

Why Retrieval-Augmented MLLMs?

\Rightarrow Multimodal LLMs (MLLMs) [1] exhibit limitations when faced with **highly specific** queries.



In what state is this building located?

LLaVA-1.5: California 🗡 **BLIP-2:** Florida 🗡



Where this fish is found?

LLaVA-1.5: Gulf of Mexico 🗡 **BLIP-2:** Alaska 🗡

Having access to external documents at generation time can be a powerful source of information!

Architecture Overview



- \Rightarrow We enable MLLMs to answer complex and specific questions that cannot be resolved through image content and pre-trained knowledge alone.
- \Rightarrow The model leverages diverse information in its responses and learns to discern the **relative impor**tance of each retrieved document.

References

- [1] D. Caffagni et al. The Revolution of Multimodal Large Language Models: A Survey, ACL Findings 2024.
- [2] C. Yang et al. Can Pre-trained Vision and Language Models Answer Visual Information-Seeking Questions?, EMNLP 2023.
- T. Mensink et al. Encyclopedic VQA: Visual Questions About Detailed Properties of Fine-Grained Categories, ICCV 2023.

Wiki-LLaVA: Hierarchical Retrieval-Augmented Generation for Multimodal LLMs

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Hierarchical Retrieval & Results

(1) Cross-modal retrieval is performed using					Enc-VQA		InfoSeek					
an input image I , k -NN is performed	Model	\mathbf{LLM}	KB	k n	Single-Hop	All	Unseen-Q	Unseen-F	E All			
within the external memory, using docu-	Zero-shot Models											
ment titles as keys	BLIP-2	$Flan-T5_{XL}$	X		12.6	12.4	12.7	12.3	12.5			
\Rightarrow the top-k documents are retrieved.	InstructBLIP	$Flan-T5_{XL}$	X		11.9	12.0	8.9	7.4	8.1			
	LLaVA-1.5	Vicuna-7B	X		16.3	16.9	9.6	9.4	9.5			
	Fine-tuned Models	5										
(2) Each retrieved doc is analyzed \Rightarrow the Contriever model identifies the most relevant passages given the input question.	LLaVA-1.5	Vicuna-7B	X		23.3	28.5	19.4	16.7	17.9			
	Wiki-LLaVA	Vicuna-7B	\checkmark	1 1	21.8	26.4	26.6	24.6	25.5			
	Wiki-LLaVA	Vicuna-7B	\checkmark	$1 \ 2$	19.9	23.2	29.1	26.3	27.6			
	Wiki-LLaVA	Vicuna-7B	\checkmark	$2 \ 1$	21.3	25.4	27.8	24.6	26.1			
(3) The raw content of these most relevant	Wiki-LLaVA	Vicuna-7B	\	1 1	34.7	37.2	41.1	41.1	41.1			
passages is employed as additional context.	Wiki-LLaVA	Vicuna-7B	\checkmark	$1 \ 2$	39.2	40.2	49.1	46.5	47.8			
Formally, the final input context is:												
$Visual tokens \qquad System + user prompt External memory tokens$												
$v_o, v_1,, v_N,$	w_0, w_1, \dots, w_{t-1} ,	e_0, e_1	,,	$e_{ au}$								

Wiki-LLaVA

- \Rightarrow Wiki-LLaVA integrates knowledge derived from an external memory as additional input context into the LLaVA model
 - \rightarrow we do not need to change the underlying LLM architecture.
- \Rightarrow The memory external (document, comprises image, text-title) triplets from Wikipedia web pages [2, 3].



Takeaways

Standard MLLMs struggle to answer questions correctly, as they rely **solely** on embedded knowledge.

- \Rightarrow Fine-tuning helps, but **retrieval is vital** to answer knowledge-intensive questions.
- \Rightarrow Training on a **mixture of datasets** preserves fluency on more general benchmarks, without sacrificing VQA performance.

But...there is large room for improvement!

 \Rightarrow **CLIP** struggles with fine-grained image-text retrieval, especially when the dataset size increases.

Dataset	KB	R@1	R@10	R@20	R@50
Encyclopedic-VQA InfoSeek	2M 100k	$\begin{array}{c} 3.3\\ 36.9\end{array}$	$\begin{array}{c}9.9\\66.1\end{array}$	$\begin{array}{c} 13.2 \\ 71.9 \end{array}$	$\begin{array}{c} 17.5 \\ 78.4 \end{array}$

 \Rightarrow Oracle entities improve accuracy but remain challenging to find answers from the correct web page.

Directly using retrieved passages to augment pre-trained MLLMs is effective, but requires a robust entity retrieval model to avoid noisy content.



LLaVA-1.5: Real Madrid X Wiki-LLaVA: FC Dynamo Kyiv 🗡



structed?

LLaVA-1.5: 1970 🗡 Wiki-LLaVA: 1927 🗸