Benchmarking Open-Source LLMs in RAG Systems with Diploma Abstracts

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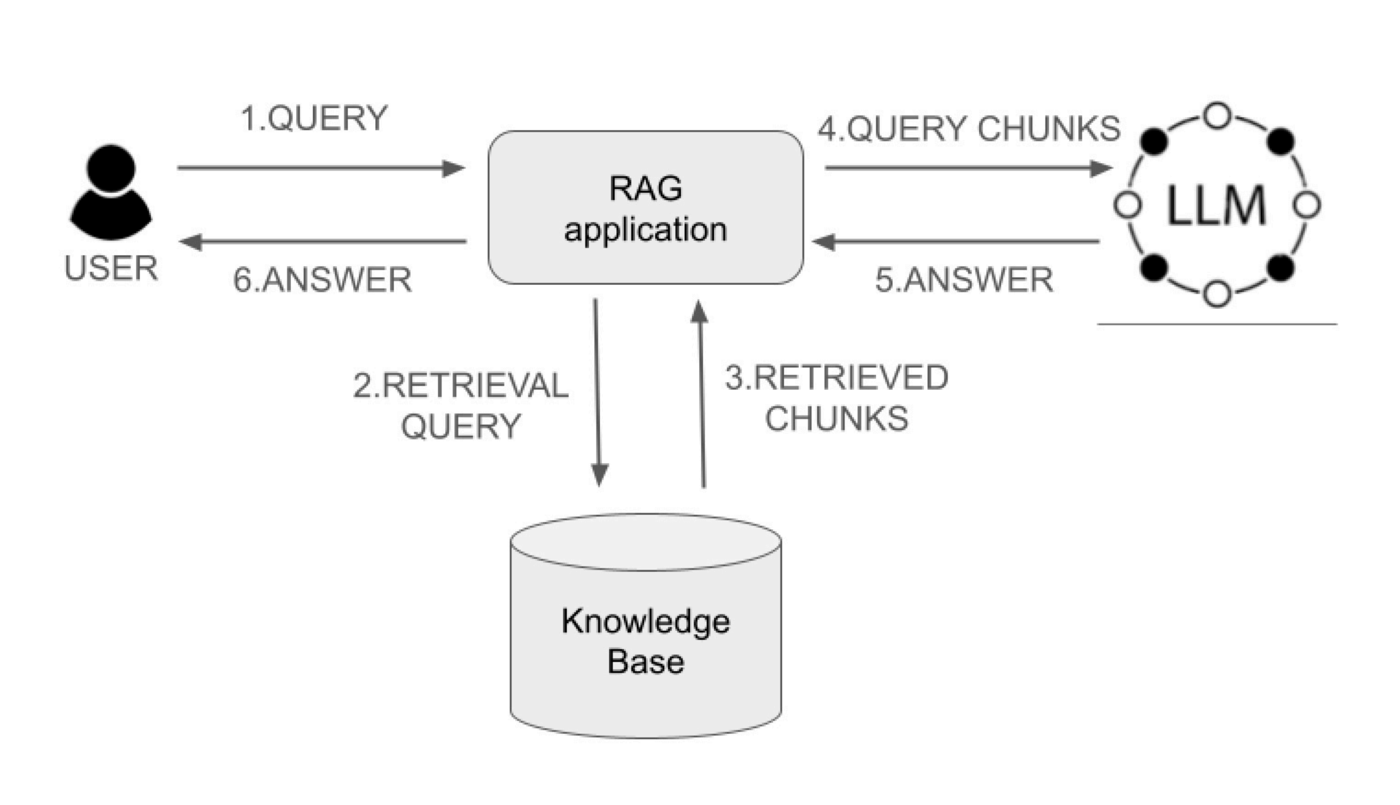
Why RAG?

- LLMs are not up to date, **hallucinate**
- You want answers based on **your own private data**

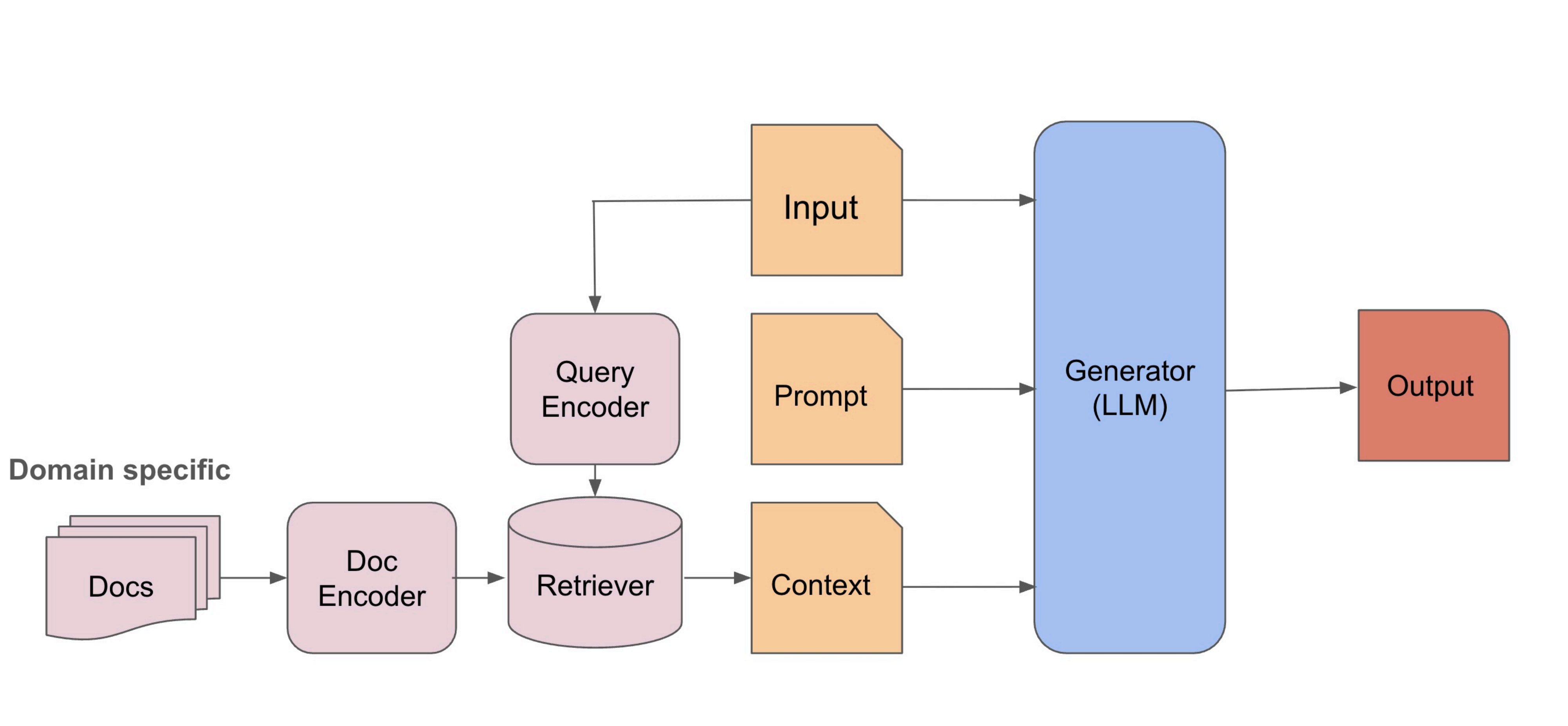
RAG System Architecture

RAG = Information Retrieval + Generative AI



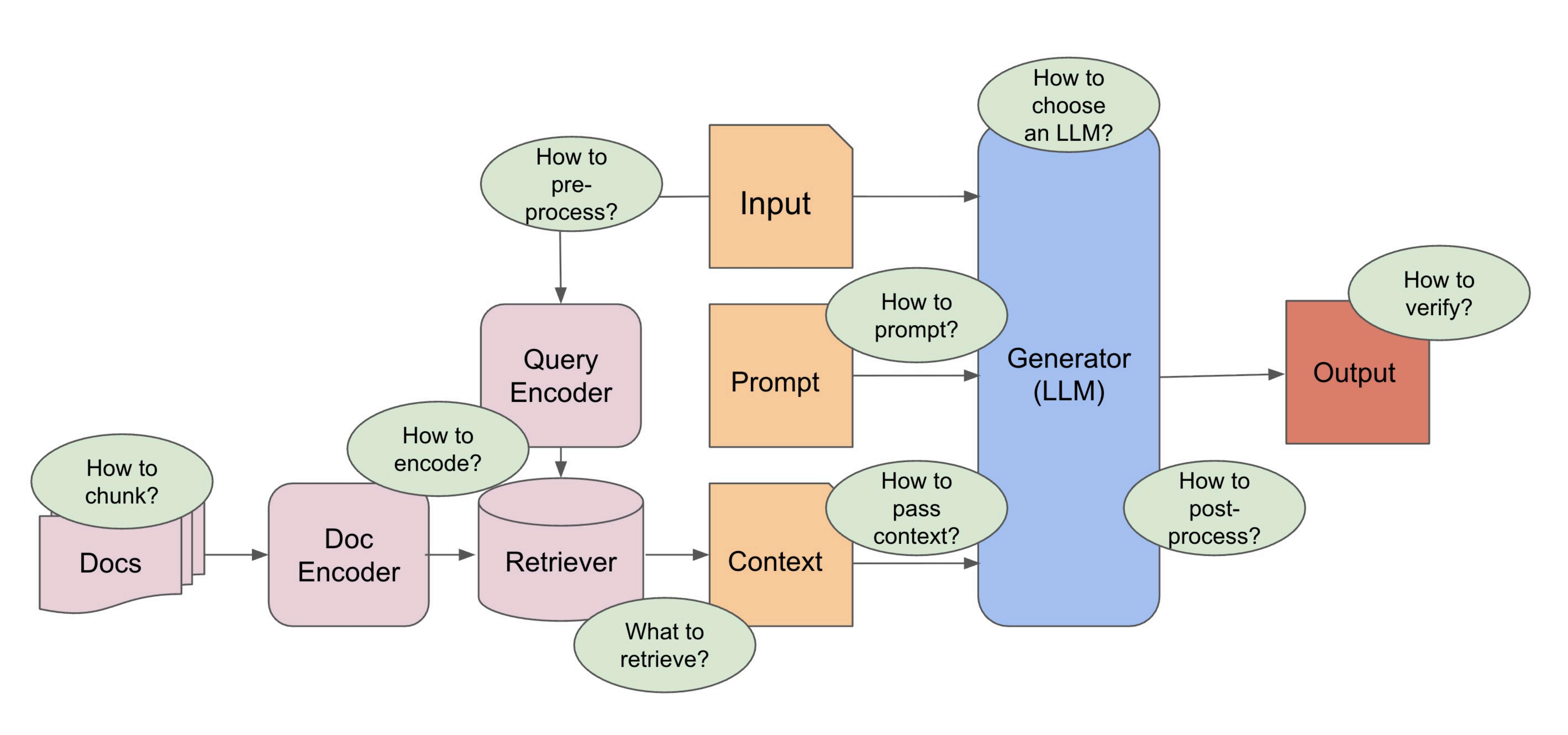
RAG Architecture

Details



RAG - Challenges

Challenges



Our RAG challenges

- How to encode?
- How to pass the context?
- How to verify?

Our RAG challenges

- How to encode? = **Embedder model**
- How to pass the context? = **Number of similar chunks + Reranking**
- How to verify? = **Dataset + Metrics**

The *SapiTheses* Dataset

Creation

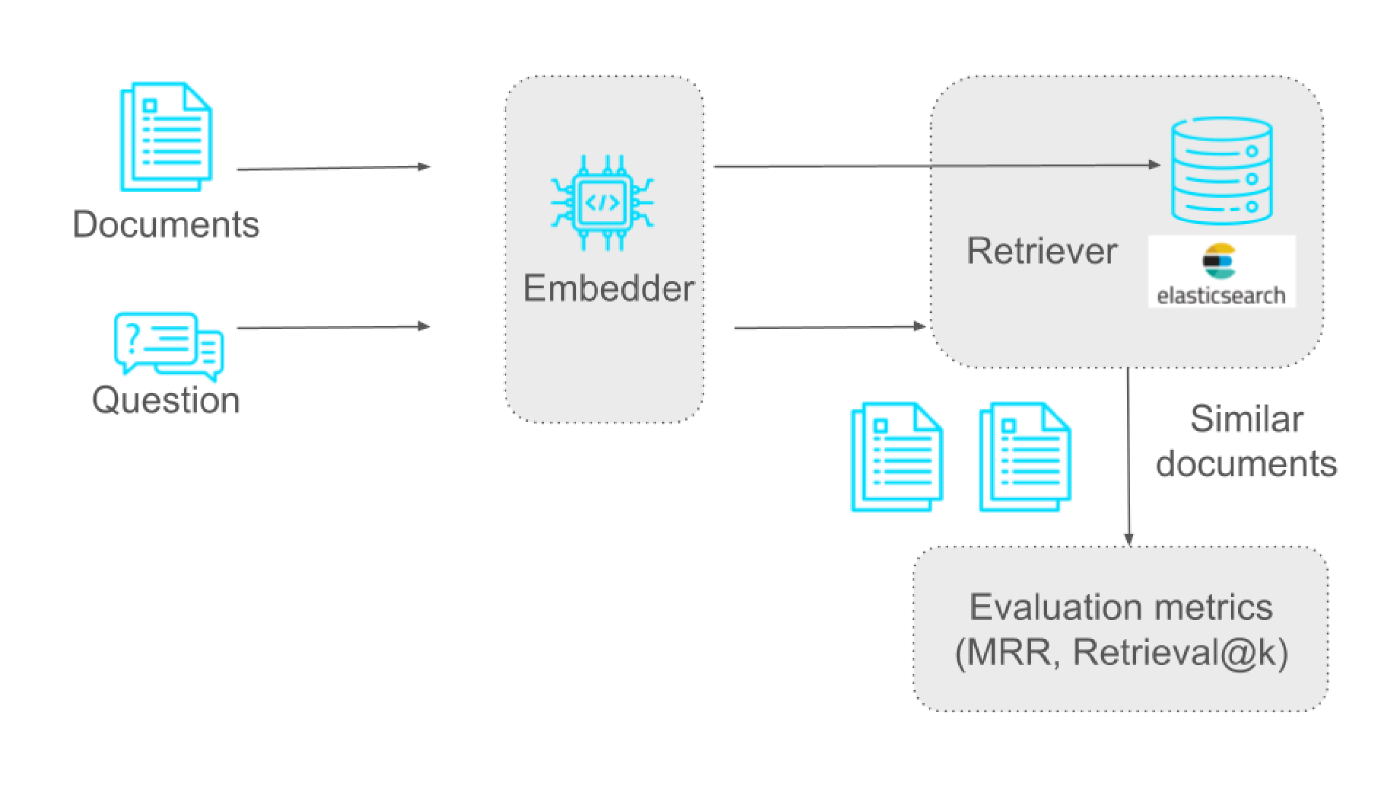
The *SapiTheses* Dataset

Question Categorization Taxonomy

- **Fact Single Questions (25)**: Seek **direct factual information** explicitly present in the abstract.
  What is the Nash equilibrium in the context of two-person games?
- **Reasoning Questions (73)**: The answer is inferred, not explicit.
  How can musical taste help in forming friendships?
- **Summary Questions (24)**: Ask for key points of the abstract. *What is the main purpose of the mobile app for Târgu Mures Zoo?*

RAG System Evaluation

Retriever Evaluation



Retrieval Subsystem

- **Tool**: *Elasticsearch*
- **Search Strategies Employed**:
  - **Lexical Search**:
    - **BM25** ranking algorithm.
  - **Semantic Search**:
    - **Embeddings** generated by the `all-mpnet-base-v2` model --> **768-dimensional** embeddings.

Retrieval Quality Metrics

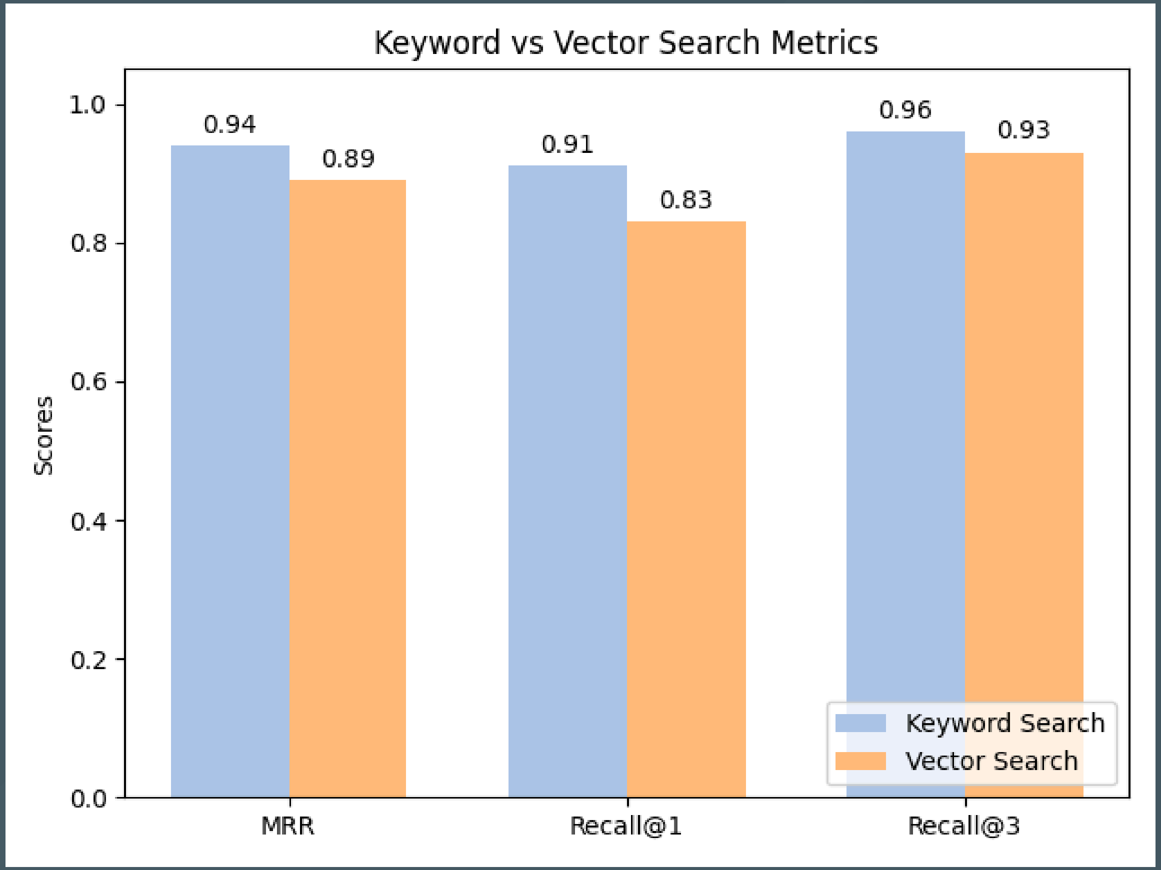
- **Mean Reciprocal Rank (MRR)**: `rank_i` - the rank position of the first relevant document for the i-th query.

$$\mathrm{MRR} = \frac{1}{|Q|}\sum_{i=1}^{|Q|}\frac{1}{\mathrm{rank}_i}.$$

- **Recall@k**: Frequency of the relevant document being found within the **top k** result.

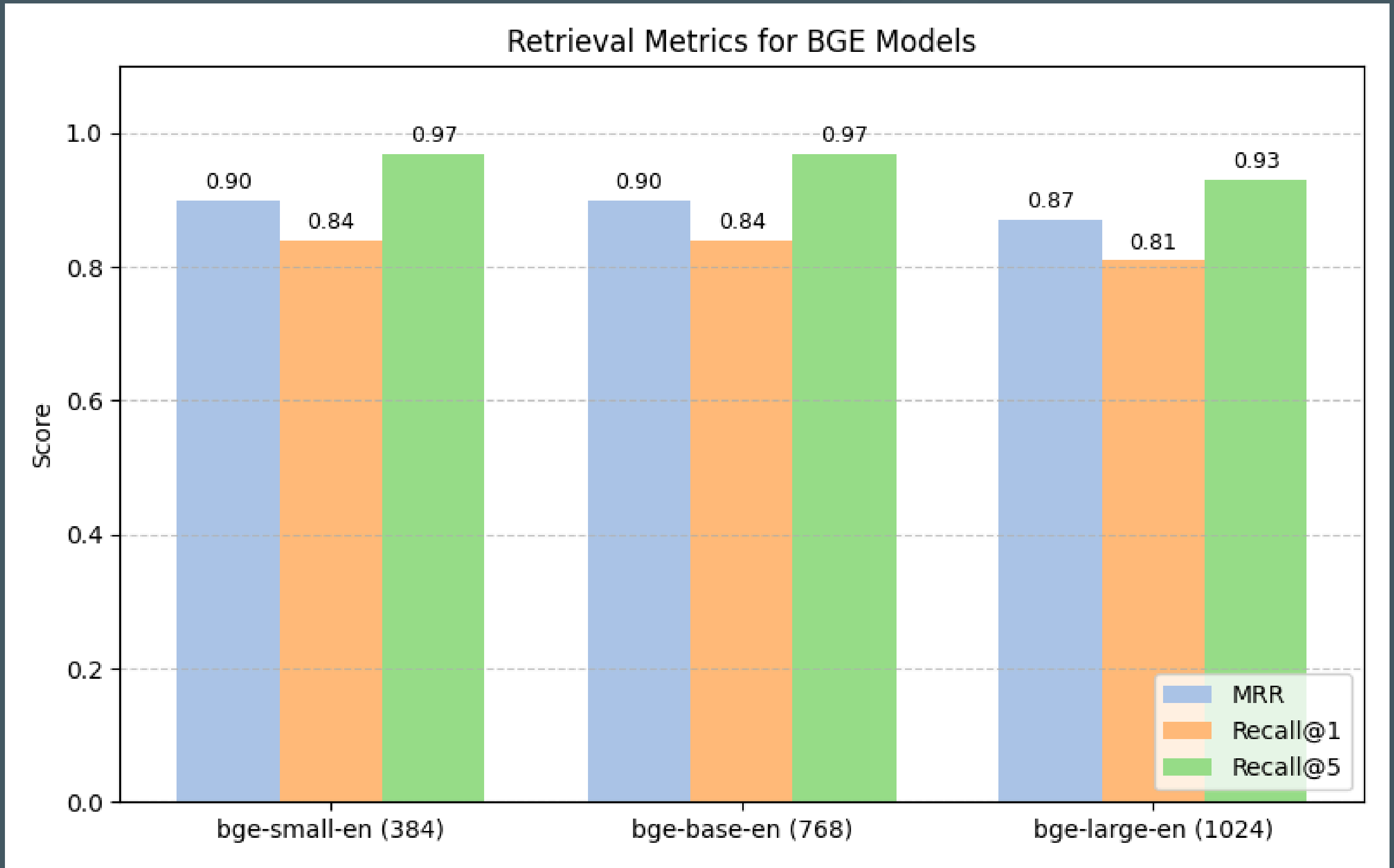
Retriever Performance Insights

Embedding model: `all-mpnet-base-v2 (768)`



Retriever Performance - BGE models

Embedding models: `small (384)`, `base (768)`, `large(1024)`



Answer Generation Subsystem

Open-Source LLMs tested:

- Mistral-Q4 (7.0B, 32K context)
- Mistral-FP16 (7.0B, 32K context)
- DeepSeek-r1-7.6B (7.6B, 128K context)
- DeepSeek-r1-32B (32.0B, 128K context)
- Llama3 (8.0B, 8K context)
- Gemma3 (7.0B, 8K context)

Generation Performance Metrics

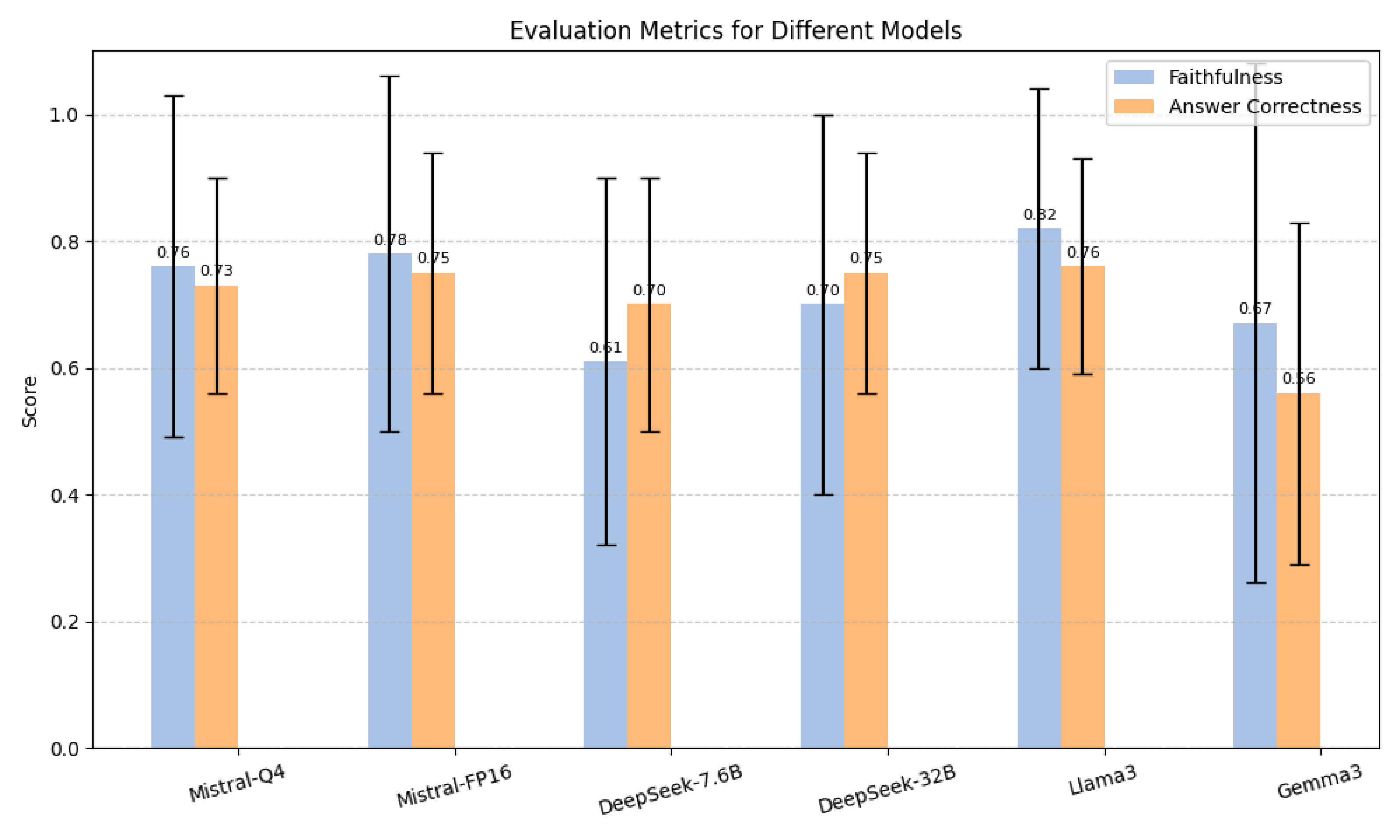
- **Faithfulness**: Checks if the answer is *factually consistent with the retrieved context*.
- **Answer Relevance**: Measures how well the *answer addresses the input question*.
- **Semantic Similarity**: Assesses *content overlap* between the generated and reference answers.
- **Answer Correctness**: Overall judgment of *accuracy*, considering factual content and semantic alignment.

Faithfulness

- **Question:** When and where was Einstein born?
- **Context:** Albert Einstein *(born 14 March 1879)* was a *German-born* theoretical physicist, widely held to be one of the greatest and most influential scientists of all time.
- **High faithfulness answer:** Einstein was born in `Germany` on `14th March 1879`.
- **Low faithfulness answer:** Einstein was born in `Germany` on `20th March 1879`.

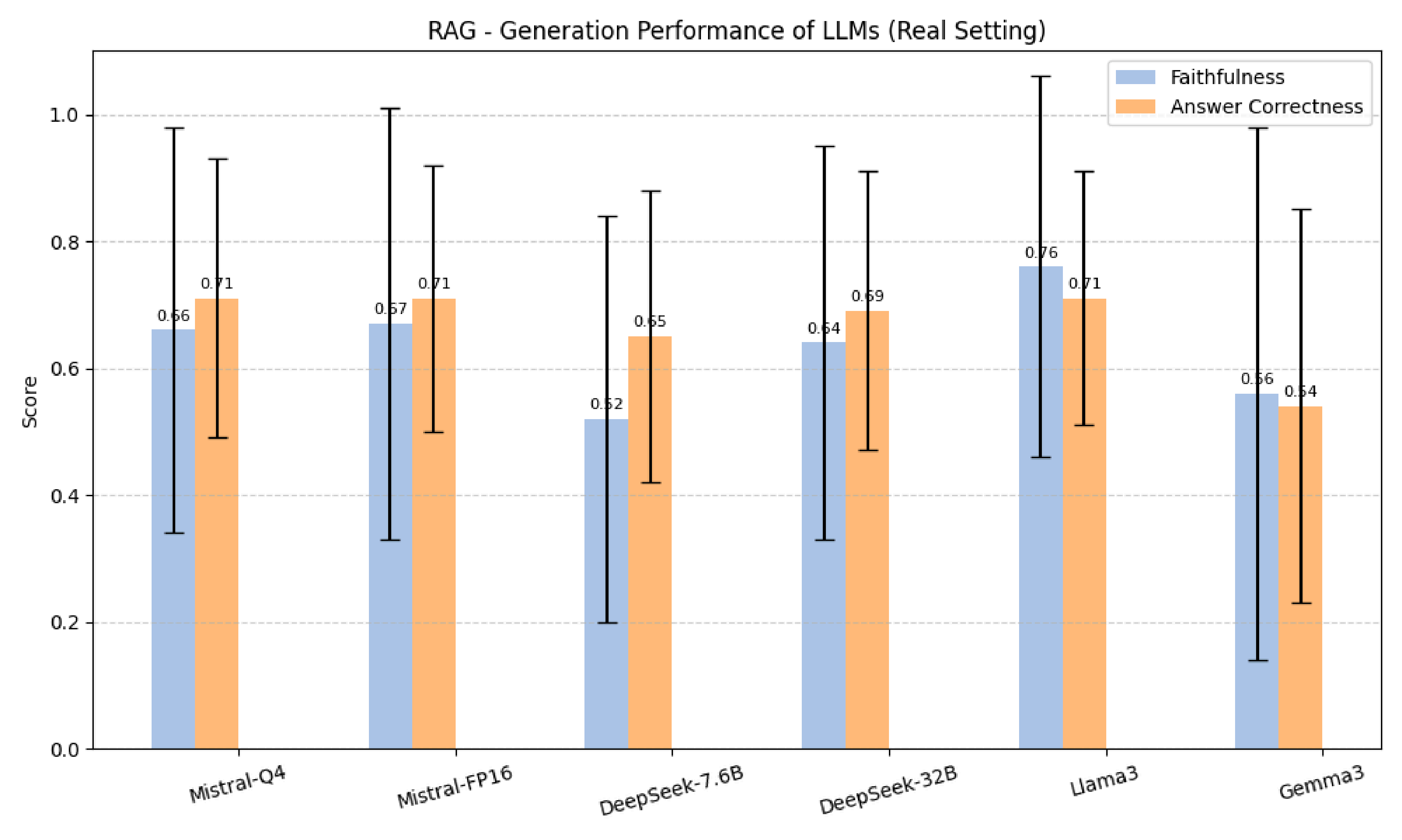
Generation Performance - Ideal Setting

LLM + original abstract (100% relevant)



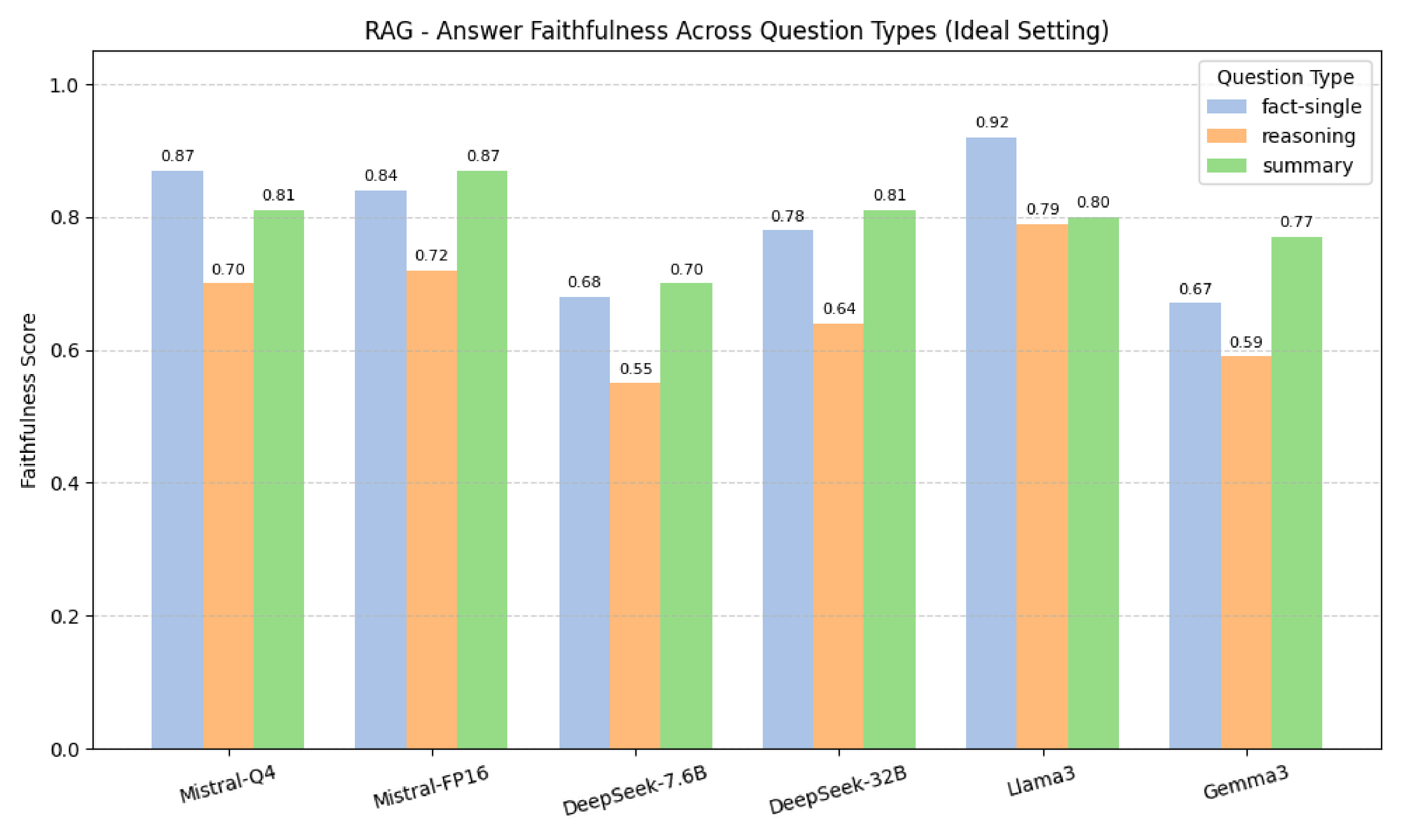
Generation Performance - Real Setting

LLM prompted + TOP 3 abstracts (reranked)



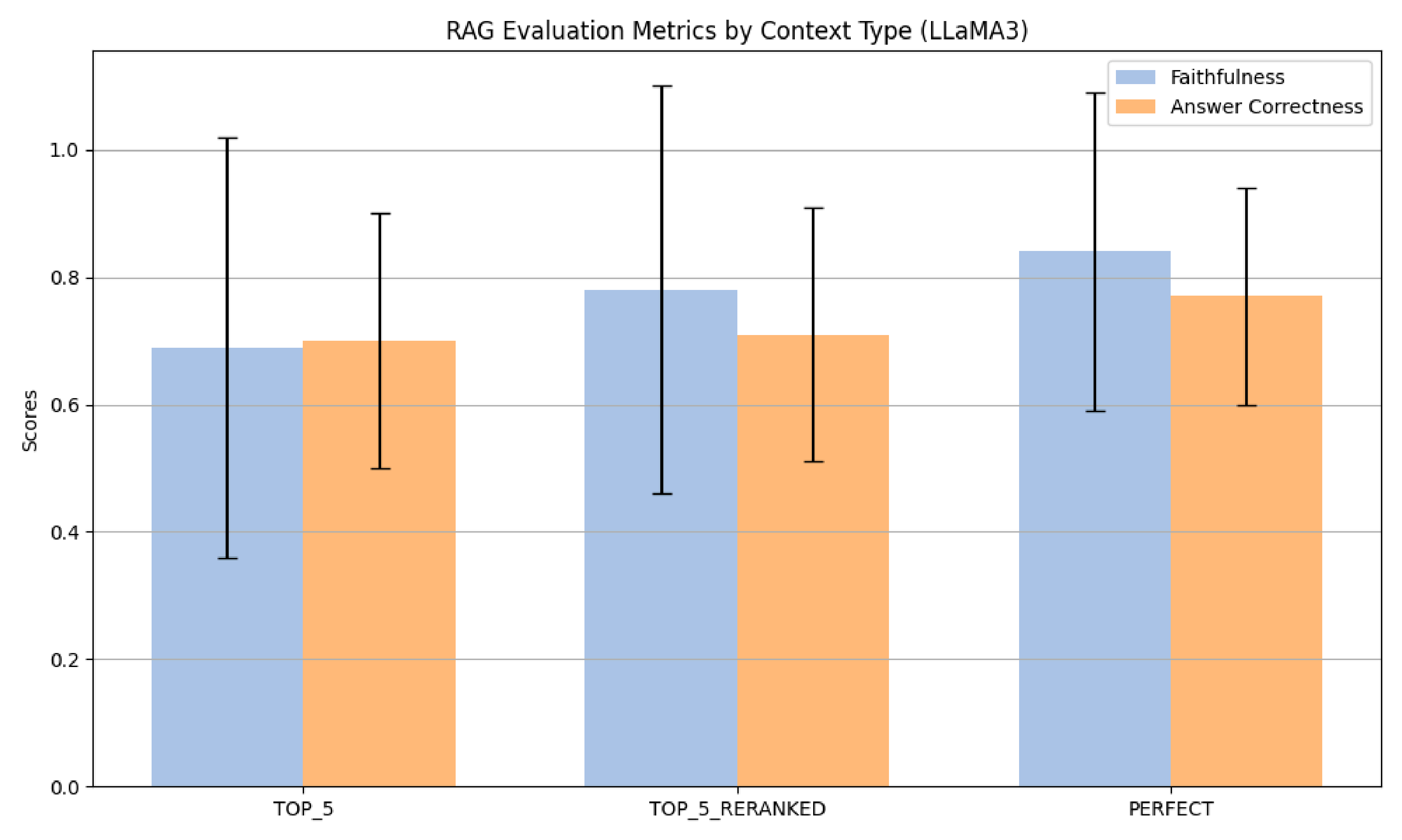
Performance Across Question Types

LLM + original abstract (PERFECT)



Reranking effect

Llama3 + (PERFECT, TOP 5, TOP 5 reranked)



Conclusions

- **Lexical** and **semantic search** methods have distinct strengths: consider **hybrid search**
- **Embedding choice is critical**: Mid-sized embeddings often outperform larger ones in retrieval tasks.
- **Llama3 and Mistral models offer balanced performance** in faithfulness and correctness.
- **Reranking** improves **generation** quality.
- **Reasoning-heavy questions remain a challenge** for RAG systems.