability, they only consider simple multimodal retrieval tasks: image-caption retrieval (Young et al., 2014; Lin et al., 2014). Concurrent to our work, Jiang et al. (2024) propose to fine-tune MLLMs on NLI dataset (Bowman et al., 2015) and demonstrate their transferability to multimodal retrieval. In this paper, we are the first to study how to fine-tune a MLLM-based universal multimodal retriever while maintaining strong text-to-text retrieval capability. Also, we are the first to explore prompting MLLMs as zero-shot rerankers in diverse multimodal retrieval tasks.

Prompting Multimodal LLMs for Reranking. Instruction tuning has enabled large language models (LLMs) to tackle a wide range of tasks in a zero-shot setting. Building on this, prior studies have investigated prompting LLMs for text reranking (Ma et al., 2023; Sun et al., 2023; Zhuang et al., 2024b). In this work, we extend this line of research to multimodal LLMs, exploring their potential as zero-shot rerankers for multimodal tasks. Notably, Qu et al. (2024) introduce a framework using multimodal LLMs for zero-shot reranking through a generative retrieval approach (Li et al., 2024). However, their method is constrained to retrieval tasks with text-only queries. In contrast, our approach broadens the scope by prompting multimodal LLMs to handle diverse multimodal reranking tasks, accommodating queries and documents that can be text, images, or interleaved text–image formats. This generalization enables more versatile applications in multimodal ranking settings.

3 UNIVERSAL MULTIMODAL RETRIEVAL

Following the framework of Lin et al. (2021), we formulate the task of retrieval as follows: given a query q, the goal is to retrieve a ranked list of candidates $\{c_1, c_2, \cdots c_k\} \in C$ to maximize some ranking metrics, such as nDCG, where C is the collection of documents. In this work, we borrow the setting of universal multimodal retrieval from Wei et al. (2023), where user queries and candidates may consist of a text, image or interleaved text–image; i.e., $q \in \{q^{\text{txt}}, q^{\text{img}}, (q^{\text{txt}}, q^{\text{img}})\}$; $c \in \{c^{\text{txt}}, c^{\text{img}}, (c^{\text{txt}}, c^{\text{img}})\}$. Additionally, there are multiple search intents behind a search query, which can be elaborated by task-specific instructions (Asai et al., 2023). For example, in task 1 and 2 of Figure 1, given the same image as a query, the search intent is to find an image caption and similar image, respectively. Thus, in universal multimodal retrieval, given a multimodal query and task instruction $inst$, we aim to retrieve a list of candidates from a pool of multimodal documents to maximize a specified ranking metric. Note that we only consider text and image in this work while more modalities, such as audio and video can be included, which we leave for future work.

4 METHOD

In this section, we describe our approach to universal multimodal retrieval by leveraging multimodal LLMs (MLLMs), LLaVa-Next (Liu et al., 2024). In Section 4.1, we first fine-tune an MLLM-based retriever to project multimodal user queries, along with task instructions, into the same semantic space as multimodal documents, enabling k-nearest neighbor search (Johnson et al., 2021). In Section 4.2, we present our method for using MLLMs to rerank the top-k candidates retrieved by the universal multimodal retriever.

4.1 Fine-tuning Multimodal LLMs for Universal Multimodal Retrieval

We fine-tune an MLLM-based retriever parameterized by θ (i.e., η^θ) under the guidance of task-specific instructions, aiming to capture the implicit intents behind retrieval tasks. Specifically, given a user query q_i with the specified task instruction $inst_i$ and its relevant candidate, c_i^+, we minimize the contrastive loss (Gutmann & Hyvärinen, 2010):

$$L = -\frac{1}{|\mathcal{B}|}\sum_{i=1}^{|\mathcal{B}|}\log\frac{\exp\left(\eta^\theta(inst_i, q_i)\cdot\eta^\theta(c_i^+)/\tau\right)}{\sum_{c'\in\mathcal{D}}\exp(\eta^\theta(inst_i, q_i)\cdot\eta^\theta(c')/\tau)}, \quad (1)$$

where $\eta^\theta(\cdot)\in\mathbb{R}^d$ is a normalized vector and τ is the temperature. $\mathcal{D}$ ideally includes all the candidate documents. However, including all the candidate documents is not computationally feasible; thus, an effective approach to mine informative negative candidates as an alternative to $\mathcal{D}$ is the key to successful contrastive learning. In this work, we propose modality-aware negative mining for contrastive learning in the scenario of universal multimodal retrieval.

4.1.1 Modality-Aware Hard Negative Mining

Prior work (Karpukhin et al., 2020; Xiong et al., 2021; de Souza P. Moreira et al., 2024) has demonstrated that hard negative mining significantly improves representation learning for text-to-text retrieval. In the previous retrieval setting, where the corpus consists of documents with a homogeneous modality, a document is considered a hard negative if it lacks the required information but is still retrieved by a model. However, in the scenario of universal multimodal retrieval, where the corpus contains documents involving diverse modalities, the users' desired modality as specified in task instructions (i.e., text, image or interleaved text–image) should be taken into consideration. For example, as shown in Figure 1, the first and second users issue the same query along with different instructions, requiring for the documents in the format of text and image, respectively. To address this, we propose modality-aware hard negative mining to guide models in retrieving candidates that meet both the users' information needs and their preferred modality.

Specifically, we first fine-tune an MLLM-based retriever using in-batch samples as random negatives; i.e., $\mathcal{D} = (c_1^+, \cdots, c_{|\mathcal{B}|}^+)$ in Eq. (1). The candidate documents in the mini batch except for c_i^+ are considered random negatives for $(inst_i, q_i)$. The fine-tuned model is denoted M^{rand}. For each query q_i and its associated instruction $inst_i$ in the training set, we generate two types of negatives from the top-50 candidates retrieved by M^{rand}: *i*) negatives with incorrect modality (C_i^1), where the candidate ranks higher than the labeled positive but has a different modality from the desired one, and *ii*) negatives with unsatisfactory information (C_i^2), where the candidate ranks lower than k' but has the same desired modality.

Previous studies on text retrieval (Xiong et al., 2021; de Souza P. Moreira et al., 2024) have shown that setting k' to a small number may include false positives while setting k' to a large number would make the negative samples too easy. In our experiment, we set $k' = 45$ following the prior state-of-the-art text retrieval training in (Lin et al., 2023). While training, given the query q_i with the associated instruction $inst_i$, we generate a triplet, $((inst_i, q_i), c_i^+, c_i^-)$, by sampling hard negative c_i^- from either C_i^1 or C_i^2 with the same probability; i.e., $\mathcal{D} = (c_1^+, c_1^-, \cdots, c_{|\mathcal{B}|}^+, c_{|\mathcal{B}|}^-)$ in Eq. (1). Thus, in the setting of hard negative mining, the negatives mined for $(inst_i, q_i)$ include *i)* the hard negative c_i^- and *ii)* all the positives and hard negatives from other queries, which are considered random negatives. Note that the setting of hard negative mining includes two times more candidate documents than that of random negative mining under the same batch size $|\mathcal{B}|$. For a fair comparison, we adopt $2\cdot|\mathcal{B}|$ and $|\mathcal{B}|$ when fine-tuning with random and hard negatives, respectively. Figure 2 in Appendix showcases the both types of negative samples. We observe that the negatives from C_1 are the sentences semantically similar to the queries but not the user desired modality.

4.1.2 Continual Text-to-Text Retrieval Fine-Tuning

Since text-to-text retrieval remains one of the most commonly used retrieval tasks, we further fine-tune M^{hard} on diverse public text-to-text retrieval tasks, including MS MARCO (Bajaj et al., 2016), HotpotQA (Yang et al., 2018), Natural Question (Kwiatkowski et al., 2019), PAQ (Lewis et al., 2021), StackExchange (Stack-Exchange-Community, 2023), Natural Language Inference (Bowman et al., 2015), SQuAD (Rajpurkar et al., 2016), ArguAna (Wachsmuth et al., 2018a), BioASQ (Nentidis et al., 2023), FiQA (Maia et al., 2018), and FEVER (Wachsmuth et al., 2018b). As these datasets do not contain negative samples, we employ the fine-tuned LLM-based retriever (NV-Embed-v1; Lee et al., 2024) to mine hard negatives in our experiments (see de Souza P. Moreira et al. (2024) for details).

During the continual fine-tuning stage, we uniformly sample triplets from both the universal multimodal and text-to-text retrieval training data. Note that for each query q_i in universal multimodal retrieval training data, we use M^{hard} to mine the second-type hard negatives C_i^2 again. Since no first-type hard negatives (i.e., $C_i^1 = \emptyset$) are mined by M^{hard}, we retain the first-type hard negative mined by M^{rand}.

4.2 Prompting Multimodal LLMs for Reranking

Prior work (Sun et al., 2023; Jin et al., 2024) has demonstrated that instruction fine-tuned LLMs can be prompted to rerank candidates in text-to-text retrieval tasks. In this work, we directly prompt pre-trained LLaVa-Next (i.e., the same MLLM backbone for retrievers but without fine-tuning) to further rerank the top-10 retrieved candidates by universal multimodal retrievers. Following the approach in Nogueira et al. (2020), we frame the reranking task as a series of true-false questions. Specifically, given a query and retrieved candidate, we prompt LLaVa-Next to determine whether the retrieved candidate satisfies the given query by answering "True" or "False". For example, in the image caption retrieval (task 1 in Figure 1), given an image query, q^{img}, and a retrieved text-based candidate, c^{txt}, we use the below prompt: "< q^{img} >*\nCaption:*< c^{txt} >*\nDoes the above daily-life image match the caption? True or False*". Additionally, in the visual question answering retrieval (task 5 in Figure 1), given a visual question, *<Qry image><Qry text>*, and a retrieved text-based candidate, *<Doc text>*, we use the below prompt: *<Qry image>\nQuestion:<Qry text>\nAnswer:<Doc text>\nDoes the answer correctly answer the question? True or False*. We refer readers to Table 15 in Appendix for the specific prompts used in different multimodal retrieval tasks.

To compute relevance scores, we apply the `Softmax` operation over the logits of the "True" and "False" tokens, using the probability of the "True" token as the relevance score for reranking. Our preliminary study in Section 5.3.3 shows that zero-shot MLLM-based rerankers mainly improve the tasks, where queries are interleaved text–image, such as composed image retrieval and visual question answering as shown in the tasks 3, 5 and 6 of Figure 1.

5 Experiments

5.1 Datasets and Models

Multimodal Retrieval Dataset. We evaluate models' universal multimodal retrieval capability using M-BEIR dataset (Wei et al., 2023), which is constructed from 10 datasets with 16 diverse multimodal retrieval tasks across 4 domains listed in Appendix Table 10.[1] We train our models on the M-BEIR 1.1M training queries and evaluate models' effectiveness on the 190K test queries. Following the global evaluation setting of M-BEIR dataset, for each query, candidates are retrieved from a merged candidate pool of 5.6M multimodal documents spanning all 10 datasets. We report the averaged Recall@5 (R@5) as retrieval accuracy across all test queries in each dataset, except for Fashion200K and FashionIQ, where we report Recall@10 (R@10). We refer readers to Wei et al. (2023) for more details on the construction of M-BEIR dataset.

Text-to-Text Retrieval Dataset. While M-BEIR contains WebQA dataset for text-to-text retrieval evaluation, we conduct a more comprehensive text-to-text retrieval evaluation using MTEB dataset (Muennighoff et al., 2023). Specifically, we evaluate our models on 15 diverse text retrieval

[1] `https://huggingface.co/datasets/TIGER-Lab/M-BEIR`

datasets.[2] Following the established procedure, we report the averaged nDCG@10 across the 15 text retrieval datasets. Note that unlike in M-BEIR, where candidates are retrieved from a merged pool across all tasks, in the MTEB retrieval tasks, we retrieve candidates from separate corpora for each task.

Backbone Model Choices. In this work, we utilize two representative backbones of vision–language models to build universal multimodal retrievers, CLIP (Radford et al., 2021) and LLaVa-Next (Liu et al., 2024). For CLIP, we initialize from CLIP-large model and employ the best-performing modeling approach from Wei et al. (2023), denoted as CLIP_{SF}.[3] This method fuses input image and text features by separately encoding each input (query or document) image and text into separate vectors, which are then summed to create a fused vector (Liu et al., 2023c). Additionally, we report the numbers for BLIP (Li et al., 2022), which fuses text information into image encoder through cross attention. We use BLIP_{FF} from Wei et al. (2023), which is fine-tuned on M-BEIR dataset with random negative.[4]

LLaVa-Next (Liu et al., 2024) is a multimodal LLM (MLLM), which integrates a CLIP image encoder, LLM and a vision–language MLP projector to align image features to the input embedding space of the LLM. We use LLaVa-Next with Mistral 7B (Jiang et al., 2023) as the backbone LLM.[5] We experiment with three variants: (1) LLaVa-E: the $<eos>$ token embedding is used to aggregate information from the multimodal input, a method commonly employed in prior work for text retrieval (Wang et al., 2023a; Ma et al., 2024b); (2) LLaVa-P: the MLLM is prompted to summarize each multimodal query (or document) input in one word, using embedding for the last token to encode multimodal input;[6] (3) NVEmb: The LLM from LLaVa-Next is replaced by the fine-tuned LLM-based text retrieval model NV-Embed-v1 (Lee et al., 2024) while all other components (i.e., image encoder and vision–language MLP projector) remain unchanged.[7] Note that the backbone of NV-Embed-v1 is Mistral 7B. The instructions for LLaVa-E (or NVEmb) and LLaVa-P are illustrated in Appendix Table 13 and 14, respectively. For reranking experiments, we also utilize LLaVa-Next with Mistral 7B and the prompts are listed in Appendix Table 15.

Retriever Training Details. For each backbone, we start from fine-tuning M^{rand} with random negatives; i.e., $\mathcal{D} = (c_1^+, \cdots, c_{|\mathcal{B}|}^+)$ in Eq. (1). The fine-tuned model is denoted M^{rand}. For CLIP backbone, following (Wei et al., 2023), we fine-tune CLIP_{SF} for 20 epochs with learning rate $1e-5$. For LLaVa-Next backbone, we fine-tune models for 2 epochs with learning rate $1e-4$. Note that for LLaVa-Next backbone, we only fine-tune the vision–language projector and LoRA ($r = 8, \alpha = 64$) added on the language model. At the stage of fine-tuning M^{hard} with hard negatives, we mine the two types of hard negatives following Section 4.1.1 using each retriever. Then, we fine-tune each retriever using its own mined hard negatives with the same training procedure as the first stage; i.e., $\mathcal{D} = (c_1^+, c_1^-, \cdots, c_{|\mathcal{B}|}^+, c_{|\mathcal{B}|}^-)$ in Eq. (1). We fine-tune models with the batch size of 128×8 and 64×8 when using random and hard negatives, respectively. When GPU memory is not enough for the designated batch size, we use gradient accumulation. Note that when fine-tuning M^{hard}, we initialize the models using the pre-trained model rather than continuously fine-tuning M^{rand}. We denote the models fine-tuned with random and hard negatives $M^{\text{rand}}(\cdot)$ and $M^{\text{hard}}(\cdot)$, respectively. We refer readers to Appendix A.1 for more detail.

To enhance text-to-text retrieval capability, we continuously fine-tune M^{hard}(NVEmb) with learning rate $2e-5$ using the mixture of training data from M-BEIR and public text retrieval datasets aforementioned in Section 4.1.2 for 4.5K steps. The final model is coined UniEmb.

[2] The 15 retrieval datasets in MTEB are derived from public datasets in BEIR (Thakur et al., 2021), excluding BioASQ, Signal-1M, TREC-NEWS, Robust04.

[3] `https://huggingface.co/openai/clip-vit-large-patch14`

[4] `https://huggingface.co/TIGER-Lab/UniIR/blob/main/checkpoint/BLIP_FF/blip_ff_large.pth`

[5] `https://huggingface.co/llava-hf/llava-v1.6-mistral-7b-hf`

[6] We refer readers to Appendix Table 14 for the prompt and more detail from the prior work (Zhuang et al., 2024a; Jiang et al., 2024).

[7] `https://huggingface.co/nvidia/NV-Embed-v1`

Table 1: Main results on retrieval. Following Wei et al. (2023), we report R@5 for all the datasets, except for Fashion200K and FashionIQ, where we report R@10. The tasks of single-modal and multi-modal queries denote tasks 1–5 and 6–8, respecetively. For MTEB text retrieval (Muennighoff et al., 2023), we report nDCG@10 averaged from 15 retrieval tasks (detailed in Appendix Table 12).

Task	Dataset	M^{rand}					M^{hard}			UniEmb
		CLIP$_{\text{SF}}$	BLIP$_{\text{FF}}$	LLaVa-E	LLaVa-P	NVEmb	CLIP$_{\text{SF}}$	LLaVa-P	NVEmb	
1. $q^{\text{txt}} \to c^{\text{img}}$	VisualNews	43.8	23.0	33.2	34.2	32.1	42.7	39.7	41.1	41.0
	MSCOCO	72.0	75.6	69.3	70.8	64.6	69.2	73.8	72.7	71.3
	Fashion200K	16.4	25.4	13.5	13.3	10.4	19.7	17.4	18.6	17.1
2. $q^{\text{txt}} \to c^{\text{txt}}$	WebQA	83.2	79.5	88.6	88.8	92.1	88.2	93.6	95.6	95.9
3. $q^{\text{txt}} \to (c^{\text{img}}, c^{\text{txt}})$	EDIS	46.5	50.3	55.9	56.6	55.1	54.2	68.8	69.8	68.8
	WebQA	76.0	79.7	80.3	81.6	81.3	80.1	84.9	84.8	85.0
4. $q^{\text{img}} \to c^{\text{txt}}$	VisualNews	39.5	21.1	32.4	33.3	30.4	40.6	39.4	41.4	41.3
	MSCOCO	91.0	88.8	91.8	92.2	90.3	88.5	89.5	88.9	90.1
	Fashion200K	17.2	27.6	13.9	14.7	13.2	20.0	17.5	19.9	18.4
5. $q^{\text{img}} \to c^{\text{img}}$	NIGHTS	31.6	33.0	31.8	30.7	30.4	31.9	31.8	31.1	32.4
6. $(q^{\text{img}}, q^{\text{txt}}) \to c^{\text{txt}}$	OVEN	40.4	38.7	37.9	39.1	36.3	40.9	42.9	42.6	42.1
	InfoSeek	26.1	19.7	31.0	32.9	33.3	27.6	37.2	35.8	42.3
7. $(q^{\text{img}}, q^{\text{txt}}) \to c^{\text{img}}$	FashionIQ	24.2	28.5	27.4	27.0	26.0	21.7	25.8	26.6	25.7
	CIRR	43.2	51.4	48.1	45.4	45.3	38.3	49.5	50.8	50.0
8. $(q^{\text{img}}, q^{\text{txt}}) \to (c^{\text{img}}, c^{\text{txt}})$	OVEN	60.9	57.8	61.6	62.6	61.7	61.6	63.9	63.5	64.1
	InfoSeek	45.9	27.7	50.3	50.0	53.4	47.1	54.4	53.5	57.7
M-BEIR Avg.	All	47.4	45.5	47.9	48.3	47.2	48.3	51.9	52.3	**52.7**
	Single-modal Qry	51.7	50.4	51.0	51.6	50.0	53.5	55.6	**56.4**	56.1
	Multi-modal Qry	40.1	37.3	42.7	42.8	42.7	39.5	45.6	45.5	**47.0**
MTEB Text Retieval Avg.		-	-	-	40.8	51.6	-	46.4	49.7	**60.3***

* ranked top-5 on MTEB retrieval task leaderboard. NVEmb (Lee et al., 2024) scores 59.36 in MTEB retrieval task.

5.2 Main Results

Universal Multimodal Retrieval. Table 1 reports the retrieval accuracy of different retrievers. In M-BEIR evaluation, we observe that when fine-tuning with random negatives, LLaVa-P achieves the highest overall retrieval effectiveness. This result indicates that LLaVa-P effectively aggregates multimodal input information into a single word representation. While MLLM-based retrievers outperform CLIP$_{\text{SF}}$ on tasks involving multi-modal queries, they still lag behind CLIP$_{\text{SF}}$ on tasks with single-modal queries, especially in cross-modality retrieval; i.e., tasks 1 and 4. In addition, NVEmb reaches the best text-to-text retrieval accuracy on WebQA task2. It is worth noting that although BLIP$_{\text{FF}}$ performs the worst overall, it demonstrates notably strong performance in the fashion domain (e.g., Fashion200K and FashionIQ) but worse in News domain (e.g., VisualNews), likely due to differences in the text–image pairs used for pre-training between CLIP and BLIP.

Observing from the models fine-tuned with hard negatives, MLLM-based retrievers show significant retrieval accuracy improvements, particularly in tasks involving single-modal queries. On the other hand, CLIP$_{\text{SF}}$ does not show similar improvement. This could attribute to the fact that CLIP has been well pre-trained for cross-modal retrieval whereas MLLM-based retrievers, fine-tuned with contrastive learning objective for only 2 epochs, may still be underfitting. Fine-tuning with hard negatives accelerates contrastive learning of MLLM-based retrievers.

Table 2: Retrieval analysis on MSCOCO. M.A.@1 denotes the modality accuracy of the top-1 candidate. More results of M.A.@1 are reported in Appendix Table 11.

Task	Metric	M^{rand}				M^{hard}		
		CLIP$_{\text{SF}}$	LLaVa-E	LLaVa-P	NVEmb	CLIP$_{\text{SF}}$	LLaVa-P	NVEmb
1.	R@1	42.6	33.9	41.7	14.1	45.8	50.7	49.8
	R@5	72.0	69.3	70.8	64.6	69.2	73.8	72.7
	M.A.@1	92.6	79.9	91.0	42.1	98.3	100.0	100.0
4.	R@1	72.3	73.0	73.4	69.3	63.8	72.7	72.4
	R@5	91.0	91.8	92.2	90.3	88.5	89.5	88.9
	M.A.@1	98.7	99.2	99.8	96.3	94.2	100.0	100.0

Table 2 reveals another factor contributing to the lower retrieval accuracy of MLLM-based retrievers for single-modal queries: text retrieval bias. This issue is particularly obvious for NVEmb. We compare models' retrieval accuracy on text–image and image–text retrieval (tasks 1 and 4) on MSCOCO. The comparison shows that M^{rand}(LLaVa-E) and M^{rand}(NVEmb) exhibit significant lower modality accuracy (M.A.@1) than M^{rand}(CLIP$_{\text{SF}}$) in the text-to-image retrieval task. Most erroneous top-1 retrieved candidates from the MLLM-based retrievers are relevant texts rather than images (see Appendix

Table 3: Experiments of zero-shot reranking on tasks 6–8 from M-BEIR.

Task	Dataset	M^{hard} (NVEmb) Retrieval	M^{hard} (NVEmb) Rerank	UniEmb Retrieval	UniEmb Rerank
6.	OVEN	42.6	44.3	42.1	43.5
	InfoSeek	35.8	37.1	42.3	43.1
7.	FashionIQ	26.6	20.0	25.7	19.0
	CIRR	50.8	48.6	50.0	48.2
8.	OVEN	63.5	65.8	64.1	65.9
	InfoSeek	53.5	54.5	57.7	57.3

Table 4: Experiments of zero-shot reranking on composed image retrieval task, CIRCO (Baldrati et al., 2023).

Retrieval Model	Retrieval	Rerank
MagicLens (Zhang et al., 2024)	24.9	32.4
E5-V (Jiang et al., 2024)	19.1	31.0
M^{rand}(CLIP$_{\text{SF}}$)	12.7	31.6
BLIP$_{\text{FF}}$ (Wei et al., 2023)	26.6	36.1
M^{hard} (LLaVa-P)	29.0	37.9
M^{hard} (NVEmb)	32.4	40.9
UniEmb	32.3	39.9

Figure 2). This result indicates that MLLM-based retrievers have a bias toward relevant text rather than images. This issue can be mitigated by our proposed modality-aware hard negative mining.

Finally, we observe that M^{hard}(NVEmb) degrades in text-to-text retrieval tasks compared to M^{rand}(NVEmb) but still outperforms M^{hard}(LLaVa-P) (i.e., WebQA task 2 and MTEB).[8] However, compared to the original NVEmb (Lee et al., 2024), the score on MTEB retrieval tasks drops almost 10 points. After continual fine-tuning (detailed in Section 4.1.2), the final model, UniEmb, not only surpasses NVEmb in MTEB but also maintains strong multimodal retrieval capability. We attribute the improvement in text-to-text retrieval to the effective hard negatives mined by NV-Embed-v1 aforementioned in Section 4.1.2. Notably, continual fine-tuning significantly enhances multimodal retrieval performance in InfoSeek (col 8 vs 7 in Table 1), highlighting its effectiveness in improving the model's ability to handle knowledge-intensive multimodal retrieval tasks.

Zero-Shot Reranking. Table 3 reports the reranked results from the top-10 retrieved candidates of M^{hard}(NVEmb) and UniEmb on the tasks involving multi-modal queries. We observe accuracy improvements in visual question answering retrieval tasks (i.e., OVEN and InfoSeek), but no improvement on composed image retrieval tasks (i.e., FashionIQ and CIRR). However, as shown in the Appendix Table 10, compared to OVEN and InfoSeek, FashionIQ and CIRR only have one relevance label per query. We hypothesize that there may be additional relevant positives that are not labeled. We refer readers to Appendix Figure 3 for case studies.

We conduct experiments on the composed image retrieval dataset with high-quality human annotations, CIRCO (Baldrati et al., 2023) validation set, consisting of 219 queries and 123K candidates in total. On average, 4.2 positives are labeled by humans per query. Table 4 reports mAP@5 for various retrievers and their reranking results. We directly use the models and code provided by the authors to get the results of MagicLens (Zhang et al., 2024)[9] and E5-V (Jiang et al., 2024)[10] retrievers. For our retrievers fine-tuned on M-BEIR, M^{rand}(CLIP$_{\text{SF}}$), M^{hard}(LLaVa-P), M^{hard}(NVEmb) and UniEmb, we directly use the same instructions as CIRR in M-BEIR for query encoding. We first observe that our MLLM-based retrievers outperform MagicLens and E5-V. More importantly, reranking upon the top-10 retrieved candidates from the different retrievers significantly improves mAP@5 by at least 7 points. The result demonstrates the effectiveness of prompting an MLLM as a reranker in composed image retrieval tasks.

5.3 Ablation Studies

5.3.1 Is Fine-Tuning with Instruction Necessary?

We fine-tune NVEmb with random negatives on the M-BEIR subtasks listed in Table 5 and evaluate models' retrieval accuracy on the development queries from each subtask. Note that, for simplicity, we encode only the corpus specific to each dataset, containing documents of the targeted modality. For example, when evaluating retrieval accuracy for VisualNews task 1, we encode the 542K images from VisualNews (see Appendix Table 10) as the index rather than the entire 5.6M documents from

[8] We hypothesize that the degradation of M^{hard}(NVEmb) in text-to-text retrieval tasks comes from the mitigation of text retrieval bias after fine-tuning with modality-aware hard negatives.

[9] https://github.com/google-deepmind/magiclens

[10] https://github.com/kongds/E5-V

Table 5: Ablation study on fine-tuning NVEmb w/o (✗) and w/ (✓) instructions.

Task	Dataset	zero-shot				fine-tuning	
		CLIP	LLaVa-P	NVEmb		NVEmb	
		✗	✗	✗	✓	✗	✓
1. $q^{\text{txt}} \rightarrow c^{\text{img}}$	VisualNews	40.9	11.7	15.3	17.4	33.1	38.7
	MSCOCO	55.4	58.1	64.2	59.9	76.7	82.8
	Fashion200K	8.9	2.4	4.2	3.2	12.3	15.6
4. $q^{\text{img}} \rightarrow c^{\text{txt}}$	VisualNews	42.0	6.3	6.5	5.9	29.3	37.2
	MSCOCO	79.6	66.8	70.6	68.2	88.9	93.0
	Fashion200K	7.7	2.9	4.0	3.6	12.0	16.8
5. $q^{\text{img}} \rightarrow c^{\text{img}}$	NIGHTS	25.4	28.4	29.3	27.7	31.6	30.9

M-BEIR. We also report CLIP and LLaVa-P (w/o instruction) zero-shot retrieval effectiveness as a reference point.[11]

From Table 5, we observe that NVEmb, as a zero-shot MLLM-based retriever, outperforms LLaVa-P and even competes CLIP in the tasks in Miscellaneous domain (i.e., MSCOCO and NIGHTS). This result indicates that a fine-tuned MLLM-based text retriever is capable to perform multimodal retrieval tasks (same finding in (Jiang et al., 2024)). Although incorporating task instructions with queries degrades the retrieval effectiveness (col 4 vs 3), the model fine-tuned with instructions significantly outperforms the one fine-tuned without instructions (col 6 vs 5). This indicates that task instructions can help elicit models' task- or domain-specific knowledge for diverse multimodal retrieval tasks.

5.3.2 Effectiveness of Continual text-to-text retrieval Fine-Tuning

In this section, we study the best strategy to enhance models' capabilities in both multimodal and text-to-text retrieval. We begin by fine-tuning NVEmb on both training data for universal multimodal retrieval and text-to-text retrieval (detailed in Section 4.1.2) for 2K steps. As shown in Table 6, joint fine-tuning for both tasks allows the model to maintain its text retrieval capability (row 3 vs 1), though it results in a drop of over 2 points in multimodal retrieval accuracy (row 3 vs 2). In contrast, consciously fine-tuning M^{hard}(NVEmb) for addition 2K steps significantly boosts its text-to-text retrieval capability with a slight drop of 0.8 points in multimodal retrieval (row 5 vs 4).[12] This experiment shows that continuously fine-tuning a multimodal retriever to enhance its text-to-text retrieval is more effective than fine-tuning a retriever on all the retrieval tasks simultaneously. This finding suggests that a more optimized curriculum learning strategy (Bengio et al., 2009) could further improve performance in universal multimodal retrieval, a direction we leave for future work.

Table 6: Abaltion study to enhance model's text-to-text retrieval capability.

Initialization	Training data		M-BEIR$*$	BEIR$*$
	Multimodal	Text-to-Text		
NVEmb	-	-	-	62.9
	✓	✗	54.3	51.7
	✓	✓	52.2	63.0
M^{hard} (NVEmb)	-	-	56.4	51.7
	✓	✓	55.6	63.1

$*$ For M-BEIR, we only evaluate on the tasks with single-modality queries (i.e., tasks 1–5) while for BIER, we evaluate on 7 tasks: ArguAna, FiQA, NFCorpus, Quora, SCIDOCS, SciFact and TREC-COVID.

5.3.3 Study on Prompting MLLMs for Reranking

In this section, we study the reranking effectiveness of MLLMs on all the tasks in M-BEIR dataset. Specifically, for each development query, we rerank the top-10 retrieved candidates from M^{rand}(CLIP$_{\text{SF}}$). As shown in Table 7, prompting LLaVa-Next for reranking further boosts the ranking accuracy in tasks 6–8, which involve multimodal queries (except for FashionIQ). However, the reranking degrades accuracy in tasks 1–5 which involve single-modal queries (except for WebQA

[11] We follow Jiang et al. (2024) to prompt LLaVa-Next to output one word embedding for each query and document. i.e., <txt>\nSummary above sentence in one word:; <img>\nSummary above image in one word:.

[12] Note that UniEmb in Table 1 is fine-tuned with the same condition with total 4.5K steps.

Table 7: Reranking study on top-10 retrieved candidates from $M^{\text{rand}}(\text{CLIP}_{\text{SF}})$ on M-BEIR development query set.

Task	**Dataset**	Retrieval	Rerank 7B	Rerank 34B
1. $q^{\text{txt}} \to c^{\text{img}}$	VisualNews	44.2	38.8	42.5
	MSCOCO	72.0	68.0	69.7
	Fashion200K	17.8	14.7	15.6
2. $q^{\text{txt}} \to c^{\text{txt}}$	WebQA	78.2	79.2	82.9
3. $q^{\text{txt}} \to (c^{\text{img}}, c^{\text{txt}})$	EDIS	48.3	46.5	47.4
	WebQA	78.2	67.7	68.3
4. $q^{\text{img}} \to c^{\text{txt}}$	VisualNews	37.4	29.3	29.8
	MSCOCO	91.0	87.3	89.0
	Fashion200K	17.3	9.9	12.0
5. $q^{\text{img}} \to c^{\text{img}}$	NIGHTS	32.1	29.4	32.7
6. $(q^{\text{img}}, q^{\text{txt}}) \to c^{\text{txt}}$	OVEN	40.6	43.2	43.7
	InfoSeek	25.6	28.4	29.0
7. $(q^{\text{img}}, q^{\text{txt}}) \to c^{\text{img}}$	FashionIQ	32.5	21.5	23.4
	CIRR	52.4	54.1	54.2
8. $(q^{\text{img}}, q^{\text{txt}}) \to (c^{\text{img}}, c^{\text{txt}})$	OVEN	60.6	63.8	63.7
	InfoSeek	45.3	48.7	50.5

task 2). This trend persists even after scaling the reranker from 7B to 34B (col 3, 2 vs 1).[13] We hypothesize that MLLM rerankers, as a more robust cross-encoder architecture compared to a bi-encoder retriever, excel at challenging tasks involving multimodal queries, even in a zero-shot manner. However, zero-shot rerankers fail to leverage task- or domain-specific knowledge, which limits their performance on relatively simple tasks involving single-modal queries. The relevance signals between queries and documents in the News, Miscellaneous, and Fashion domains can vary significantly. Thus, optimizing prompts or instruction tuning for MLLMs to better capture domain- or task-specific knowledge offers a promising direction for improving reranking accuracy.

6 Conclusion and Future Work

In this paper, we present techniques for advancing information retrieval with multimodal large language models (MLLMs). We first study fine-tuning MLLM-based retrievers to tackle a general information retrieval scenario: universal multimodal retrieval, where models are required to deal with diverse retrieval tasks, multimodal queries and documents. Our study shows that MLLM-based retrievers exhibit *modality bias* in cross-modal retrieval tasks compared to CLIP-based retrievers. To address the issue, we propose modality-aware hard negative mining, which significantly improves our MLLM-based retrievers' accuracy by 5 points in M-BEIR dataset, a benchmark for universal multimodal retrieval. Additionally, with our proposed continual fine-tuning, our MLLM-based retriever, UniEmb, is the first model to yield state-of-the-art retrieval accuracy in universal multimodal retrieval tasks while maintaining strong text-to-text retrieval capability (ranked top-5 on MTEB retrieval task leaderboard). Finally, we explore to prompt MLLMs as reranker in M-BEIR tasks. We find that MLLMs can be used as zero-shot rerankers to further boost retrieval accuracy in the challenging tasks, which require the understanding of multimodal queries, such as visual question answering and composed image retrieval. For example, our zero-shot MLLM-based reranker improves the retrieval accuracy upon the state-of-the-art retrievers by over 7 points in CIRCO.

Our work also suggests two promising future directions: (1) Distilling our MLLM-based retriever, UniEmb, to smaller multimodal retrievers, such as CLIP (Radford et al., 2021) or BLIP (Li et al., 2022), to trade better retrieval efficiency (see the efficiency comparisons in Appendix A.2); (2) Distilling MLLM-based reranker to retriever to further improve its retrieval capability in tasks involving multimodal queries. The other directions, such as iterative retrieval with relevance feedback (Han et al., 2024) and generative retrieval (Qu et al., 2024), are also worth exploring in the tasks of universal multimodal retrieval. In addition, recent work (Ma et al., 2024a; Faysse et al., 2024) has demonstrated that MLLMs can be fine-tuned to tackle visual document retrieval tasks, which could be integrated into universal multimodal retrieval.

[13] We use `llava-hf/llava-v1.6-34b-hf` in the experiment.

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A Appendix

A.1 Implementation Details

We implement our training and inference using Tevatron (Gao et al., 2023). For CLIP-based retrievers, we follow all the settings from Wei et al. (2023). For MLLM-based retriever, we fine-tune models with DeepSpeed Zero 2 (Rajbhandari et al., 2020) and gradient checkpointing. During fine-tuning on M-BEIR training data, we set maximum length for queries and documents to 128. While continual fine-tuning on both M-BEIR and text-to-text retrieval training data, we set maximum length for queries and documents to 128 and 512, respectively. All fine-tuning are conducted on 8×80GB A100 GPUs. Note that image input only occupies single token length after being tokenized; however, each image will be converted to multiple image tokens. Thus, the actual input length to MLLM is longer than the maximum length we set. To speed fine-tuning and inference for MLLM-based retrievers, we only use the global image patches, which occupy 576 (24×24) image tokens.

A.2 Retrieval Efficiency Comparisons

Table 8: Retrieval efficiency comparisons on M-BEIR dataset.

	Storage (GBs)	Latency (ms)	
Retriever	Index	Encoding (1^{st} / 50^{th} / 99^{th} perc.)	Vector search
CLIP_{SF}	16	26 / 27 / 39	6
BLIP_{FF}	16	37 / 38 / 44	6
UniEmb	86	81 / 194 / 203	33

Table 8 compares the retrieval efficiency in terms of storage and latency for different retrievers adopted in the paper. We measure the index storage required for the 5.6M document from the M-BEIR datatset. As for retrieval latency, we measure the latencies of query encoding and vector search. For query latency, we randomly sample 100 queries from each test query pool in the 16 M-BEIR tasks and measure per query encoding and vector search latency with a batch size of 1. Since query encoding latency is varied with query length, we report the latency at 1^{th}, 50^{th} and 99^{th} percentiles. The latency is masured using one thread on a Linux machine with a 2.2 GHz Intel Xeon Silver 4210 CPU and NVIDIA RTX A6000 GPUs, respectively. Note that we perform brute-force search on the sharded index with two GPUs since the full index from UniEmb cannot be loaded into a single A6000 GPU.

A.3 Baseline Reproducing

Since we implement our fine-tuning and inference following the setting from Wei et al. (2023), our fine-tuned $M^{\text{rand}}(\text{CLIP}_{\text{SF}})$ should be equal to $\text{CLIP}_{\text{SF}}$from Wei et al. (2023). In Table 9, we compare the results from our fine-tuned $M^{\text{rand}}(\text{CLIP}_{\text{SF}})$ and the checkpoint provided by the authors.[14]

Table 9: A comparison of $M^{\text{rand}}(\text{CLIP}_{\text{SF}})$ fine-tuned by us and Wei et al. (2023).

Task	**Dataset**	$M^{\text{rand}}(\text{CLIP}_{\text{SF}})$	
		Wei et al. (2023)	Ours
M-BEIR Avg.	All	47.4	47.4
	Single-modal Qry	52.5	51.7
	multi-modal Qry	39.1	40.1

[14]https://huggingface.co/TIGER-Lab/UniIR/blob/main/checkpoint/CLIP_SF/clip_sf_large.pth

Table 10: M-BEIR dataset statistics.

Task	Dataset	Domain	# Query			# Relevance / Query			# Candid.
			Train	Dev	Test	Train	Dev	Test	
1. $q^{\text{txt}} \to c^{\text{img}}$	VisualNews (Liu et al., 2021a)	News	99K	20K	20K	1.0	1.0	1.0	542K
	MSCOCO (Lin et al., 2014)	Misc.	100K	24.8K	24.8K	1.0	1.0	1.0	5K
	Fashion200K (Han et al., 2017)	Fashion	15K	1.7K	1.7K	3.3	3.1	2.8	201K
2. $q^{\text{txt}} \to c^{\text{txt}}$	WebQA (Chang et al., 2022)	Wiki	16K	1.7K	2.4K	2.0	2.0	2.0	544K
3. $q^{\text{txt}} \to (c^{\text{img}}, c^{\text{txt}})$	EDIS (Liu et al., 2023b)	News	26K	3.2K	3.2K	2.6	2.6	2.6	1M
	WebQA (Chang et al., 2022)	Wiki	16K	1.7K	2.4K	1.4	1.4	1.4	544K
4. $q^{\text{img}} \to c^{\text{txt}}$	VisualNews (Liu et al., 2021a)	News	100K	20K	20K	1.0	1.0	1.0	537K
	MSCOCO (Lin et al., 2014)	Misc.	113K	5K	5K	5.0	5.0	5.0	25K
	Fashion200K (Han et al., 2017)	Fashion	15K	4.8K	4.8K	1.0	1.0	1.0	61K
5. $q^{\text{img}} \to c^{\text{img}}$	NIGHTS (Fu et al., 2023)	Misc.	16K	2K	2K	1.0	1.0	1.0	40K
6. $(q^{\text{img}}, q^{\text{txt}}) \to c^{\text{txt}}$	OVEN (Hu et al., 2023)	Wiki	150K	50K	50K	8.5	10.0	9.9	676K
	InfoSeek (Chen et al., 2023)	Wiki	141K	11K	11K	6.8	6.7	6.5	611K
7. $(q^{\text{img}}, q^{\text{txt}}) \to c^{\text{img}}$	FashionIQ (Wu et al., 2021)	Fashion	16K	2K	6K	1.0	1.0	1.0	74K
	CIRR (Liu et al., 2021b)	Misc.	26K	2K	4K	1.0	1.0	1.0	21K
8. $(q^{\text{img}}, q^{\text{txt}}) \to (c^{\text{img}}, c^{\text{txt}})$	OVEN (Hu et al., 2023)	Wiki	157K	14.7K	14.7K	17.8	17.5	17.7	335K
	InfoSeek (Chen et al., 2023)	Wiki	143K	17.6K	17.6K	9.1	7.5	7.5	481K
M-BEIR (Wei et al., 2023)		4 domains	1.1M	182K	190K	6.5	5.9	5.7	5.6M

Table 11: Retrieval models' Top-1 modality accuracy (M.A.@1). We can observe that most MLLM-based retrievers suffer from low modality accuracy on Task 1 due to modality bias, especially for NVEmb with superior text retrieval capability. The issue can be resolved with our modality-aware hard negative mining. Even though UniEmb exhibits strong text-retrieval effectiveness, no modality bias issue is observed.

Task	Dataset	M^{rand}				M^{hard}			UniEmb
		CLIP$_{\text{SF}}$	LLaVa-E	LLaVa-P	NVEmb	CLIP$_{\text{SF}}$	LLaVa-P	NVEmb	
1. $q^{\text{txt}} \to c^{\text{img}}$	VisualNews	0.97	0.82	0.94	0.76	0.98	1.00	1.00	1.00
	MSCOCO	0.93	0.80	0.91	0.42	0.98	0.99	1.00	1.00
	Fashion200K	0.97	1.00	1.00	0.78	1.00	1.00	1.00	0.99
2. $q^{\text{txt}} \to c^{\text{txt}}$	WebQA	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00
3. $q^{\text{txt}} \to (c^{\text{img}}, c^{\text{txt}})$	EDIS	0.94	1.00	0.96	1.00	0.90	0.99	1.00	0.99
	WebQA	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
4. $q^{\text{img}} \to c^{\text{txt}}$	VisualNews	0.33	0.90	0.84	0.84	0.97	1.00	1.00	1.00
	MSCOCO	0.99	0.99	1.00	0.96	0.94	0.99	1.00	0.99
	Fashion200K	0.99	0.99	1.00	0.99	1.00	1.00	1.00	1.00
5. $q^{\text{img}} \to c^{\text{img}}$	NIGHTS	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00
6. $(q^{\text{img}}, q^{\text{txt}}) \to c^{\text{txt}}$	OVEN	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99
	InfoSeek	0.94	1.00	1.00	1.00	0.97	0.99	1.00	0.99
7. $(q^{\text{img}}, q^{\text{txt}}) \to c^{\text{img}}$	FashionIQ	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	CIRR	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00
8. $(q^{\text{img}}, q^{\text{txt}}) \to (c^{\text{img}}, c^{\text{txt}})$	OVEN	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	InfoSeek	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table 12: Detailed results on MTEB retrieval tasks.

Model	AA	CF	CQ	DB	Fe	FQ	HQ	MS	NF	NQ	Qu	SD	SF	T2	TC	Avg.
NVEmb (Lee et al., 2024)	68.2	34.7	50.5	48.3	87.8	63.1	79.9	46.5	38.0	71.2	89.2	20.2	78.4	28.4	85.9	59.4
M^{Rand} (LLaVa-P)	48.4	12.9	34.0	34.0	52.2	33.7	50.1	12.3	30.4	36.5	83.8	17.9	72.3	73.4	19.6	40.8
M^{Rand} (NVEmb)	51.5	23.7	43.6	44.9	78.6	46.5	70.2	32.5	38.9	54.1	87.5	20.3	74.5	83.4	23.4	51.6
M^{hard} (LLaVa-P)	38.6	20.4	38.0	36.9	78.1	36.2	61.2	23.2	35.1	45.1	86.1	19.2	72.7	27.7	77.2	46.4
M^{hard} (NVEmb)	37.2	30.8	44.0	44.3	86.4	45.5	70.6	34.2	37.4	49.7	86.9	13.9	64.1	23.5	76.7	49.7
UniEmb	69.0	39.3	49.7	50.6	92.6	60.1	81.4	45.1	40.5	70.6	88.7	21.8	78.3	31.1	85.4	60.3

* Dataset Legend: AA=ArguAna, CF=Climate-FEVER, CQ=CQADupStack, DB=DBPedia, Fe=FEVER, FQ=FiQA, HQ=HotpotQA, MS=MSMARCO, NF=NFCorpus, NQ=NaturalQuestions, Qu=Quora, SD=SCIDOCS, SF=SciFact, T2=Touché-2020, TC=TREC-COVID

Table 13: NVEmb (and LLaVa-E) instructions for M-BEIR and MTEB, which are from Wei et al. (2023) and Lee et al. (2024), respectively. For all the candidates, we use the prompt to generate the embedding: $< c^{img} >$\n$< c^{txt} >$<eos>.

Task	Dataset	M-BEIR task instruction
1. $q^{\text{txt}} \to c^{\text{img}}$	VisualNews	*Identify the news-related image in line with the described event.\nQuery:* $< q^{txt} >$*<eos>*
	MSCOCO	*Find me an everyday image that matches the given caption.\nQuery:* $< q^{txt} >$*<eos>*
	Fashion200K	*Based on the following fashion description, retrieve the best matching image.\nQuery:* $< q^{txt} >$*<eos>*
2. $q^{\text{txt}} \to c^{\text{txt}}$	WebQA	*Retrieve passages from Wikipedia that provide answers to the following question.\nQuery:* $< q^{txt} >$*<eos>*
3. $q^{\text{txt}} \to (c^{\text{img}}, c^{\text{txt}})$	EDIS	*Find a news image that matches the provided caption.\nQuery:* $< q^{txt} >$*<eos>*
	WebQA	*Find a Wikipedia image that answers this question.\nQuery:* $< q^{txt} >$*<eos>*
4. $q^{\text{img}} \to c^{\text{txt}}$	VisualNews	*Find a caption for the news in the given photo.\nQuery:* $< q^{img} >$*<eos>*
	MSCOCO	*Find an image caption describing the following everyday image.\nQuery:* $< q^{img} >$*<eos>*
	Fashion200K	*Find a product description for the fashion item in the image.\nQuery:* $< q^{img} >$*<eos>*
5. $q^{\text{img}} \to c^{\text{img}}$	NIGHTS	*Find a day-to-day image that looks similar to the provided image.\nQuery:* $< q^{img} >$*<eos>*
6. $(q^{\text{img}}, q^{\text{txt}}) \to c^{\text{txt}}$	OVEN	*Retrieve a Wikipedia paragraph that provides an answer to the given query about the image.\nQuery:* $< q^{img} >$*\n*$< q^{img} >$*<eos>*
	InfoSeek	*Retrieve a Wikipedia paragraph that provides an answer to the given query about the image.\nQuery:* $< q^{img} >$*\n*$< q^{img} >$*<eos>*
7. $(q^{\text{img}}, q^{\text{txt}}) \to c^{\text{img}}$	FashionIQ	*Find a fashion image that aligns with the reference image and style note.\nQuery:* $< q^{img} >$*\n*$< q^{img} >$*<eos>*
	CIRR	*Retrieve a day-to-day image that aligns with the modification instructions of the provided image.\nQuery:* $< q^{img} >$*\n*$< q^{img} >$*<eos>*
8. $(q^{\text{img}}, q^{\text{txt}}) \to (c^{\text{img}}, c^{\text{txt}})$	OVEN	*Retrieve a Wikipedia image-description pair that provides evidence for the question of this image.\nQuery:* $< q^{img} >$*\n*$< q^{img} >$*<eos>*
	InfoSeek	*Retrieve a Wikipedia image-description pair that provides evidence for the question of this image.\nQuery:* $< q^{img} >$*\n*$< q^{img} >$*<eos>*

Task	Dataset	MTEB task instruction
9. $q^{\text{txt}} \to c^{\text{txt}}$	ArguAna	*Given a claim, find documents that refute the claim\nQuery:* $< q^{txt} >$*<eos>*
	Climate-FEVER	*Given a claim about climate change, retrieve documents that support or refute the claim\nQuery:* $< q^{txt} >$*<eos>*
	CQADupStack	*Given a question, retrieve detailed question descriptions from Stackexchange that are duplicates to the given question\nQuery:* $< q^{txt} >$*<eos>*
	DBPedia	*Given a query, retrieve relevant entity descriptions from DBPedia\nQuery:* $< q^{txt} >$*<eos>*
	FEVER	Given a claim, retrieve documents that support or refute the claim\nQuery: $< q^{txt} >$<eos>
	FiQA	*Given a financial question, retrieve user replies that best answer the question\nQuery:* $< q^{txt} >$*<eos>*
	HotpotQA	*Given a multi-hop question, retrieve documents that can help answer the question\nQuery:* $< q^{txt} >$*<eos>*
	MSMARCO	*Given a web search query, retrieve relevant passages that answer the query\nQuery:* $< q^{txt} >$*<eos>*
	NFCorpus	*Given a question, retrieve relevant documents that best answer the question\nQuery:* $< q^{txt} >$*<eos>*
	NaturalQuestions	*Given a question, retrieve Wikipedia passages that answer the question\nQuery:* $< q^{txt} >$*<eos>*
	Quora	*Find questions that have the same meaning as the input question\nQuery:* $< q^{txt} >$*<eos>*
	SICDOCS	*Given a scientific paper title, retrieve paper abstracts that are cited by the given paper\nQuery:* $< q^{txt} >$*<eos>*
	SciFact	*Given a scientific claim, retrieve documents that support or refute the claim\nQuery:* $< q^{txt} >$*<eos>*
	Touch´e-2020	*Given a question, retrieve detailed and persuasive arguments that answer the question\nQuery:* $< q^{txt} >$*<eos>*
	TREC-COVID	*Given a query on COVID-19, retrieve documents that answer the query\nQuery:* $< q^{txt} >$*<eos>*

Table 14: LLaVa-P instructions for M-BEIR and MTEB. [image], [text] and [image,text] are used to inform LLaVa-P the user desired modality. For all the candidates, we use the prompt to generate the embedding: $< c^{img} >$\n$< c^{txt} >$*\nDescribe the above in one word:*

Task	Dataset	M-BEIR task instruction
1. $q^{\text{txt}} \to c^{\text{img}}$	VisualNews	*[image]* $< q^{txt} >$*\nDescribe the news-related caption in one word:*
	MSCOCO	*[image]* $< q^{txt} >$*\nDescribe the everyday caption in one word:*
	Fashion200K	*[image]* $< q^{txt} >$*\nDescribe the fashion description in one word:*
2. $q^{\text{txt}} \to c^{\text{txt}}$	WebQA	*[text]* $< q^{txt} >$*\nAnswer the question using Wikipedia in one word:*
3. $q^{\text{txt}} \to (c^{\text{img}}, c^{\text{txt}})$	EDIS	*[image,text]* $< q^{txt} >$*\nDescribe the news-related caption in one word:*
	WebQA	*[image,text]* $< q^{txt} >$*\nAnswer the question using Wikipedia in one word:*
4. $q^{\text{img}} \to c^{\text{txt}}$	VisualNews	*[text]* $< q^{img} >$*\nDescribe the news-related image in one word:*
	MSCOCO	*[text]* $< q^{img} >$*\nDescribe the everyday image in one word:*
	Fashion200K	*[text]* $< q^{img} >$*\nDescribe the fashion image in one word:*
5. $q^{\text{img}} \to c^{\text{img}}$	NIGHTS	*[image]* $< q^{img} >$*\nDescribe the everyday image in one word:*
6. $(q^{\text{img}}, q^{\text{txt}}) \to c^{\text{txt}}$	OVEN InfoSeek	[text] $< q^{img} >$*\n*$< q^{txt} >$*\nAnswer the question based on the image from Wikipedia in one word:*
7. $(q^{\text{img}}, q^{\text{txt}}) \to c^{\text{img}}$	FashionIQ	*[image]* $< q^{img} >$*\nChange the style of this shirt/dress/toptee to* $< q^{txt} >$*\nDescribe this modified shirt/dress/toptee in one word:*
	CIRR	*[image]* $< q^{img} >$*\nModify this image with* $< q^{txt} >$*\nDesribe modified image in one word:*
8. $(q^{\text{img}}, q^{\text{txt}}) \to (c^{\text{img}}, c^{\text{txt}})$	OVEN InfoSeek	*[image,text]* $< q^{img} >$*\n*$< q^{txt} >$*\nAnswer the question based on the interleaved image-text passage from Wikipedia in one word:*

Task	Dataset	MTEB task instruction
9. $q^{\text{txt}} \to c^{\text{txt}}$	ArguAna	*[text]* $< q^{txt} >$*\nGiven a claim, generate a document that refute the claim in one word:*
	Climate-FEVER	*[text]* $< q^{txt} >$*\nGiven a claim about climate change, generate a document that supports or refutes the claim in one word:*
	CQADupStack	*[text]* $< q^{txt} >$*\nDescribe the Stackexchange question in one word:*
	DBPedia	*[text]* $< q^{txt} >$*\nGiven a query, generate a relevant entity description from DBPedia in one word:*
	FEVER	*[text]* $< q^{txt} >$*\nGiven a claim, generate a document that supports or refutes the claim in one word:*
	FiQA	*[text]* $< q^{txt} >$*\nAnswer the financial question in one word:*
	HotpotQA	*[text]* $< q^{txt} >$*\nAnswer the multi-hop question in one word:*
	MSMARCO	*[text]* $< q^{txt} >$*\nAnswer the web search query in one word:*
	NFCorpus	*[text]* $< q^{txt} >$*\nAnswer the question in one word:*
	NaturalQuestions	*[text]* $< q^{txt} >$*\nAnswer the question using Wikipedia in one word:*
	Quora	*[text]* $< q^{txt} >$*\nDescribe the question in one word:*
	SICDOCS	*[text]* $< q^{txt} >$*\nGiven a scientific paper title, generate a paper abstract that is cited by the given paper in one word:*
	SciFact	*[text]* $< q^{txt} >$*\nGiven a scientific claim, generate a document that support or refute the claim in one word:*
	Touch´e-2020	*[text]* $< q^{txt} >$*\nAnswer the question with detailed and persuasive arguments in one word:*
	TREC-COVID	*[text]* $< q^{txt} >$*\nAnswer the query on COVID-19 in one word:*

Table 15: Prompts for reranking tasks in M-BEIR .

Task	Dataset	Prompt
1. $q^{\text{txt}} \to c^{\text{img}}$	VisualNews	$< c^{img} >$\nNews:$< q^{txt} >$\nDoes the above News image match the News story? True or False
	MSCOCO	$< c^{img} >$\nCaption:$< q^{txt} >$\nDoes the above daily-life image match the caption? True or False
	Fashion200K	$< c^{img} >$\nDescription:$< q^{txt} >$\nDoes the above image match the cloth style description? True or False
2. $q^{\text{txt}} \to c^{\text{txt}}$	WebQA	Question: $< q^{txt} >$\nAnswer: $< c^{txt} >$\nDoes the answer correctly answer the question? True or False
3. $q^{\text{txt}} \to (c^{\text{img}}, c^{\text{txt}})$	EDIS WebQA	Question: $< q^{txt} >$\nAnswer: $< c^{txt} >$\nDoes the answer correctly answer the question? True or False
4. $q^{\text{img}} \to c^{\text{txt}}$	VisualNews	$< q^{img} >$\nNews:$< c^{txt} >$\nDoes the above News image match the News story? True or False
	MSCOCO	$< q^{img} >$\nCaption:$< c^{txt} >$\nDoes the above daily-life image match the caption? True or False
	Fashion200K	$< q^{img} >$\nDescription:$< c^{txt} >$\nDoes the above image match the cloth style description? True or False
5. $q^{\text{img}} \to c^{\text{img}}$	NIGHTS	$< q^{img} >$\n$< c^{img} >$\nDoes the above two images have the same scene? True or False
6. $(q^{\text{img}}, q^{\text{txt}}) \to c^{\text{txt}}$	OVEN InfoSeek	$< q^{img} >$\nQuestion:$< q^{txt} >$\nAnswer:$< c^{txt} >$Does the answer correctly answer the question? True or False
7. $(q^{\text{img}}, q^{\text{txt}}) \to c^{\text{img}}$	FashionIQ CIRR	$< c^{img} >$\nCaption:$< q^{txt} >$\nDoes the above caption describe the modification of the image? True or False
8. $(q^{\text{img}}, q^{\text{txt}}) \to (c^{\text{img}}, c^{\text{txt}})$	OVEN InfoSeek	$< q^{img} >$\nQuestion:$< q^{txt} >$\nAnswer:$< c^{txt} >$Does the answer correctly answer the question? True or False

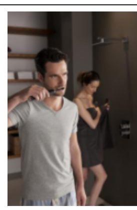
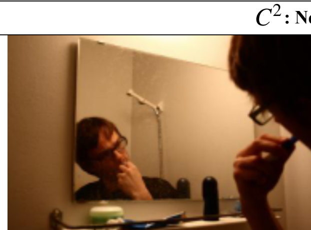
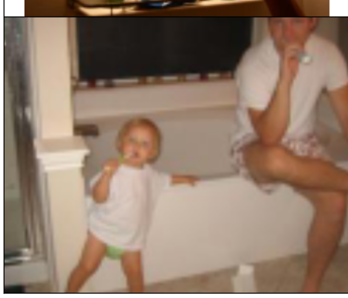
Instruction: Find me an everyday image that matches the given caption. **Query**: A man brushes his teeth while a woman wraps in a towel.	**Instruction**: Identify the news-related image in line with the described event. **Query**: The Q Street NW entrance to the Dupont Circle Metro station.	**Instruction**: Find me an everyday image that matches the given caption. **Query**: A large tow truck towing a double decker bus.
Correct Answer		
		
C^1: Negative samples with incorrect modality		
A man brushes his teeth while a woman behind him wraps a towel around herself.	Dupont Circle metro station, Q Street escalator.	A tow truck towing a double decker bus.
A man brushing his teeth with woman in wrapping herself in a towel in the background.	Riding escalator to Q Street exit of Dupont Circle Metro.	A tow truck is in front of a double decker bus.
C^2: Negative samples with unsatisfactory information needs		
		
		

Figure 2: Examples of modality-aware negative samples mined by M^{rand}(NVEmb). We observe that negative samples with incorrect modality show similar semantic meaning as queries while negative samples with unsatisfactory information needs show less accurate information compared to the correct answers

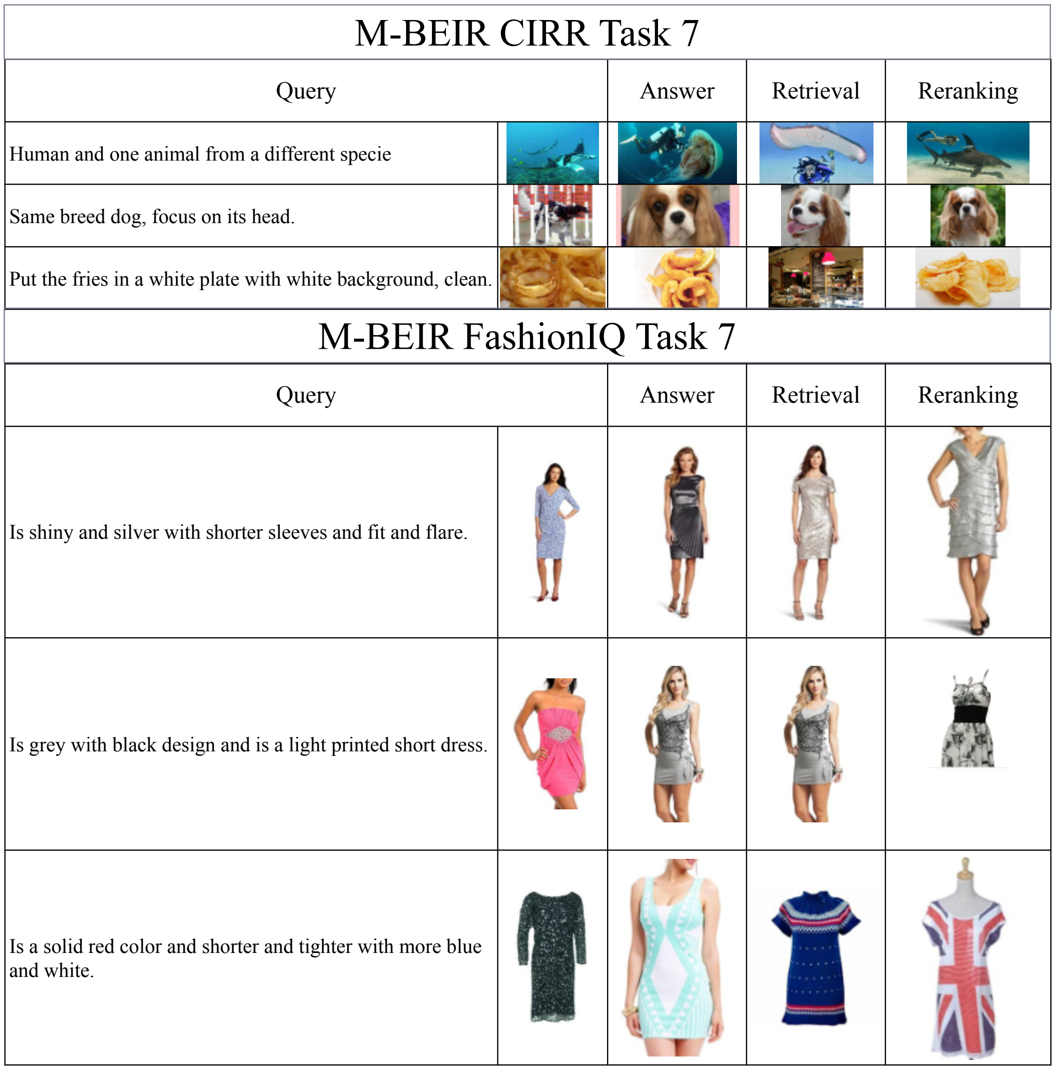


Figure 3: Top-1 candidates for the tasks of composed image retrieval and reranking. In many cases, retrieval and reranking yields different top-1 results from labeled positives but appears to be correct since each query only has single labeled positive candidate (see Table 10).