VisRAG: Vision-based Retrieval-augmented Generation on Multi-modality Documents

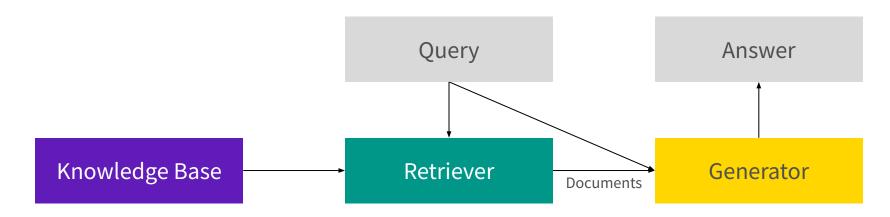
Shi Yu^{1*} (Speaker), Chaoyue Tang^{2*}, Bokai Xu^{2*}, Junbo Cui^{2*}, Junhao Ran³, Yukun Yan¹, Zhenghao Liu⁴, Shuo Wang¹, Xu Han¹, Zhiyuan Liu¹, Maosong Sun¹

¹Tsinghua University ²ModelBest Inc. ³Rice University ⁴Northeastern University

* equal contribution

yus21@mails.tsinghua.edu.cn

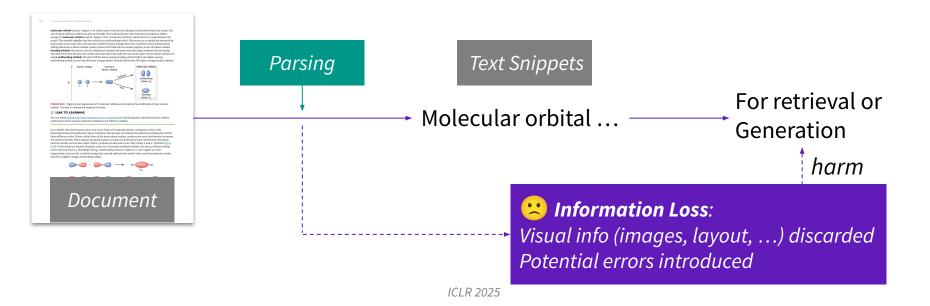
Background: Retrieval-augmented Generation (RAG)



- RAG supplements the LLM (generator) with external information
- Text snippets are usually the processing units of traditional RAG

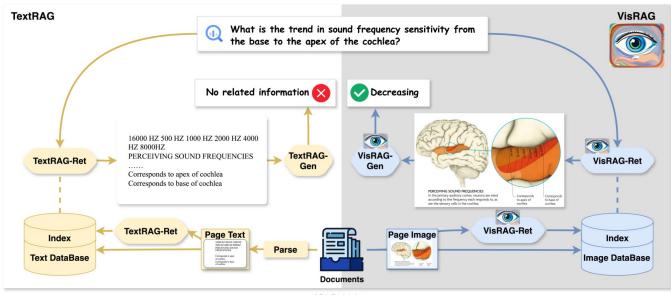
RAG for Real-world Multi-modality Documents

- Real-world documents are often presented in mixed modality, where texts, images, (tables, ...) are interleaved on a page with a specific layout
- Document parsing is introduced in RAG frameworks to extract texts



VisRAG: Parsing-free Vision-based RAG

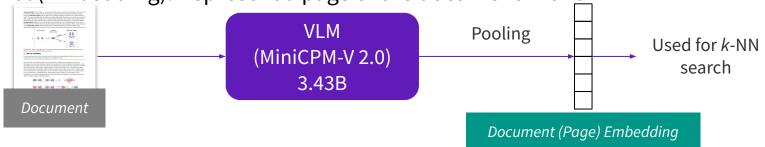
- Parsing-free: Use document image as the processing unit
- Vision-based: Use VLMs rather than LLMs for retrieval & generation



ICLR 2025

VisRAG: Method

Retrieval (Embedding): Represent a page of the document with a VLM



Generation:

(MiniCPM-V antibonding molecular 2.0/2.6/GPT-4o...) orbitals? Query Document

Answer

VisRAG: Data

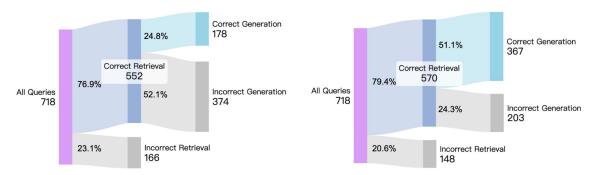
- Synthetic data for training
 - Collect PDFs from the Web
 - Prompt GPT-4o on document images to generate queries
- Open-source data from VQA datasets for training & evaluation
 - We collect VQA question-document pairs and pool the documents to build retrieval corpus
 - Filtering
 - Some queries from the VQA datasets are *context-dependent*: Where was *the conference* held?
 - We prompt GPT-4o with demonstrations to filter them out
- Data Statistics

| Source | Document Type | Train | Evaluation | | |
|------------------|-----------------------------|-------------|-------------------|------------|----------------|
| | | # Q-D Pairs | # Q (% Preserved) | # D | # Pos. D per Q |
| ArXivQA (2024b) | Arxiv Figures | 25,856 | 816 (8%) | 8,066 | 1.00 |
| ChartQA (2022) | Charts | 4,224 | 63 (5%) | 500 | 1.00 |
| MP-DocVQA (2023) | Industrial Documents | 10,624 | 591 (11%) | 741 | 1.00 |
| InfoVQA (2022) | Infographics | 17,664 | 718 (26%) | 459 | 1.00 |
| PlotQA (2020) | Scientific Plots | 56,192 | 863 (4%) | 9,593 | 1.00 |
| SlideVQA (2023) | Slide Decks | 8,192 | 556 (25%) | 1,284 | 1.26 |
| Synthetic | Various | 239,358 | - | = 1 | _ |

VisRAG: Overall Results

• The *cascade effect* (retrieval+generation) results in significant performance boost over text-based RAG (TextRAG)

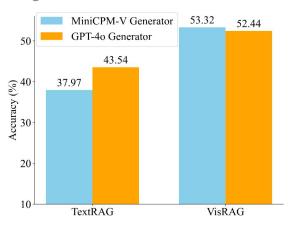
On InfographicsVQA



(a) TextRAG with MiniCPM (OCR) as the retriever (b) VisRAG with VisRAG-Ret as the retriever and and MiniCPM-V 2.6 (OCR) as the generator.

MiniCPM-V 2.6 as the generator.

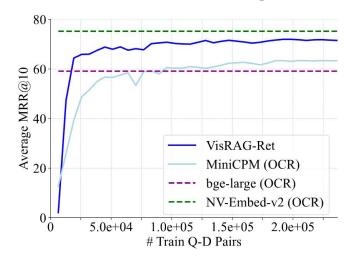
Avg. Performance on all Datasets



VisRAG: Analysis

- Training data efficiency
 - VisRAG-Ret (the retriever, 3.4B) surpasses bge-large
 (OCR) after trained on ~20K synthetic data
 - ... and achieves 95% of the performance of NV-Embed-v2 (7.9B) after trained on 240K (all) synthetic data
 - Bge-large and NV-Embed-v2 are trained on *millions of* curated query-document pairs

 Capturing multi-modal information is more effective and efficient than merely increasing training data and model parameters but relying solely on the text modality All runs in the out-of-domain setting

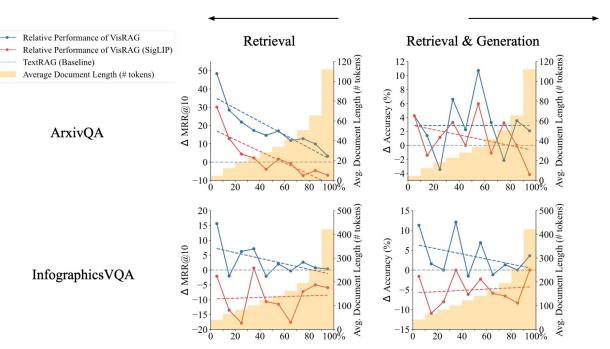


VisRAG: Analysis

 VisRAG performs better than TextRAG on all subsets of documents including text-emphasized ones

Vision-emphasized

Text-emphasized



Conclusion

- VisRAG shows that building a parsing-free, vision-based RAG pipeline is possible and performs better than text-based RAG (TextRAG) pipelines
- Training the retriever of VisRAG is more data-efficient and it generalizes better than text retrieval models

 VisRAG is a more effective and efficient RAG pipeline than TextRAG for multi-modality documents

Check out our code and models at https://github.com/openbmb/visrag