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MoLoRAG: Bootstrapping Document Understanding via Multi-modal Logic-aware Retrieval

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Motivation

Document Question Answering (DocQA) Answer a question based on the content of a document

- Interpreting medical reports
- Assisting with academic literature
- Supporting financial decision-making

Existing LLM-based Methods First convert the document into text using OCR, and then retrieve relevant paragraphs from text to feed into LLM

✗ Inevitable **multi-modal information loss** like tables, figures, document layouts, etc

Existing LVLM-based Methods

- Direct:** Directly feeding all image snapshots of the document to an LVLM for question answering ✗ Exceed **LVLM context**
- Retrieval-based:** Use a document encoder to encode pages and retrieve relevant ones based on vector similarity ✗ Only **semantic relevance**

Precise question answering requires pages that are **logically relevant** to the query, e.g., providing clues for the derivation of the answer

Methodology

Graph-based Index

Construct a page graph to represent the dependencies between pages

$$E_{p_i} = \text{DocEncoder}(p_i)$$

$$\mathcal{E} = \{(p_i, p_j) | \langle E_{p_i}, E_{p_j} \rangle \geq \theta\}$$

Graph Traversal for Retrieval

Leverage a VLM to serve as the retrieval engine, reasoning over the graph through traversal to identify logically relevant pages

Question Answering

Combine both logical and semantic relevance into a unified similarity score to re-rank pages

$$s_i = \text{Combine}(s_i^{\text{sem}}, s_i^{\text{logi}})$$

✓ **Compatibility with arbitrary LVLMs**

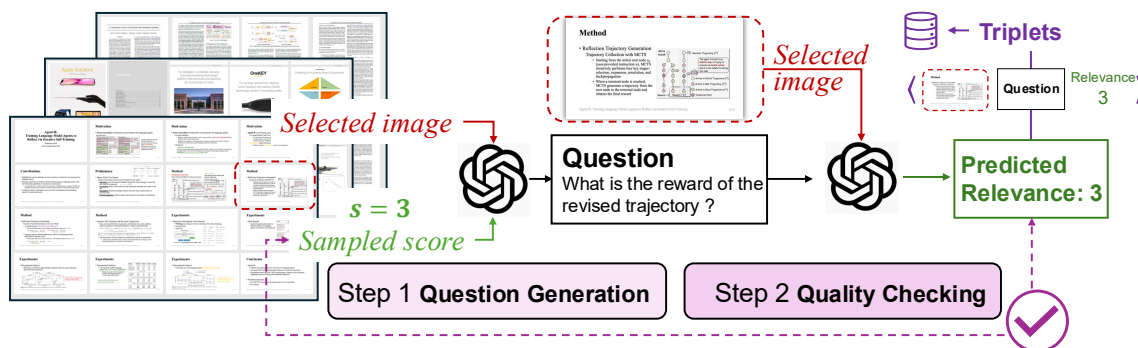
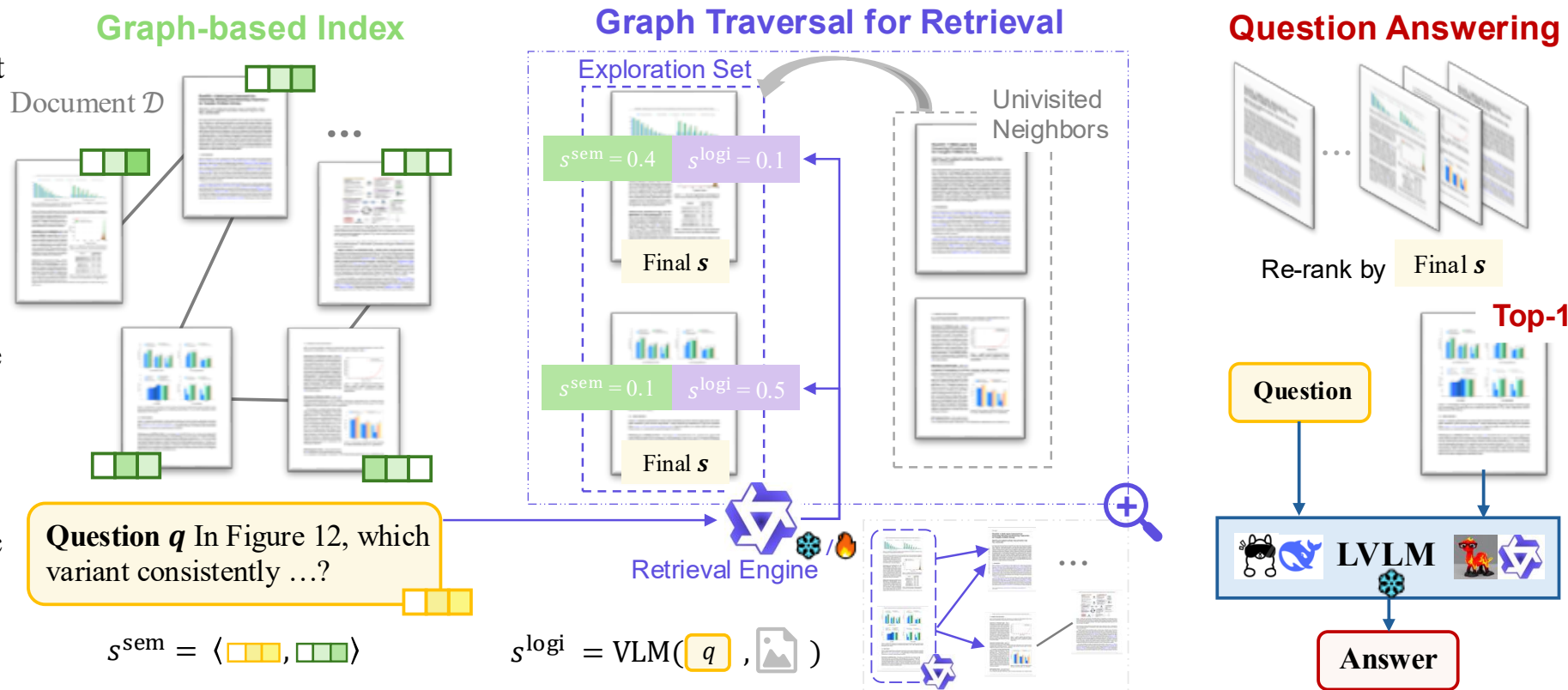
✓ **Enhanced retrieval accuracy**

✓ **Efficiency of controlled graph traversal**

MoLoRAG+: Fine-tuned Retrieval Engine

Replace the pre-trained VLM retrieval engine with a fine-tuned version, acquiring the specialized logical relevance score checking capability via SFT using curated <Question, Image, Relevance Score> triplets

Backbone: Qwen2.5-VL-3B

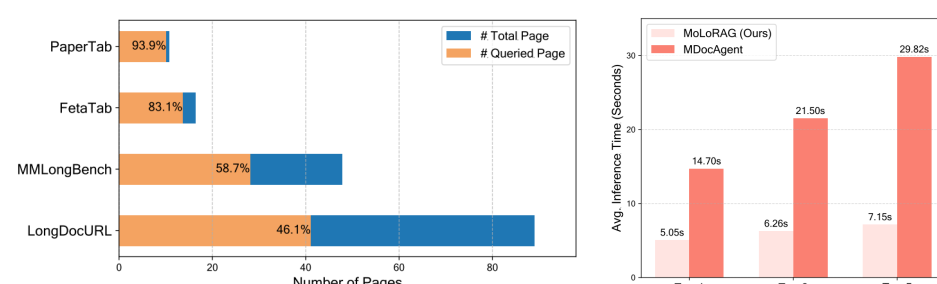


Experiments

| Type | Model | Method | MMLongBench | LongDocURL | PaperTab | FetaTab | Avg. |
|--------------------|----------------------------------------|----------|--------------|--------------|--------------|--------------|--------------|
| LLM-based | Mistral-7B | Text RAG | 24.47 | 25.06 | 11.45 | 41.14 | 25.53 |
| | Qwen2.5-7B | Text RAG | 25.52 | 27.93 | 12.72 | 40.06 | 26.56 |
| | LLaMA3.1-8B | Text RAG | 22.56 | 29.80 | 13.49 | 45.96 | 27.95 |
| | GPT-4o | Text RAG | 27.23 | 32.74 | 14.25 | 50.20 | 31.11 |
| | DeepSeek-V3 | Text RAG | 29.82 | 34.73 | 17.05 | 52.36 | 33.49 |
| LVLM-based | LLaVA-Next-7B | Direct | 7.15 | 10.78 | 3.05 | 11.61 | 8.15 |
| | | M3DocRAG | 10.10 | 13.85 | 5.34 | 13.98 | 10.82 |
| | | MoLoRAG | 9.37 | 13.49 | 4.83 | 13.78 | 10.37 |
| | | MoLoRAG+ | 9.47 | 13.58 | 5.60 | 13.48 | 10.53 |
| | DeepSeek-VL-16B | Direct | 8.40 | 14.72 | 6.11 | 16.14 | 11.34 |
| | | M3DocRAG | 18.12 | 29.60 | 7.89 | 27.07 | 20.67 |
| | | MoLoRAG | 20.43 | 29.98 | 9.67 | 38.98 | 24.77 |
| | | MoLoRAG+ | 25.47 | 37.21 | 10.94 | 41.54 | 28.79 |
| | Qwen2.5-VL-3B | Direct | 26.65 | 24.89 | 25.19 | 51.57 | 32.08 |
| | | M3DocRAG | 29.11 | 44.40 | 24.68 | 53.25 | 37.86 |
| | | MoLoRAG | 32.11 | 45.79 | 24.43 | 57.68 | 40.00 |
| | | MoLoRAG+ | 32.47 | 45.27 | 27.23 | 58.76 | 40.93 |
| Multi-agent | Qwen2.5-VL-7B | Direct | 32.77 | 26.38 | 29.77 | 64.07 | 38.25 |
| | | M3DocRAG | 36.18 | 49.03 | 28.50 | 63.78 | 44.37 |
| | | MoLoRAG | 39.28 | 51.71 | 32.32 | 69.09 | 48.10 |
| | | MoLoRAG+ | 41.01 | 51.85 | 31.04 | 69.19 | 48.27 |
| | M3DocAgent (LLaMA3.1-8B+Qwen2.5-VL-7B) | | 38.53 | 46.91 | 30.03 | 66.34 | 45.45 |

| Top-K | Method | MMLongBench | | | | LongDocURL | | | |
|-------|--------------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
| | | Recall | Precision | NDCG | MRR | Recall | Precision | NDCG | MRR |
| 1 | M3DocRAG | 43.31 | 56.67 | 56.67 | 56.67 | 46.84 | 64.66 | 64.66 | 64.66 |
| | M3DocAgent (Text) | 29.30 | 38.99 | 38.99 | 38.99 | 42.03 | 58.37 | 58.37 | 58.37 |
| | M3DocAgent (Image) | 43.79 | 57.49 | 57.49 | 57.49 | 46.80 | 64.57 | 64.57 | 64.57 |
| | MoLoRAG | 45.46 | 59.95 | 59.95 | 59.95 | 48.98 | 67.71 | 67.71 | 67.71 |
| | MoLoRAG+ | 51.32 | 66.86 | 66.86 | 66.86 | 50.82 | 70.08 | 70.08 | 70.08 |
| 3 | M3DocRAG | 64.17 | 31.62 | 54.13 | 65.36 | 67.00 | 33.78 | 58.23 | 72.51 |
| | M3DocAgent (Text) | 43.21 | 20.77 | 37.13 | 45.26 | 58.53 | 29.33 | 54.12 | 65.28 |
| | M3DocAgent (Image) | 64.74 | 31.97 | 54.75 | 66.12 | 66.67 | 33.62 | 58.26 | 72.47 |
| | MoLoRAG | 67.22 | 40.81 | 57.34 | 68.56 | 70.04 | 36.41 | 61.56 | 75.78 |
| | MoLoRAG+ | 68.87 | 48.67 | 64.49 | 73.50 | 68.92 | 47.53 | 64.90 | 77.14 |
| 5 | M3DocRAG | 72.00 | 22.58 | 54.06 | 66.92 | 74.32 | 23.34 | 58.05 | 73.83 |
| | M3DocAgent (Text) | 50.60 | 15.48 | 37.19 | 46.98 | 65.41 | 20.41 | 53.97 | 66.55 |
| | M3DocAgent (Image) | 71.45 | 22.37 | 54.58 | 67.53 | 74.60 | 23.50 | 58.06 | 73.90 |
| | MoLoRAG | 74.13 | 35.83 | 57.29 | 69.63 | 77.14 | 26.13 | 61.30 | 76.88 |
| | MoLoRAG+ | 72.37 | 45.34 | 64.36 | 73.97 | 73.69 | 42.47 | 64.74 | 77.89 |

Retrieval Accuracy MoLoRAG identifies relevant pages



DocQA Performance

MoLoRAG consistently boosts diverse LVLM's performance

Retrieval scalability and inference efficiency of MoLoRAG