MLLM Is a Strong Reranker: Advancing Multimodal Retrieval-augmented Generation via Knowledge-enhanced Reranking and Noise-injected Training

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Abstract

Multimodal Large Language Models (MLLMs) have demonstrated remarkable capabilities in processing and generating content across multiple data modalities. However, a significant drawback of MLLMs is their reliance on static training data, leading to outdated information and limited contextual awareness. This static nature hampers their ability to provide accurate and up-to-date responses, particularly in dynamic or rapidly evolving contexts. To address these limitations, we propose **RagVL**, a novel framework with knowledge-enhanced reranking and noise-injected training. We instruction-tune the MLLM with a simple yet effective instruction template to induce its ranking ability and serve it as a reranker to precisely filter the top-k retrieved images. For generation, we inject visual noise during training at the data and token levels to enhance the generator's robustness. Extensive experiments on four datasets verify the effectiveness of our method. Code and models are available at `https://anonymous.4open.science/r/RagVL-F694`.

1 Introduction

As an attempt towards Artificial General Intelligence (AGI), Large Language Models (LLMs) have made significant strides in language understanding and human-like text generation (Brown et al., 2020; Achiam et al., 2023; Touvron et al., 2023). However, true AGI requires more than just linguistic capabilities. It necessitates a comprehensive understanding and interaction with the world, encompassing multiple modalities beyond text. Thus, the recent progress of Multimodal Large Language Models (MLLMs) in handling multimodal information has attracted the community. By processing and generating content across different modalities, MLLMs aim to create a more holistic and nuanced understanding of the world, closer to how humans perceive and interpret information. This integration of modalities enables MLLMs to perform tasks that require contextual understanding from multiple data sources, such as Visual Question Answering (VQA) (Goyal et al., 2017; Hudson and Manning, 2019; Marino et al., 2019), Table Question Answering (Lu et al., 2022), Text-to-image Generation (Ramesh et al., 2021; Yu et al., 2022; Aghajanyan et al., 2022), etc.

Nevertheless, the promising performance of language models primarily relies on the knowledge implicitly stored in their massive parameters, leading to several issues such as long-tail knowledge gaps (Asai et al., 2024), generating hallucinations (Ye and Durrett, 2022), and poor model interpretability. To better adapt to knowledge-intensive tasks and real-world scenarios, Retrieval-augmented Language Models (RALM) (Lewis et al., 2020; Lin et al., 2023; Izacard and Grave, 2020; Karpukhin et al., 2020) employ a dense retriever to retrieve up-to-date knowledge from external memories for grounded generation. Similarly, Multimodal Retrieval-augmented Generation (Multimodal RAG) enhances MLLMs by dynamically retrieving relevant information from external multimodal data sources before generation. This allows the models to incorporate real-time, contextually accurate visual information, significantly improving the factuality and accuracy of their outputs.

As illustrated in Figure 1, to answer the information-seeking query, the model must retrieve and reason over external visual knowledge, which differs from traditional VQA on the left and is non-trivial. To solve this, MuRAG (Chen et al., 2022) makes the first endeavor to extend RAG to multiple modalities. It is built upon ViT (Dosovitskiy et al., 2020) and T5 (Raffel et al., 2020) and pre-trained to encode image-text pairs for both answer generation and retrieval. MuRAG embeds items into an external memory and handles queries for retrieving multimodal knowledge from the same memory.

However, integrating multimodal RAG would inevitably introduce the multi-granularity noisy cor-

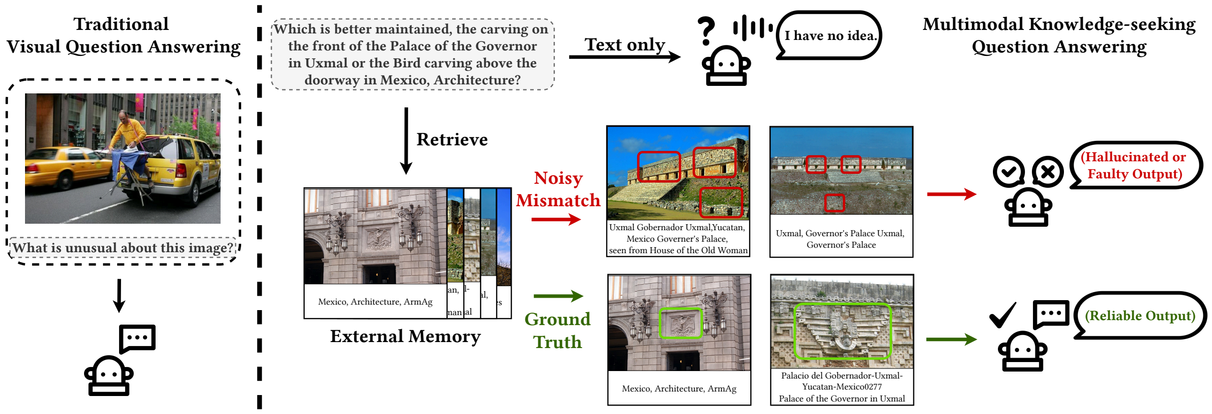


Figure 1: Difference between traditional VQA and multimodal knowledge-seeking question answering. An example from WebQA (Chang et al., 2022) reveals the challenge of multi-granularity noisy correspondence (MNC).

respondence problem (MNC) (Huang et al., 2021). As shown in Figure 1, MNC refers to the noise at two different granularities: (I) *Coarse-grained noise (query-caption)*. During the retrieval stage, coarse-grained captions result in retrieving similar but negative images. (II) *Fine-grained noise (query-image)*. The retriever and generator must distinguish fine-grained visual elements to formulate the responses. Any discrepancies between the images and the question can introduce noise, compromising the accuracy. In this scenario, CLIP (Radford et al., 2021) struggles to match the query with the image during the retrieval phase (see in Table 1). Also, identifying the correct correspondence amidst the fine-grained noise to provide an answer to the query is a challenge.

To this end, we propose **RagVL**, a novel framework with knowledge-enhanced reranking and noise-injected training, to mitigate MNC in multimodal RAG. In the retrieval stage, we instruction-tune the MLLM with a simple yet effective instruction template to induce its ranking ability. Given that MLLMs are inherently capable of understanding cross-modal information, we employ the fine-tuned model as a reranker to evaluate the relevance between the query and the image, which precisely selects top-N candidates that are more related to the query semantically. Subsequently, we apply an adaptive threshold to filter the candidates, collaborating with the reranker to alleviate the fine-grained mismatches. To further mitigate the impact of fine-grained mismatches during the generation phase, we introduce noise at both data and token levels in the training process. Specifically, at the data level, we perform negative sampling for single-image input questions within the single/multiple-image interleaved dataset, supplementing them with references from hard negative images. At the token level, we introduce additional visual uncertainty to images through Gaussian noise and reassign training loss weights by comparing the logits of the distorted and original inputs.

In a nutshell, the main contributions of this work are as follows: (I) We achieve effective and robust multimodal retrieval-augmented generation with a three-stage pipeline. Additionally, we address the inherent multi-granularity noisy correspondence (MNC) problem in multimodal retrieval-augmented generation. (II) We introduce the knowledge-enhanced reranking and noise-injected training technique to mitigate the coarse-grained and fine-grained noise from MNC. (III) Extensive experiments on multimodal knowledge-seeking QA and retrieval tasks demonstrate the effectiveness of the proposed framework.

2 Related Work

2.1 Multimodal Large Language Model

Recent advances in MLLMs have demonstrated impressive performances in handling multi-format information (Driess et al., 2023; Huang et al., 2024; Achiam et al., 2023). MLLMs are generally built upon existing LLMs and integrating visual information as input tokens by utilizing an additional vision encoder and a bridging connector. For instance, LLaVA (Liu et al., 2024b,a) adopts one/two linear MLP to project visual tokens and align the feature dimension with word embeddings, while BLIP-2 (Li et al., 2023) leverages a group of learnable query tokens to extract information in a query-

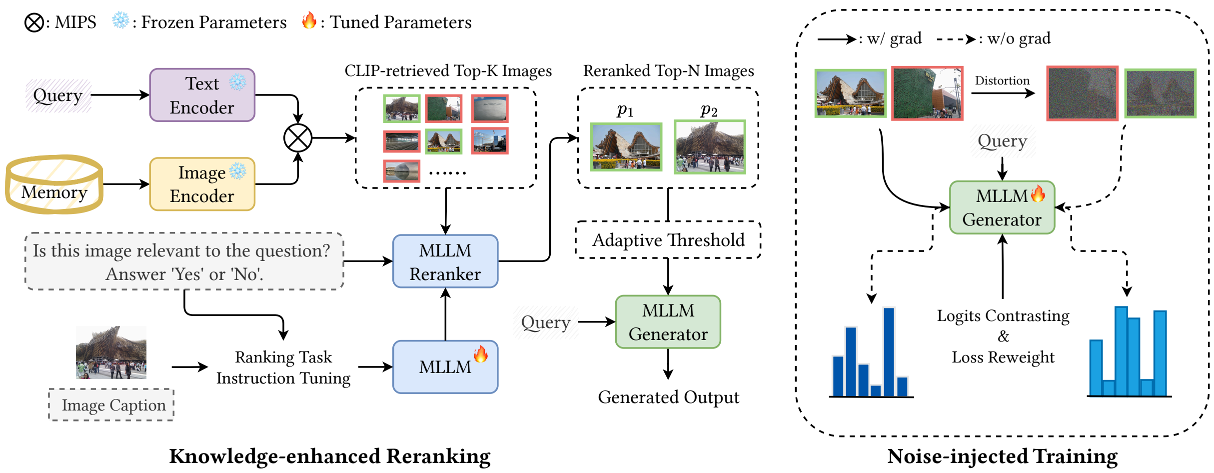


Figure 2: Overview of our proposed RagVL. In the retrieval stage, we utilize the CLIP model and faiss to find the top-K most relevant images through Maximum Inner Product Search (MIPS) (Guo et al., 2020). Subsequently, the highly similar top-K images are reranked into top-N with the fine-tuned MLLM reranker. Finally, the top-N images are fed into the MLLM generator along with the query for accurate generation.

based manner. Despite these advances, MLLMs tend to underperform in knowledge-intensive tasks (*e.g.* WebQA and MultimodalQA (Talmor et al., 2021)) that require seeking up-to-date information. Since the knowledge stored in their massive parameters is currently limited, MLLMs must resort to external memories for grounded generation.

2.2 Multimodal Retrieval-augmented Generation

Enhancing language models by incorporating relevant information from diverse knowledge sources has been shown to improve performance across various NLP tasks (Borgeaud et al., 2022; Lewis et al., 2020). REALM (Guu et al., 2020) and RAG (Lewis et al., 2020) treat the retrieved passages as latent variables and train the retriever-generator system jointly, leading to more effective retrieval-augmented generation models. Inspired by textual RAG, Plug-and-play (Tiong et al., 2022) retrieves relevant image patches using GradCAM (Selvaraju et al., 2017) to localize relevant parts based on the query. MuRAG (Chen et al., 2022) proposes the first multimodal retrieval-augmented Transformer, which accesses an external non-parametric multimodal memory to augment language generation. Sun et al. (2024) emphasize high-quality dataset construction, where positive and negative labels are pre-generated by MLLMs. During inference, their retriever directly passes Top-K candidates to the generator without reranking. However, none of these works specifically focus on MNC in multimodal RAG, which is primary in our research.

3 Methodology

3.1 Preliminaries

The traditional RALM acquires knowledge from the external memory $\mathcal{M}$ and utilizes the knowledge in grounded outputs to promote accurate and explainable generation. The retriever $\mathcal{R}$ first retrieves the top-K most relevant contexts $\mathcal{C} = \{c_1, \cdots, c_k\}$ from $\mathcal{M}$ for the given question q. Subsequently, the autoregressive language model generates answers based on these retrieved contexts. Under the multimodal setting, the retriever needs to compare the textual queries with the multimodal documents and find the best matches for the generator $\mathcal{G}$.

3.2 Multimodal Retriever

We follow the dual-encoder architecture based on CLIP text encoder Φ_{text} and image encoder Φ_{img}. Before the retrieval stage, given image-query pairs (v, q) from the dataset $\mathcal{D}$, we first apply the image encoder Φ_{img} to encode each image and build the image memory $\mathcal{M}$ using faiss (Douze et al., 2024). From the external memory $\mathcal{M}$, the retriever aims to retrieve a small set of images that support the textual query q. Specifically, we encode the query with the text encoder Φ_{text} and use MIPS over all of the image candidates $v \in \mathcal{M}$ as follows,

$$\hat{\mathcal{M}} = TopK(\mathcal{M}|q) = \underset{v\in\mathcal{M}}{TopK}\ \Phi_{text}(q) \cdot \Phi_{img}(v). \tag{1}$$

The top-K images with the highest inner product scores, *i.e.* the nearest top-K neighbors $\hat{\mathcal{M}}$ =

$\{v_1, v_2, \cdots, v_k\}$, are retrieved as the candidate images for answer generation.

3.3 Inducing Ranking Ability of MLLMs

CLIP stands out across a wide range of multimodal representations and retrieval tasks as a powerful and highly transferable model. However, when encountering long-tail distribution or domain-specific terms, CLIP fails to match the proper pairs across text and images. To mitigate this, we resort to MLLMs for their capabilities of semantic understanding. In general, MLLMs are pre-trained on vast image-text pairs for feature alignment and fine-tuned on language-image instruction-tuning datasets for instruction following. With this pre-injected multimodal knowledge, they are inherently capable of understanding semantically relevant contents across both visual and textual modalities at a deeper level. Therefore, to mitigate the bottleneck challenge of multimodal RAG, we introduce the flexible knowledge-enhanced reranking to induce the ranking ability of MLLMs.

Ranking Data Construction We construct the instruction-following data based on WebQA and MultimodalQA and design two tasks requiring the model to generate "Yes" for the relevant pairs and "No" for the irrelevant pairs. We treat each query and the ground truth images as relevant, while the hard negative images are irrelevant. Intuitively, the caption-aware style brings additional knowledge to the model to distinguish the relevance between the image and query. Therefore, we train the reranker with the caption-aware ranking task. See the details of the instruction template in Table 8.

Knowledge-enhanced Reranking By asking the question "*Based on the image and its caption, is the image relevant to the question? Answer 'Yes' or 'No'.*", we measure the relevance between the image and query with the probability p of generating "Yes" on the first token calculated from the output logits. Thus, reranking the top-K candidates into top-N can be formulated as follows,

$$\tilde{\mathcal{M}} = TopN(\hat{\mathcal{M}}|\phi) = \underset{(v,c)\in\hat{\mathcal{M}}}{TopN}\, p_\phi(v, c, q), \quad (2)$$

$$p_\phi(v, c, q) = \frac{\exp(o(\text{"Yes"}|v, c, q))}{\exp(o(\text{"Yes"}|v, c, q)) + \exp(o(\text{"No"}|v, c, q))}, \quad (3)$$

where v, c, q, and o denote the image, corresponding caption, query, and logit respectively. ϕ is the weight of the reranker.

Adaptive Threshold The reranked images may still exhibit low relevance p to the query, which could adversely impact the generation of answers. Consequently, their inclusion might lead to poorer performance compared to scenarios where the images are not included at all. To further improve the retrieval accuracy, we apply an adaptive threshold η to filter out candidates when $p < \eta$. We set two types of thresholds: the natural threshold and the adaptive threshold. The natural threshold refers to $\eta = 0.5$, which is the natural boundary for our binary classification ranking. For more precise retrieval, we experiment on the validation set and utilize the intersection point of the interpolated curve of exact match and mismatch as the adaptive threshold. In this way, the model can avoid the distractions from irrelevant images.

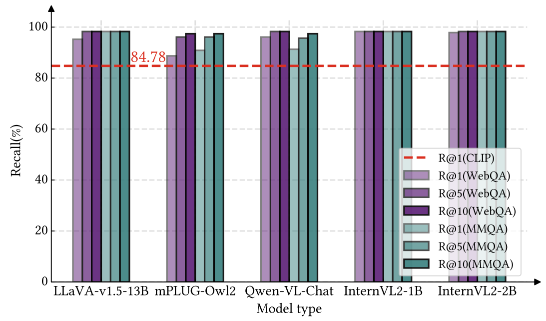
3.4 Noise-injected Training

Compared to providing a fixed number of images each time, the task with single/multiple images interleaved is more aligned with real-world scenarios. It is challenging to determine the optimal number of images to refer to each time and extract relevant information from the images, while irrelevant ones still inevitably disturb the accurate generation.

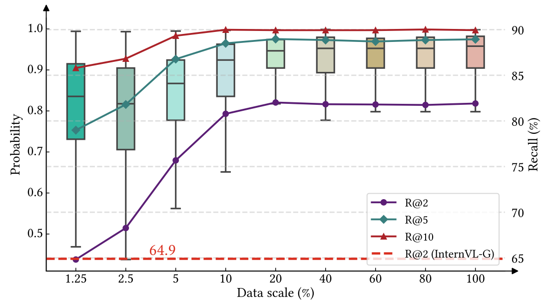
Inspired by VCD (Leng et al., 2024): visual uncertainty can amplify language priors, and contrasting the logits from the enhanced priors with the original ones can better highlight visual relevance [1]. We propose injecting visual noise during training at the data and token level to enhance robustness: (I) For single-image/multi-image interleaved tasks, we sample randomly from the hard negatives to ensure that each instruction-following data has the same amount of image input. (II) We introduce Gaussian noise as additional visual uncertainty and contrast the logits to reweight the loss for each token.

Noise-injected Data Construction We standardize the number of image inputs for each sample in the instruction-following data to the maximum number needed for any question. In the case of WebQA, where each question requires 1-2 images for answering, we randomly sample 1 image from the hard negatives as an injected noise for the single-image query. The model is required to distinguish relevant visual information, which strengthens its capability of visual understanding.

[1]Refer to Appendix A for the comparison of motivations and implementation details between VCD and RagVL.



(a) Generalizability of reranking.



(b) Low-resource settings on WebQA.

Figure 3: Generalizability of caption-aware instruction tuning. (a) compares the reranker fine-tuned on WebQA with the one fine-tuned on MultimodalQA, evaluated on MultimodalQA. (b) visualizes the changes in the probability distribution of correctly recalled items and the recall of the reranker under low-resource settings.

Noise-injected Logits Contrasting To inject noise at the token level, we employ forward diffusion (Ho et al., 2020) to distort the image:

$$f\left(v_t \mid v_{t-1}\right) = \mathcal{N}\left(v_t; \sqrt{1-\gamma} v_{t-1}, \gamma \mathbf{I}\right), \quad (4)$$

$$f\left(v_T \mid v_0\right) = \prod_{t=1}^{T} f\left(v_t \mid v_{t-1}\right), \quad (5)$$

where $\mathbf{I}$ and v_0 denote an identity matrix and the original image, respectively. We gradually distort the original image by adding the Gaussian noise for T steps and γ controls the amount of noise added in each step. Subsequently, to guide the model in more effectively learning the visual relevance highlighted in the contrasted logits, we propose reweighting the training loss by contrasting vanilla and noisy logits to highlight the visual relevance. Given a textual query x and an image input v, the model generates two logit distributions conditioned on different visual posteriors: the original v and distorted v^*. By contrasting the logit distributions obtained from these two conditions, we can get the contrastive probability distribution of the i-th sample at time step t as follows,

$$\begin{aligned} \mathbf{w}_{i,t} &= \Delta o(y_{i,t}|v_i, v_i^*, x_i, y_{i,<t}) & (6)\\ &= o_\theta(y_{i,t}|v_i) - o_\theta(y_{i,t}|v_i^*), & (7) \end{aligned}$$

where $y_{i,t}$ and $y_{i,<t}$ denote the token at time step t and the generated tokens sequence up to the time step $t-1$ of the i-th sample, respectively. Subsequently, we reassign the weight of each token in the vanilla MLE loss as follows,

$$\mathcal{L}_{INJ}^{i,t} = -\frac{\mathbf{w}_{i,t}}{\sum_{k=1}^{l} \mathbf{w}_{i,k}} \cdot logp_\theta(y_{i,t}|v_i, x_i, y_{i,<t}), \quad (8)$$

where l and $\tilde{\mathbf{w}}$ represent the length of textual tokens and the smooth weight, respectively.

4 Experiments and Analysis

4.1 Experiment Setup

Datasets and Evaluation Metrics For evaluation, we consider the image-related subsets of two multimodal QA datasets WebQA and MultimodalQA. Since the test set labels from both datasets are not publicly available, the training and validation sets in our work are subsets of the original training data, while the test sets are sourced from the original validation sets. Each query is associated with a set of hard negative distractors so that two evaluation setups can be used, namely distractor and full-wiki. We only consider the full-wiki setting to demonstrate the superiority of our proposed pipeline. Additionally, we conduct more experiments on Flickr30K (Young et al., 2014) and MS-COCO (Lin et al., 2014) to evaluate the performance on caption-to-image retrieval tasks. More details can be found in Appendix B, C and G.

4.2 Evaluation on Multimodal Knowledge-seeking

Results of Retrieval Table 1 shows the performance on MulitmodalQA and WebQA. The retriever performs weakly regarding precise recall (R@1 and R@2) on both datasets, making it difficult for accurate generation. Since the captions from the two datasets are names of objects or places, it is not trivial to adapt to the scenarios using vanilla contrastive learning, as proven in the table. After inducing the ranking abilities of MLLMs, our proposed method effectively improves performance by a large margin. Specifically, with five MLLMs, our method consistently improves R@2 on WebQA by an average of 40%. The results of

Methods	MultimodalQA			WebQA		
	R@1	R@5	R@10	R@2	R@5	R@10
CLIP-ViT-L/14-336px	**84.78**	94.35	95.65	57.10	71.96	84.86
w/ SFT	83.04	94.35	94.78	55.09	73.23	81.94
Vis-BGE-base	49.57	74.78	82.61	28.78	43.62	54.56
Vis-BGE-m3	43.48	66.52	72.17	26.69	40.75	51.14
InternVL-C	82.17	**95.65**	96.96	**64.90**	**81.22**	88.09
InternVL-G	82.17	95.22	**97.39**	**64.90**	80.23	**88.28**
Reranking Top-K from CLIP-ViT-L/14-336px						
LLaVA-v1.5-13B	72.61	90.87	95.22	45.35	65.87	80.56
w/ caption-aware IT	**98.26**	**98.26**	**98.26**	79.74	88.14	89.77
mPLUG-Owl2	67.83	87.39	93.91	43.26	63.80	79.38
w/ caption-aware IT	90.87	96.09	97.39	71.27	85.08	88.97
Qwen-VL-Chat	68.26	89.57	92.61	47.64	67.22	80.42
w/ caption-aware IT	91.30	95.65	97.39	80.12	88.53	**89.96**
InternVL2-1B	47.39	84.78	93.91	34.99	57.49	74.72
w/ caption-aware IT	**98.26**	**98.26**	**98.26**	**82.00**	88.78	89.94
InternVL2-2B	66.52	88.70	93.91	42.79	62.48	77.97
w/ caption-aware IT	**98.26**	**98.26**	**98.26**	81.91	**88.94**	89.94
Reranking Top-K from Different Retrievers						
LLaVA-v1.5-13B						
w/ Vis-BGE-base	88.70	88.70	88.70	59.61	64.71	65.70
w/ Vis-BGE-m3	84.78	84.78	84.78	57.57	62.26	63.03
w/ InternVL-C	**98.70**	**98.70**	**98.70**	**82.08**	**90.79**	**92.72**
w/ InternVL-G	97.83	97.83	97.83	81.91	90.24	92.31

Table 1: Performance of rerankers on multimodal knowledge-seeking. The reranking is conducted based on the top 20 candidates from the retrievers (see details in Appendix B). The best scores in each setting are in **bold**.

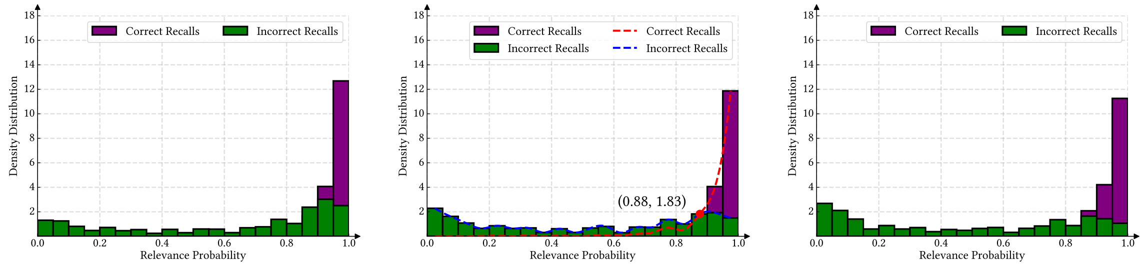
four different retrievers are significantly improved after reranking the Top-K candidates. Notably, on MultimodalQA, it reaches the upper bound of Recall@20 (98.26%) from CLIP on LLaVA-v1.5-13B and InternVL2-1/2B.

Generalizability of Caption-aware Instruction Tuning To further validate the generalizability of our method, on one hand, we test the reranker, which is fine-tuned on WebQA, on MultimodalQA. As shown in Figure 3a, the reranker trained on WebQA exhibits competitive performances and even matches the original reranker's performance with InternVL2-1/2B. On the other hand, we select different portions of data from WebQA to train InternVL2-2B in a low-resource setting, and obtain the probability distribution of the reranker outputting "*Yes*" for correctly recalled images. Figure 3b shows the robust performance of our proposed method under the low-resource settings. With only 2.5% of the original data, the reranker significantly outperforms the strong retriever baseline, InternVL-G, in R@2. As the data scale increases, the probability of correctly recalling images also improves, stabilizing around 20%, and the recall follows a similar trend. In summary, these two points fully demonstrate the strong generalizability of our proposed method, making it easily adaptable to more scenarios. We make a further discussion in Appendix H.

4.3 Evaluation on Multimodal RAG

Reranking Performance with Thresholds Since the reranker performs excellently in low-resource settings, we train InternVL2-1/2B as the rerankers using only 20% of the data, considering efficiency. As shown in Figure 4, we collect the relevance of the image candidates after reranking. Among all sets, the probabilities of correct recalls are concentrated in the highest range. For WebQA, since there is still a portion of erroneous recalls, we plot the interpolated curves of correct recalls and erroneous recalls on the validation set and take the x-coordinate of their intersection point as the adaptive threshold. For MultimodalQA, we set the adaptive threshold to 0.5.

As demonstrated in Table 2, our proposed knowledge-enhanced reranking demonstrates superior performances. We achieve better performance



(a) Train set (b) Validation set (c) Test set

Figure 4: Density distribution of the relevance probability of correct and incorrect recalls on WebQA after reranking with the InternVL2-2B reranker.

Methods	MultimodalQA			WebQA		
	P	R	F1	P	R	F1
CLIP Top-N	84.78	84.78	84.78	41.24	57.10	47.89
Caption-aware Instruction Tuning						
CLIP Top-K + Reranker	98.26	**98.26**	98.26	59.26	**82.05**	68.82
w/ Natural Threshold	**100.00**	97.83	**98.90**	74.89	80.59	**77.64**
w/ Adaptive Threshold	**100.00**	97.83	**98.90**	**88.34**	68.29	77.03

Table 2: Performance of InternVL2-2B reranker on two benchmark datasets. *P* and *R* denote precision and recall, respectively. The best scores in each setting are in **bold**.

across all metrics compared to directly using CLIP for top-N retrieval. When the adaptive threshold η is activated, the model accurately filters out irrelevant images, improving *accuracy* and *F1* score. Specifically, in WebQA, when η is set to an intuitively reasonable value of 0.5, the corresponding F1 score increases by 29.75%. In MultimodalQA, the reranker successfully identifies all ground truth images from the retrieved top-K candidates when η is set to 0.5, proving the strong capability of our proposed method in retrieval reranking.

Results of RAG Table 3 displays the results on multimodal question answering which requires retrieving images. The baselines without retrieval show limited performance, even the powerful GPT-3.5 fails to answer the knowledge-intensive questions. Notably, the backbone LLMs of InternVL2-1/2B (Qwen2-0.5B-Instruct and internlm2-chat-1_8b) perform poorly while their multimodal counterparts are improved. This phenomenon indicates that MLLMs can indeed learn world knowledge from different modalities and RAG offers the potential for a more timely and flexible knowledge integration in MLLMs.

After applying our proposed pipeline, all configurations on InternVL2-1B and InternVL2-2B demonstrate excellent performance, approaching or even surpassing *Oracle*. When the natural threshold is activated, there is a significant increase in the accuracy of recalling the correct images (as shown in Table 2), leading to substantial improvements in all metrics. Moreover, this improvement is more evident in the single-image scenario. This is because we fixed the number of images recalled each time, and setting the threshold allows filtering out erroneously recalled images, resulting in a consistent performance enhancement. However, when adopting adaptive thresholds, the improvement in results is not as significant as with natural thresholds. This can be seen from Table 2, where, despite a substantial increase in accuracy, there is a significant drop in recall. Therefore, natural thresholds are a better and more efficient choice for RAG.

Ablation Studies To validate the efficacy of each component in our proposed method, we conduct a set of ablation experiments on WebQA with InternVL2-2B, and the results are reported in Table 4. For "*w/o Reranker*", we directly retrieve Top-2 images with CLIP in the inference stage. The use of the reranker in RagVL shows an improvement in all metrics compared to "*w/o Reranker*". For "*w/o ND*", we replace the noise-injected dataset with the vanilla dataset. The results show that introducing noise at both data and token levels helps the

Methods	MultimodalQA	WebQA		
	EM	Single.	Multi.	Overall
w/o Retrieval-augmented Generation				
Qwen2-0.5B-Instruct	10.43	17.29	19.33	18.20
internlm2-chat-1_8b	10.43	23.25	32.58	27.40
gpt-3.5-turbo-0125	**25.22**	**40.80**	**54.49**	**46.88**
InternVL2-1B	19.57	26.10	43.57	33.86
InternVL2-2B	**25.22**	30.37	48.20	38.29
InternVL2-1B w/ Retrieval-augmented Generation				
InternVL2-1B				
w/ CLIP Top-N	50.87	35.98	48.65	41.61
w/ InternVL-G Top-N	49.57	38.88	49.11	43.43
RagVL *w/o NIT*	54.78	38.09	50.91	43.79
w/ Natural Threshold	54.78	40.43	50.96	45.11
w/ Adaptive Threshold	54.78	40.64	50.98	45.23
RagVL *w/ NIT*	68.26	53.07	72.53	61.72
w/ Natural Threshold	**68.70**	56.68	72.49	63.71
w/ Adaptive Threshold	**68.70**	**56.71**	**72.60**	**63.78**
Oracle	69.13	60.09	73.23	65.93
InternVL2-2B w/ Retrieval-augmented Generation				
InternVL2-2B				
w/ CLIP Top-N	61.30	40.80	48.88	44.39
w/ InternVL-G Top-N	60.00	41.92	48.45	44.82
RagVL *w/o NIT*	64.78	41.68	48.40	44.67
w/ Natural Threshold	65.65	44.71	48.97	46.60
w/ Adaptive Threshold	65.65	44.37	48.98	46.42
RagVL *w/ NIT*	73.04	53.91	72.62	62.23
w/ Natural Threshold	73.48	57.25	**73.01**	64.25
w/ Adaptive Threshold	**73.48**	**57.94**	72.47	**64.40**
Oracle	73.48	60.66	73.59	66.41

Table 3: Performance of multimodal knowledge-seeking question answering on WebQA and MultimodalQA. In addition to the overall results, we report the accuracy of single-image and multi-image input with *Single.* and *Multi.* for WebQA, respectively. *Oracle* refers to directly feeding the ground truth image to the generator after *NIT (Noise-injected Training)*. The best scores in each setting are in **bold**.

Methods	WebQA		
	Single.	Multi.	Overall
RagVL ($\eta = 0.5$)	**57.25**	**73.01**	**64.25**
w/o Reranker	53.63	71.79	61.70
w/o ND	57.11	71.24	63.39
w/o NLC	56.42	72.40	63.52
w/o ND & NLC	56.27	70.10	62.42

Table 4: Ablation study on WebQA with InternVL2-2B. *NLC* and *ND* refer to Noise-injected Logits Contrasting and Noise-injected Data, respectively.

model distinguish relevant candidates more effectively in real-world scenarios. Since *NLC* enhances the model's robustness at the token level, ablating it leads to a decrease in all metrics. This decline is more pronounced when both *NLC* and *ND* are ablated, especially in multi-image inference scenarios. Therefore, our proposed method, which injects noise at the data and token levels, helps reduce the distractions from noise and mitigate MNC.

5 Conclusion

In this paper, we present a robust framework for enhancing Multimodal Large Language Models (MLLMs) through knowledge-enhanced reranking and noise-injected training to tackle the multi-granularity noisy correspondence (MNC) problem in multimodal retrieval-augmented generation. Our comprehensive approach addresses both coarse-grained and fine-grained noise, significantly improving retrieval accuracy and generation robustness.

Limitations

Although our approach demonstrates strong performance in single-image and multi-image retrieval-augmented generation scenarios, the effectiveness in long-context situations remains unexplored. Furthermore, the current retrieval mechanism is limited to images; whereas in real-world applications, a wealth of information can be extracted from videos or other modalities. In future work, we will emphasize exploring retrieval-augmented generation across more modalities and extended contexts.

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A Comparison of Motivations and Implementation Details between VCD and RagVL

Although both our method and VCD use contrastive logit calculation, there are fundamental differences in their implementation and motivation. Our approach employs contrastive logit calculation during fine-tuning, rather than inference. VCD, by contrast, applies this calculation exclusively during inference and does not involve fine-tuning. Additionally, we introduce two types of noise during training: token-level noise and data-level noise (negatively sampled images). VCD only incorporates token-level noise during inference. By injecting noise at both levels during training, we leverage the Δlogits as visual correlation weights to reassign the loss for each token, guiding the model to focus on relevant visual elements. Importantly, inference in our method involves standard decoding, not contrastive decoding. Our motivation extends beyond mitigating irrelevant factors from a single retrieved image to addressing those arising from multiple images. In contrast, VCD focuses on better attending to visual tokens within a single ground truth image.

Another study (Xiao et al., 2024) also follows VCD to highlight the visual relevance. It retrains the MLLMs from the pre-training stage aiming to focus more on matching image-text pairs from potentially mismatched datasets. In contrast, we aim to achieve noise-resistant generation in practical multimodal RAG scenarios. Therefore, we

Dataset	Train	Dev	Test
WebQA	15K	3.7K	2.5K
MultimodalQA	2K	420	230
Flickr30K	29K	1K	1K
MS-COCO	113K	5K	5K

Table 5: Overall statistics of datasets.

Methods	MultimodalQA	WebQA	Flickr30K	MS-COCO
CLIP	98.26	90.27	96.54	96.84
Vis-BGE-base	88.70	65.89	93.64	95.86
Vis-BGE-m3	84.78	63.14	91.48	91.98
InternVL-C	98.70	93.27	98.92	98.64
InternVL-G	97.83	92.78	99.22	99.02

Table 6: Recall@20 of different retrievers.

actively inject noise at both the data level and the token level, and we only performed LoRA fine-tuning on knowledge-intensive tasks. In addition, the logits used for contrasting with the original logits in (Xiao et al., 2024) are derived solely from text input, whereas RagVL utilizes noise-injected images to obtain the logits for comparison.

B Data Statistics and Evaluation Metrics

WebQA consists of queries requiring 1-2 images or text snippets, while 44% of image-based and 99% of text-based queries need multiple knowledge sources. Following the vanilla evaluation setting, we measure the overlap of key entities between the generated output and ground truth answer as *Accuracy*.

MultimodalQA contains multimodal questions over tables, text, and images. We focus on the QA pairs requiring only image information, which are annotated as 'ImageQ' and attached to 1 image each. The evaluation metric used is Exact Match (*EM*).

Flickr30K consists of 31,000 images sourced from Flickr, each accompanied by five captions. Consistent with the setup of (Lee et al., 2018), we allocate 1,000 images for validation, 1,000 for testing, and use the remaining images for training.

MS-COCO comprises 123,287 images, each paired with five captions. Following the protocol in (Lee et al., 2018), we designate 113,287 images for training, 5,000 for validation, and 5,000 for testing.

Approach	Time Cost
CLIP Top-K	1.23s
+ InternVL2-2B reranker	5.11s
+ LLaVA-v1.5-13B reranker	6.24s

Table 7: Inference time per sample. Each inference with the reranker involves 20 evaluations of image relevance and one generation of an answer.

C Implementation Details

To evaluate the effectiveness and generalizability of our proposed method, this paper leverages several cutting-edge MLLMs as the backbone, including LLaVA-v1.5-13B (Liu et al., 2024a), mPLUG-Owl2 (Ye et al., 2024), Qwen-VL-Chat (Bai et al., 2023), and InternVL (Chen et al., 2024). We employ the frozen CLIP-ViT-L/14-336px as the vision and text encoder. For *RagVL*, we first train the reranker model with the caption-aware ranking task. Subsequently, we use CLIP to retrieve top-K candidates and rerank them into top-N with the fine-tuned reranker. K is set to 20, while N is set to 2 for WebQA and 1 for MultimodalQA. All trainings are conducted under the LoRA (Hu et al., 2021) setting. For evaluation, we use greedy decoding to ensure reproducibility and report the best performance. All experiments are conducted on 8 40G NVIDIA A100 GPUs.

D Computational Efficiency

Table 7 presents the inference time for different settings on 4 A100 GPUs. As shown, *"CLIP Top-K"* only requires a small amount of time due to fast inner product search, while our proposed method requires more time on reranking the retrieved candidates. Though the MLLM reranker shows powerful retrieval performance, the efficiency will be a major issue that limits its development.

Thanks to advances in inference acceleration, we can address the efficiency issue from different perspectives. For example, FlashAttention (Dao et al., 2022) enables faster inference with lower resources by using tiling to reduce the number of memory reads/writes between GPU memories. PagedAttention (Kwon et al., 2023) resorts to the classical virtual memory and paging techniques in operating systems to achieve near-zero waste and flexible sharing of KV cache memory. To be more specific, we can share the attention calculation of textual tokens among different candidates and parallelize the computation of visual tokens to maximize resource

Task	Instruction	Answer
Multimodal Retrieval-augmented QA	<image> $\cdots$ <image> `{question}`	A phrase
Caption-agnostic Ranking	<image> Question:`{question}` Is this image relevant to the question? Answer 'Yes' or 'No'.	Yes / No
Caption-aware Ranking (QA)	<image> Image Caption:`{caption}` Question:`{question}` Based on the image and its caption, is the image relevant to the question? Answer "Yes" or "No".	Yes / No

Table 8: The instruction template for ranking and generation tasks. The retrieval-augmented QA task allows multi-image input, whereas the ranking tasks consider one image at a time.

Methods	WebQA Ranking	WebQA QA
	Acc	Recall@2
CLIP-ViT-L/14-336px	-	57.10
LLaVA-v1.5-13B	67.74	45.35
w/ caption-agnostic IT	89.62	54.45
w/ caption-aware IT	**93.99**	**79.74**

Table 9: Ablation study of captions in instruction tuning (IT) on WebQA.

Models	MME	MMBench-en	SEED^{I}
InternVL2-1B	1769.2	61.72	65.60
w/ WebQA NIT	1671.3	60.76	64.32
InternVL2-2B	1839.8	72.25	71.60
w/ WebQA NIT	1743.2	70.46	70.60

Table 10: Evaluation on three general benchmark datasets.

utilization and accelerate inference since the textual instructions of all candidates during the reranking process are identical. As a successful attempt, Prompt Cache (Gim et al., 2024) has made similar efforts to reduce latency in time-to-first-token, which improves 8x for GPU-based inference and maintains output accuracy.

E Effect of Captions

We conduct experiments on test sets of WebQA ranking and QA datasets to verify the validity of captions in retrieving relevant sources. In WebQA QA task, we retrieve top-20 candidate images using CLIP and rerank them into top-2 with our instruction-tuned reranker models. As shown in Table 9, the vanilla LLaVA-v1.5-13B performs poorly on both tasks. The models trained on the ranking task outperform the baseline, particularly the one trained on the caption-aware task. This demonstrates the superiority of our simple yet effective instruction templates in inducing the ranking ability of MLLMs.

F Evaluation on General Benchmark Datasets

While training a model on specific tasks can reduce its generalization capabilities (Ling et al., 2023), a moderate trade-off in universality is often acceptable to significantly enhance task-specific performance. As demonstrated in Table10, we evaluated our approach on three general datasets: MME (Fu et al., 2024), MMBench (Liu et al., 2025), and SEED-Image (Li et al., 2024). Following noise-injected fine-tuning on WebQA, performance declined only marginally—by 5.2%–5.5%, 1.6%–2.5%, and 1.4%–1.9% on MME, MMBench, and SEED-Image, respectively. However, this fine-tuning resulted in a substantial improvement of approximately 40% on WebQA as shown in Table 3, highlighting the effectiveness of our method in balancing specialization and generalization.

G Performance on Caption-to-image Retrieval

To further verify the effectiveness and generalizability of our proposed reranking method, we conduct more experiments on Flickr30K and MS-COCO. We construct the reranking tasks and prompt the reranker with the instruction "*<image> Image Caption: {caption} Is the image relevant to the caption? Answer 'Yes' or 'No'*". As shown in Table 11, our proposed method still outperforms the majority of existing retrievers across all metrics, except for InternVL-G, which is specifically designed for image-text matching. Our approach primarily focuses on cases where the query is a question, and the keys are captions and images. In contrast, in these two caption-to-image retrieval datasets, the query is a caption, and the key is an

Methods	Flickr30K			MS-COCO		
	R@1	R@5	R@10	R@1	R@5	R@10
CLIP-ViT-L/14-336px	66.90	89.00	93.36	57.18	83.24	91.90
Vis-BGE-base	57.38	83.28	89.60	52.94	81.22	90.12
Vis-BGE-m3	52.18	78.18	86.06	43.14	73.44	84.42
InternVL-C	81.50	95.94	97.82	71.82	92.06	96.62
InternVL-G	**84.28**	**96.88**	**98.44**	**76.20**	**94.24**	**97.54**
Reranking Top-K from CLIP-ViT-L/14-336px						
LLaVA-v1.5-13B	79.90	94.52	96.24	71.10	92.02	95.96
w/ caption-aware IT	83.04	**95.34**	96.34	74.64	93.16	95.62
mPLUG-Owl2	76.16	94.12	95.98	65.44	90.34	95.38
w/ caption-aware IT	81.38	94.70	96.08	69.96	91.30	95.36
Qwen-VL-Chat	82.70	94.80	96.26	74.40	92.72	95.98
w/ caption-aware IT	**84.40**	95.18	96.30	**76.62**	**93.56**	**96.26**
InternVL2-1B	67.74	92.56	96.04	55.76	87.14	94.02
w/ caption-aware IT	83.02	95.12	**96.38**	74.24	92.78	96.02
InternVL2-2B	67.74	92.56	96.04	71.32	92.06	95.82
w/ caption-aware IT	83.78	95.14	96.32	75.86	93.40	96.10
Reranking Top-K from Different Retrievers						
LLaVA-v1.5-13B						
w/ Vis-BGE-base	80.76	92.56	93.44	74.12	92.36	95.02
w/ Vis-BGE-m3	79.64	90.46	91.34	71.94	88.96	91.18
w/ InternVL-C	**83.56**	97.12	98.58	75.00	94.26	97.36
w/ InternVL-G	83.26	**97.16**	**98.80**	**75.06**	**94.36**	**97.60**

Table 11: Performance of knowledge-enhanced rerankers on caption-to-image retrieval. The best scores in each setting are in **bold**.

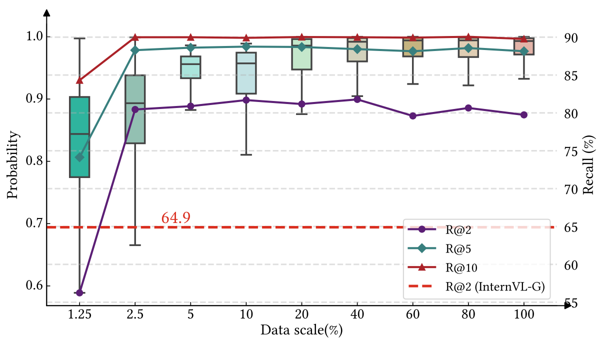


Figure 5: Retrieval performance on WebQA with LLaVA-v1.5-13B under low-resource settings.

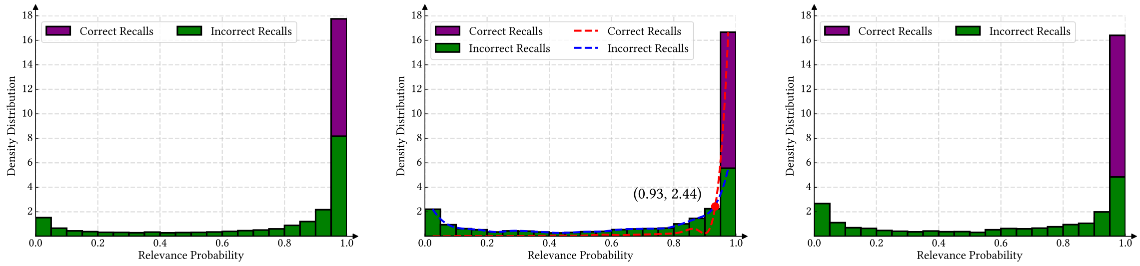
image. Thus, our method not only demonstrates superior performance in multimodal RAG but also maintains generalizability and competitiveness in traditional text-to-image retrieval.

H More Evaluations on LLaVA-v1.5-13B

Low-resource Settings on WebQA As shown in Figure 5, the experiments with LLaVA-v1.5-13B under low-resource settings also verified the robustness of our proposed method in reranker training. With only 2.5% of the original data, the reranker significantly surpasses the original baseline, InternVL-G, in R@2 and almost reaches the performance peak. This inspires us to further explore the performance of low-resource instruction fine-tuning for models with different parameter sizes in future work, aiming to enhance the generalizability and efficiency of MLLMs in instruction fine-tuning and downstream task deployment.

Reranking Performance with Thresholds Similarly, we train LLaVA-v1.5-13B as the reranker using only 20% of the data. As shown in Figure 6, the relevance probabilities of correct recalls are concentrated in the highest range. The adaptive threshold is high enough to filter out most of the incorrect candidates.

As shown in Table 12, our proposed knowledge-enhanced reranking method demonstrates superior performances. We train the reranker under two settings: (i)Blended training of ranking and QA tasks. (ii) Training exclusively with the ranking task. Whether training with the blended or separate setting, our approach achieves better performance across all metrics than directly using CLIP for top-N retrieval. When the adaptive threshold η is activated, the model accurately filters out irrelevant



(a) Train set

(b) Validation set

(c) Test set

Figure 6: Density distribution of the relevance probability of correct and incorrect recalls on WebQA after reranking from the LLaVA-v1.5-13B reranker.

Methods	MultimodalQA			WebQA		
	P	R	F1	P	R	F1
CLIP Top-N	84.78	84.78	84.78	41.24	57.10	47.89
Blended Instruction Tuning						
CLIP Top-K + Reranker	98.26	**98.26**	98.26	57.05	**78.99**	66.25
w/ Natural Threshold	**100.00**	97.39	**98.68**	67.94	78.00	**72.62**
w/ Adaptive Threshold	**100.00**	97.39	**98.68**	**84.13**	62.70	71.85
Ranking-only Instruction Tuning						
CLIP Top-K + Reranker	98.26	**98.26**	98.26	57.59	**79.74**	66.87
w/ Natural Threshold	**100.00**	97.83	**98.90**	68.31	78.52	73.06
w/ Adaptive Threshold	**100.00**	97.83	**98.90**	**80.38**	68.35	**73.88**

Table 12: Performance of LLaVA-v1.5-13B reranker on two benchmark datasets. *P* and *R* denote precision and recall, respectively. The best scores in each setting are in **bold**.

images, resulting in improved *accuracy* and *F1* score. Specifically, in WebQA, when η is set to an intuitively reasonable value of 0.5, the corresponding F1 score increases by 25.17% after training on the ranking-only task. In MultimodalQA, the reranker successfully identifies all ground truth images from the retrieved top-K candidates when η is set to 0.5, proving the strong capability of our proposed method in retrieval reranking.

For "*w/ Blended Reranker*", we utilize the blended reranker for both reranking and generation, which is trained with noise-injected data and vanilla MLE loss. Though we directly mix the ranking and QA datasets due to a lack of sufficient datasets, the blended reranker still performs competitively. Since training the blended reranker requires precise adjustments (Yu et al., 2024) to the composition of the training datasets to achieve better results, the results show a promising direction for future research (unifying reranker and generator), which further demonstrates the generalizability and superiority of our proposed method.

Results of Retrieval-augmented Generation Table 13 displays the results of LLaVA-v1.5-13B on MultimodalQA and WebQA. Our proposed approach still outperforms baselines on all configurations. Due to a larger amount of parameters, LLaVA-v1.5-13B outperforms InternVL2-1/2B in answer generation. What's more, the adaptive threshold works better on LLaVA-v1.5-13B because the relevance probabilities of correct recalls are more focused in the high range. Therefore, our proposed method is also applicable to models with larger parameters.

Ablation Studies As shown in Table 14, we ablate the proposed approaches on WebQA with LLaVA-v1.5-13B. Similar to the results from InternVL2-2B, the benefits from reranking and noise injection are still significant. Specially, to explore the possibility of unifying reranker and generator, we utilize the blended reranker for both retrieval and generation. The results are very promising, and there is still significant room for optimization.

Methods	MultimodalQA	WebQA		
	EM	Single.	Multi.	Overall
w/o Retrieval-augmented Generation				
Vicuna-v1.5-13B	8.26	32.43	42.82	37.05
Llama-2-13b-chat-hf	0.43	16.23	21.27	18.47
LLaVA-v1.5-13B	42.61	31.92	50.37	40.12
LLaVA-v1.5-13B w/ Retrieval-augmented Generation				
LLaVA-v1.5-13B				
w/ CLIP Top-N	75.65	41.29	47.54	44.07
w/ InternVL-G Top-N	75.22	42.37	47.71	44.74
RagVL *w/o NIT*	78.70	41.03	48.09	44.17
w/ Natural Threshold	79.57	44.50	48.47	46.26
w/ Adaptive Threshold	79.57	44.05	49.00	46.25
RagVL *w/ NIT*	78.70	57.06	76.18	65.56
w/ Natural Threshold	**79.57**	60.86	76.83	67.95
w/ Adaptive Threshold	**79.57**	**61.76**	**76.90**	**68.49**
Oracle	79.13	65.51	77.04	70.63

Table 13: Performance of multimodal question answering on two benchmark datasets requiring image retrieval. In addition to the overall results, we report the accuracy of single-image and multi-image input with *Single.* and *Multi.* for WebQA, respectively. *Oracle* refers to directly feeding the ground truth image to the generator. The best scores in each training setting are in **bold**.

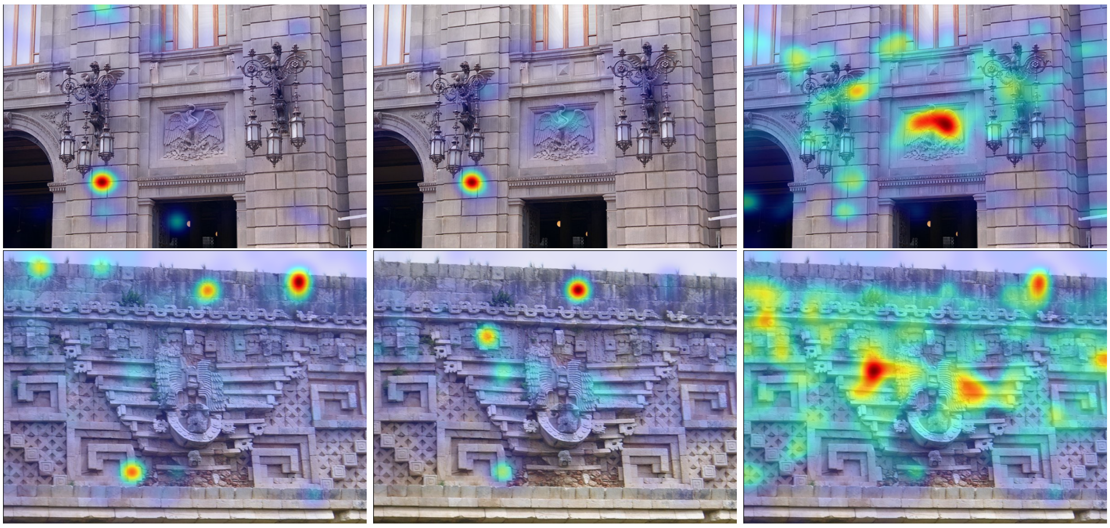
Methods	WebQA		
	Single.	Multi.	Overall
RagVL ($\eta = 0.5$)	60.86	**76.83**	**67.95**
w/o Reranker	58.67	75.66	66.22
w/o ND	**61.67**	75.19	67.68
w/o NLC	60.08	76.24	67.26
w/o ND & NLC	60.68	74.92	67.01
w/ Blended Reranker	58.15	74.97	65.63

Table 14: Ablation study on WebQA with LLaVA-v1.5-13B. *NLC* and *ND* refer to Noise-injected Logits Contrasting and Noise-injected Data, respectively.

I More Case Studies

As illustrated in Figure 7, we visualize the attention heatmaps of three methods. The attention weights are calculated by accumulating the attention score between image tokens and text tokens across all layers. Obviously, the model *w/ NIT* provides more focused attention on the crucial parts of the query than the other two models. Figure 8 and 9 show more cases requiring single image or multiple images for inferencing.

(a) "How many primary colors are found on the head of the Violet Turaco?"

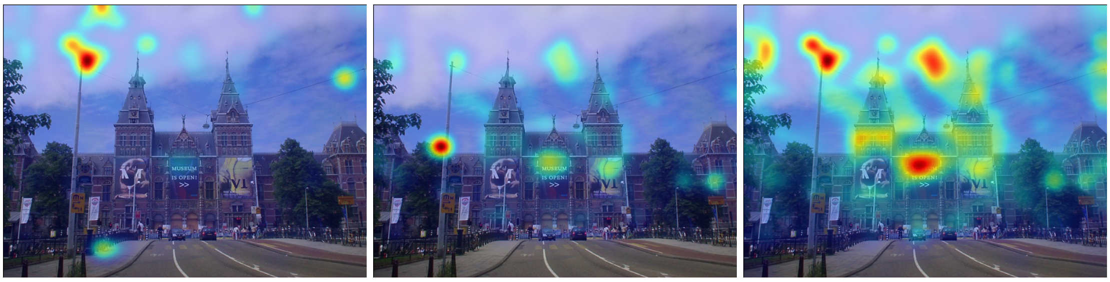


(b) "Which is better maintained, the carving on the front of the Palace of the Governor in Uxmal or the Bird carving above the doorway in Mexico, Architecture?"

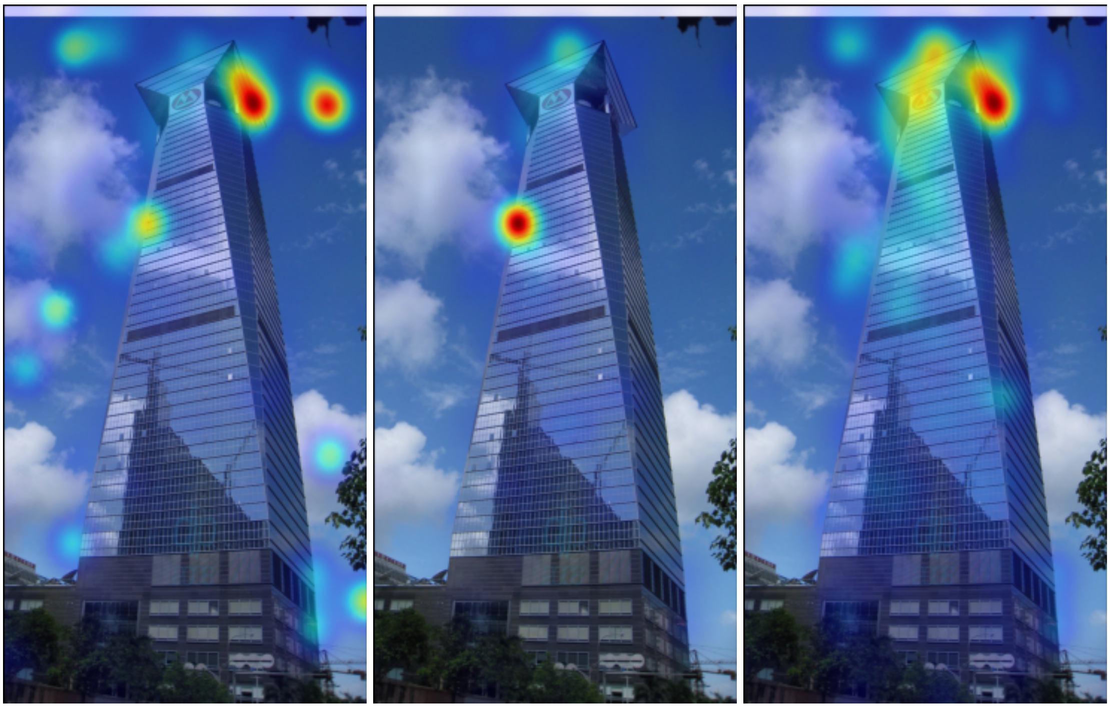
Figure 7: Visualization of attention heatmaps *w/* and *w/o NIT*. Displayed from left to right are the attention maps for the base model (*w/o IT*), the model fine-tuned *w/o NIT*, and the model fine-tuned *w/ NIT*, respectively, with each corresponding to its respective question in the caption.

(a) "Are the homes at the Main Shopping Street in Enniskillen or the church behind it taller?"

(b) "What color is the facade of bakery Sattin et Fils in Rethel, France?"

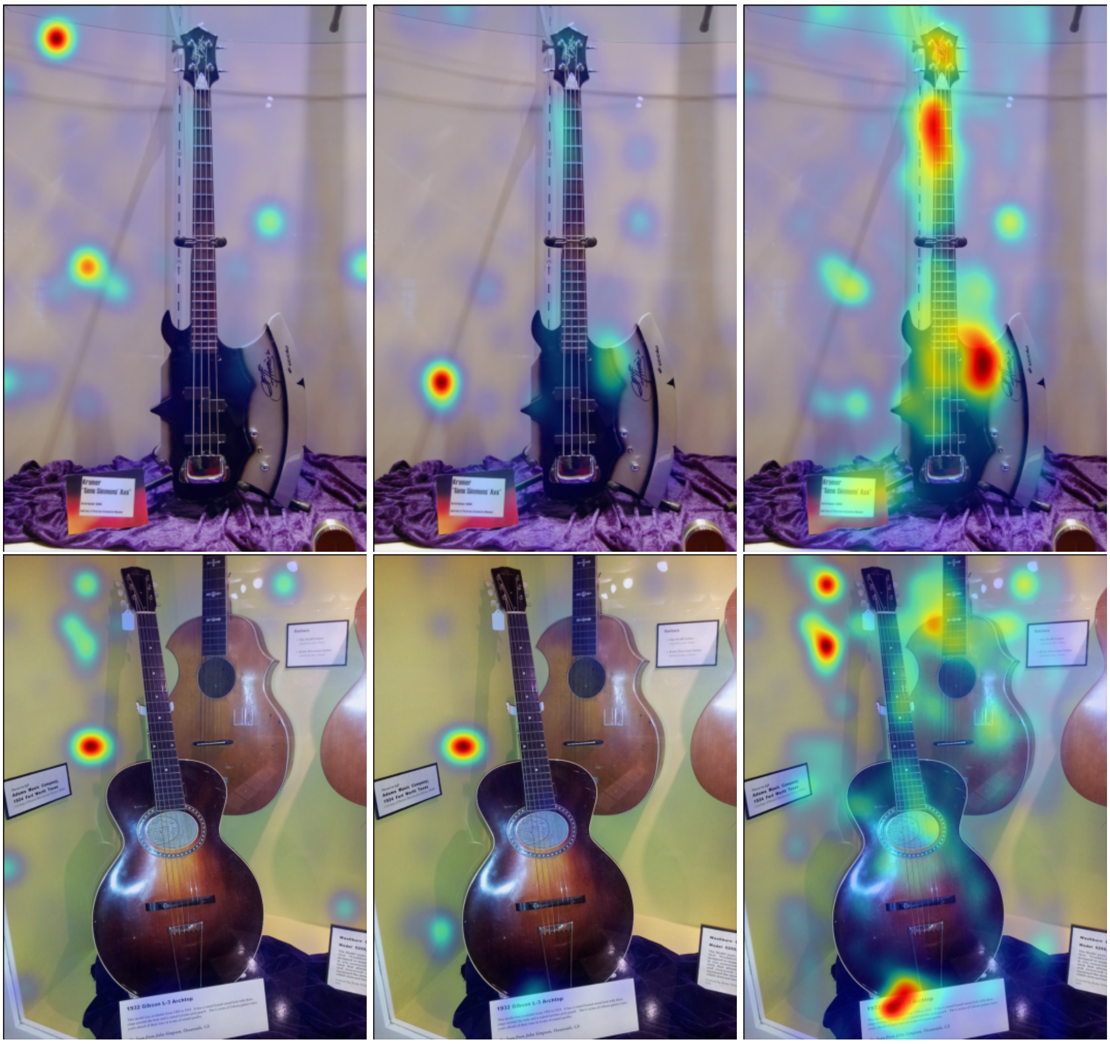


(c) "What text is on the signage in front of the Rijksmuseum?"



(d) "What color is the logo on China Merchants Bank Tower?"

Figure 8: More single-image cases on WebQA.



(a) "Which guitar looks more like a tool that might cut a tree; Gene Simmons' Guitar or Gibson L-3 archtop guitar?"

(b) "Are the colors of the word lyric different in the Lyric Theater, Blacksburg and Lyric Theater, Georgia signs?"

Figure 9: More multi-image cases on WebQA.