

RAG-inspired Open-source based Q&A system for scholarly articles in EIC

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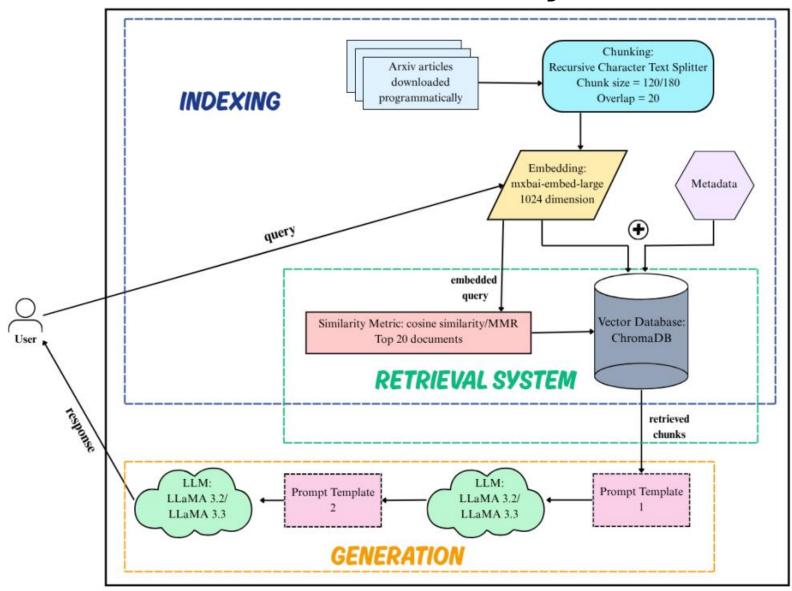
Objectives:

 Build an in-house knowledge base of EIC-related scholarly articles.

 Implement Retrieval Augmented Generation(RAG) to improve the factual accuracy of a Q&A system for EIC.

 Extend the previous work built on proprietary model such as OpenAl to open-source models/frameworks.

Flowchart of the end-to-end RAG system:



Indexing: Vectorized Database

- In-house Knowledge base: Around 200 pdf articles from arXiv
- Chunking strategy: Recursive Character Text Splitter model
- Chink size: 120 and 180 tokens with an overlap of 20 characters
- **Metadata**: indexed with arXiv ID, title, categories, primary categories, authors and publication date.
- Embedding model: 1024-dim vector representations; all-MiniLM and mxbai-embed-large models.
- Database: Pinecone (cloud-based) and ChromaDB (in-house) were explored

Retrieval:

- Query embedding: Same *mxbai-embed-large* model to convert user queries with 1024-dim vector
 - Hosted locally via Ollama.
 - This ensures semantic consistency between database embeddings and the user queries.
- Vector Search: The top 20 most relevant chunks using Cosine Similarity or Maximum Marginal Relevance (MMR) methods.

Answer Generation and Tracing:

- Prompt Stuffing: Retrieved context is combined with user query
- LLM processing: The Llama 3.2 and Llama 3.3 models, deployed locally via Ollama
 - *Llama3.2*: A quantized model with 3.21B parameters
 - Llama3.3: A quantized model with 70B parameters with 1,28,000-token context window.
- Answer generation: through a two-stage LLM processing mechanism.
- Pipeline management and Tracing:
 - **LangChain**: Manages the flow between the query embedding, retrieval and answer generation
 - **LangSmith**: Platform to trace the intermediate steps of the RAG-pipeline, essential for debugging

Evaluation: OpenAI RAGAS framework

Benchmark dataset:

- GPT4.0 to create a set of Q&A pairs from EIC-related arXiv articles on theory, simulation, hardware etc.
- Scrutinized by domain expert
- Each question in the dataset is explicitly
 - linked to a defined number of "claims"
 - corresponding answer that specifies individual claim and an ideal response
 - a comprehensive overall response

Retrieval Quality evaluation metrics:

Context Entity Recall, Context Precision and Context Recall,

Generated answer evaluation metrics:

Answer Relevancy, Answer Correctness and Faithfulness

Evaluation Metrics:

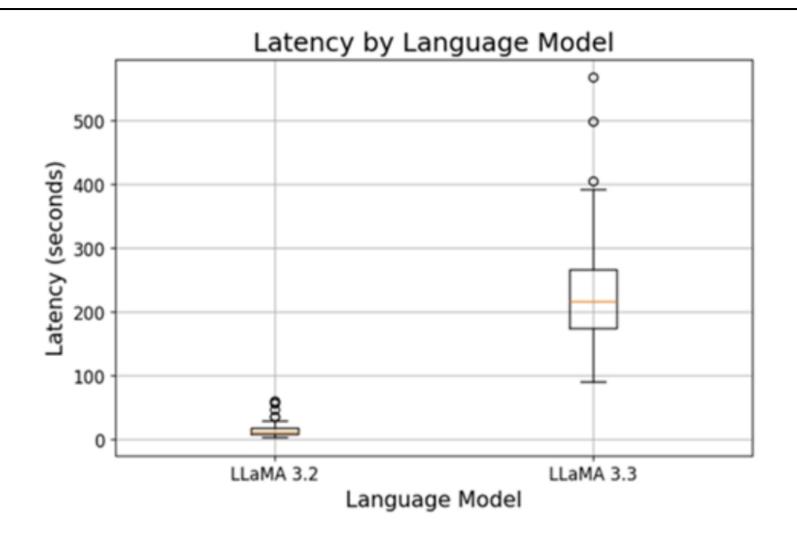
Retrieval:

- Context Precision: Proportion of the retrieved context chunks that are relevant to user query
- Context Recall: Proportion of the context that is being supported by the ground truth answer
- Context Entity Recall: Determines whether the entities in the ground truth answer are successfully recalled within the retrieved context

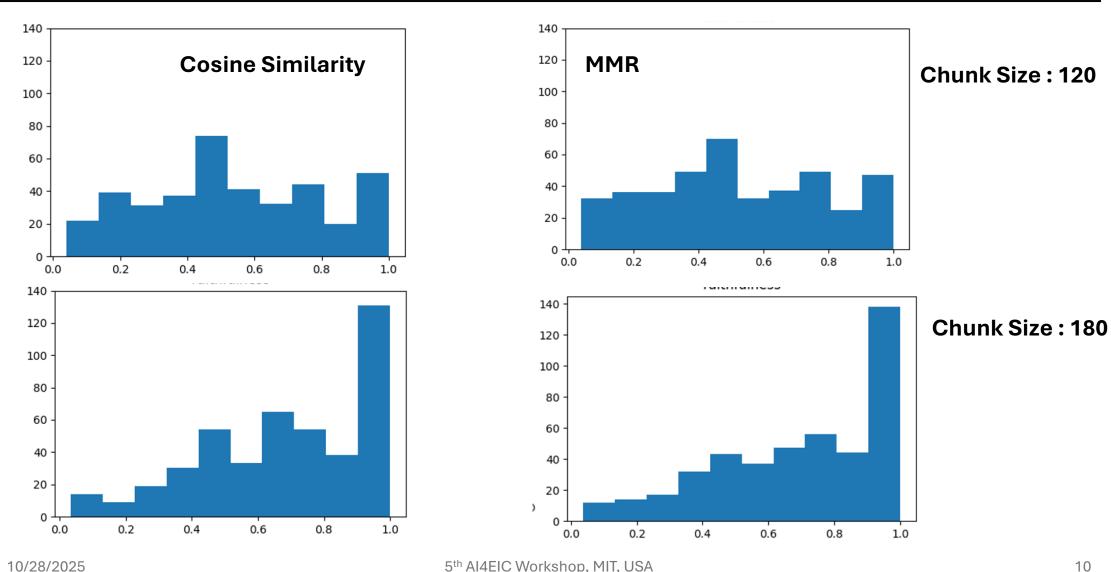
Generation:

- **Answer Correctness**: Factual alignment and factual similarity of the generated answer w.r.t. ground truth
- Answer Relevancy: Semantic alignment b/w the generated answer and the query
- **Faithfulness**: Examines whether the generated answer is factually consistent with the retrieved context calculated based on the claims.
 - Identify instances of hallucinations or unsupported claims

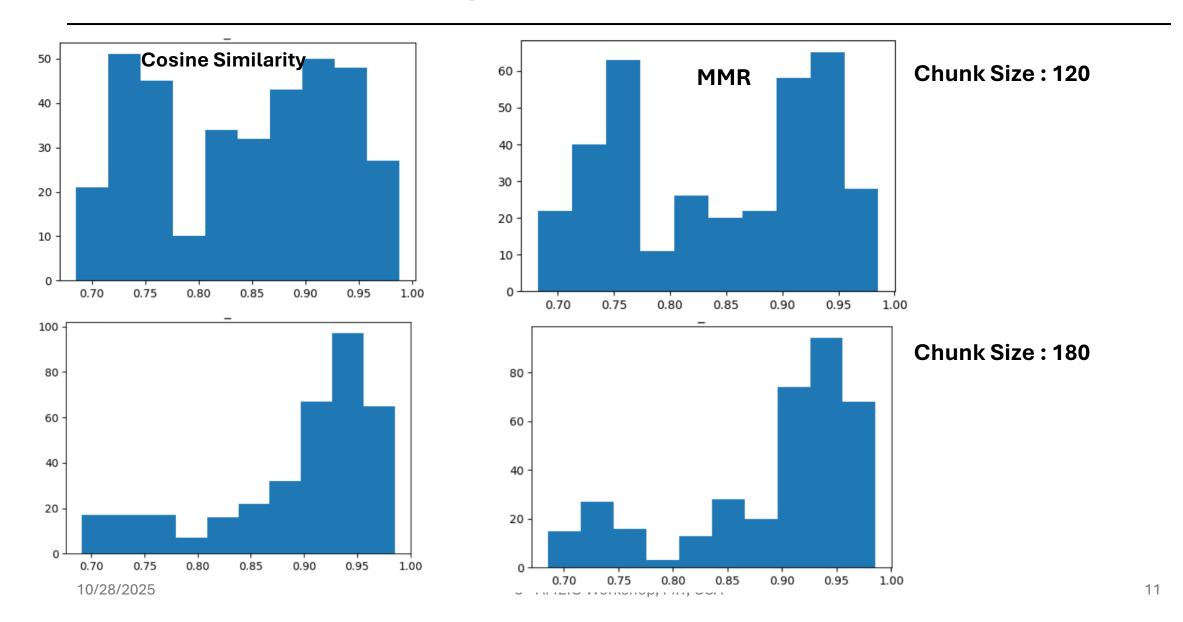
Results: Latency in sec (26 Gb GPU)



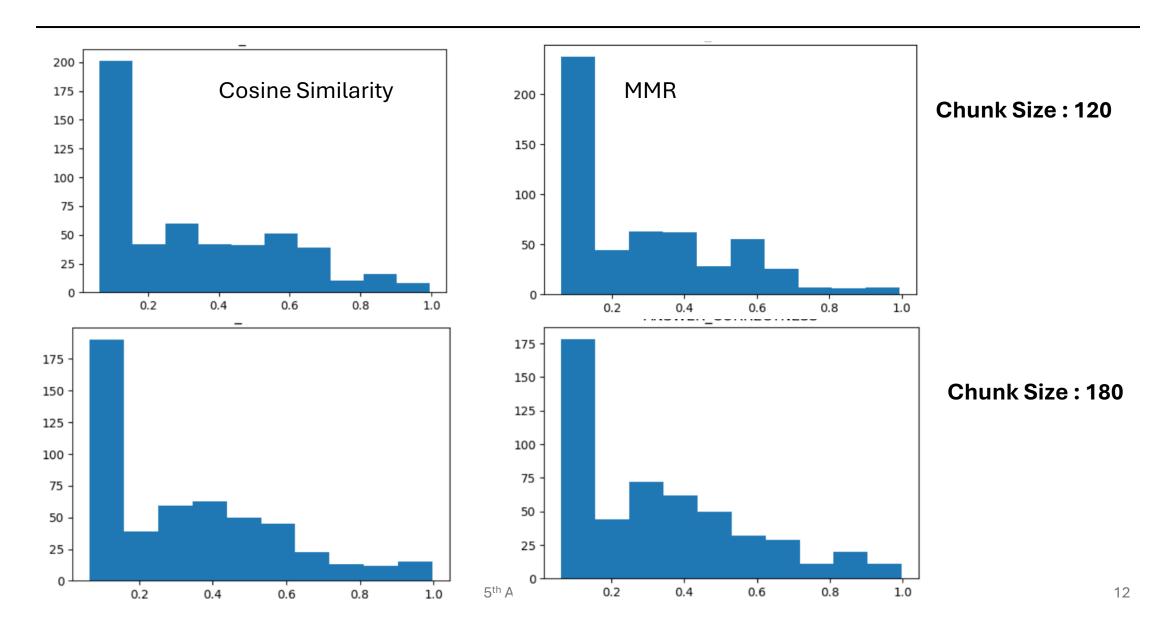
Performance: Faithfulness



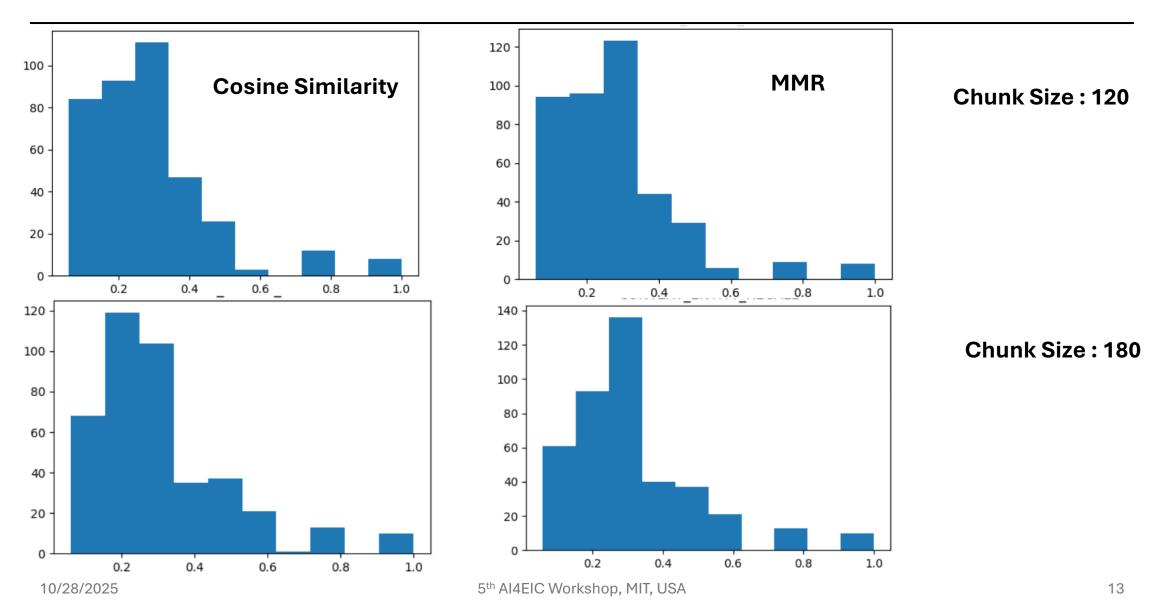
Answer Relevancy:



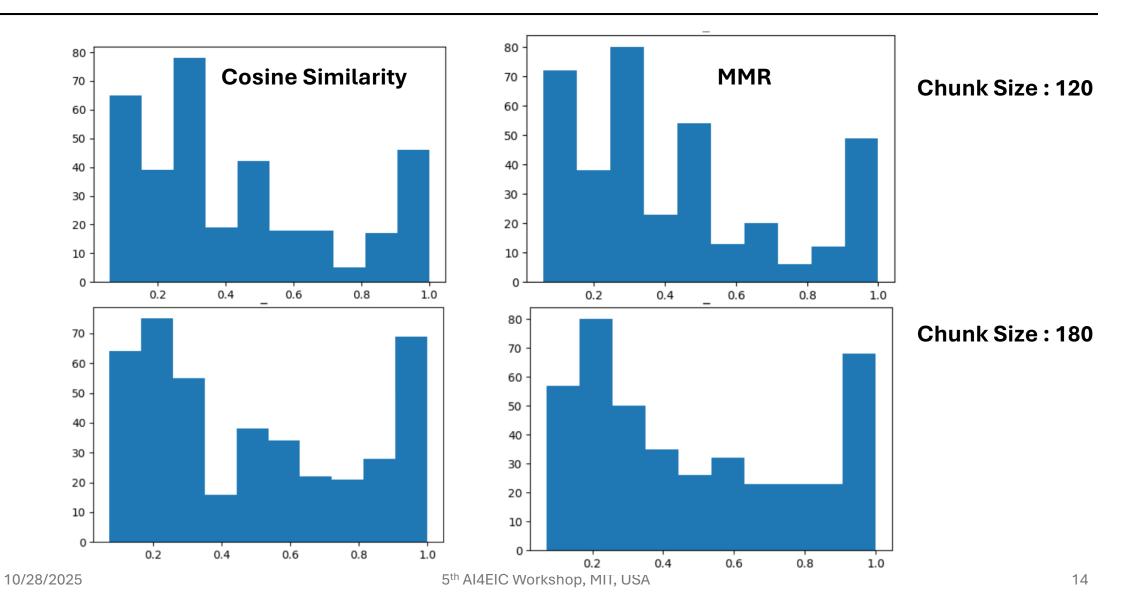
Answer Correctness:



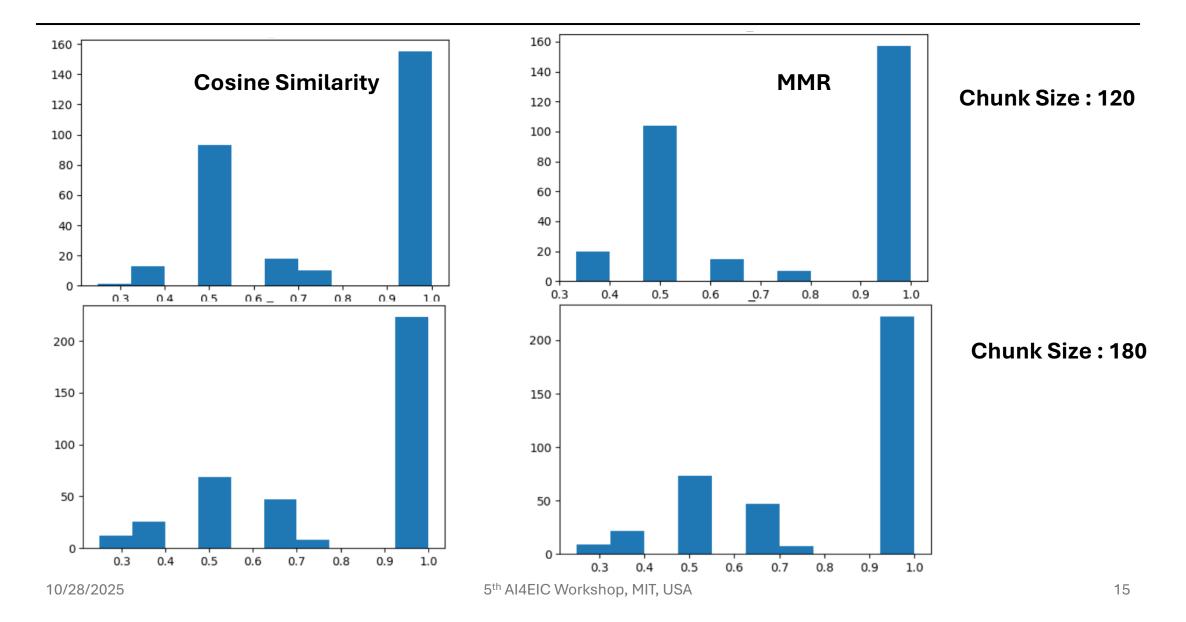
Context Entity Recall:



Context Precision:



Context Recall:



Result Summary:

- Faithfulness and Answer Relevancy:
 - 180 chunk size with Cosine Similarity and MMR combinations demonstrates a positive trend achieving scores around 90%
 - 120 chunk size showed a slightly bimodal distribution and higher variability in scores across the range.
- Answer Correctness, Context Precision and Context Entity Recall: All configurations demonstrated poor performance, with most answers receiving low correctness scores.
- Context Recall: Robust performance was evident across all configurations
- Insight: Increasing chunk size contributes to more factually grounded responses, regardless of the similarity metric.

Conclusions and Future outlook:

Conclusion:

- A RAG-based QA system for FIC-related articles built entirely on open-source tools offers competitive
 performance and practical trade-off compared to large proprietary model.
- A smaller model (~3B parameters) that reduces memory footprint and latency but offers cost effective and performant alternatives.

Challenges:

- For some questions, the generated response contains repetition of same answer multiple times. This is also reflected with higher latency.
- Instances of hallucination observed

Outlook:

- Extending the knowledge base into multimodal format and diverse content ingestion PPT, indico page contents.
- Improving uncertainty quantification of the generated answer.
- Integrating agentic RAG for a comprehensive workflow.

Acknowledgement:

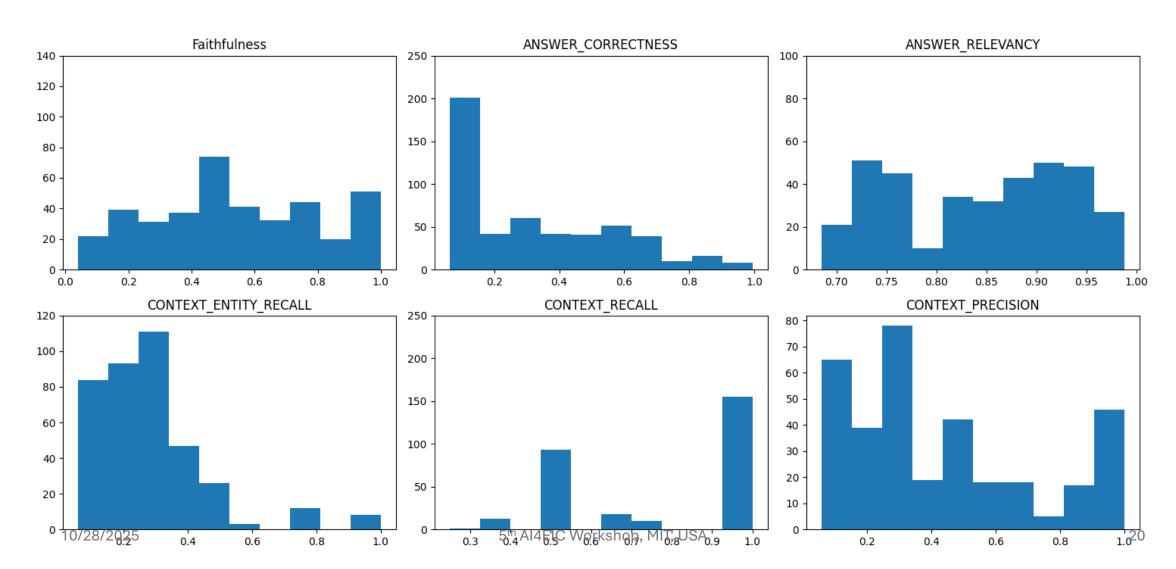
- Tina J Jat, B.Sc. Student
- Karthik Suresh and Cristiano Fanelli, College of W&M
- The Ramaiah University of Applied Sciences
- The organizers of AI4EIC workshop

Thank You

Backup

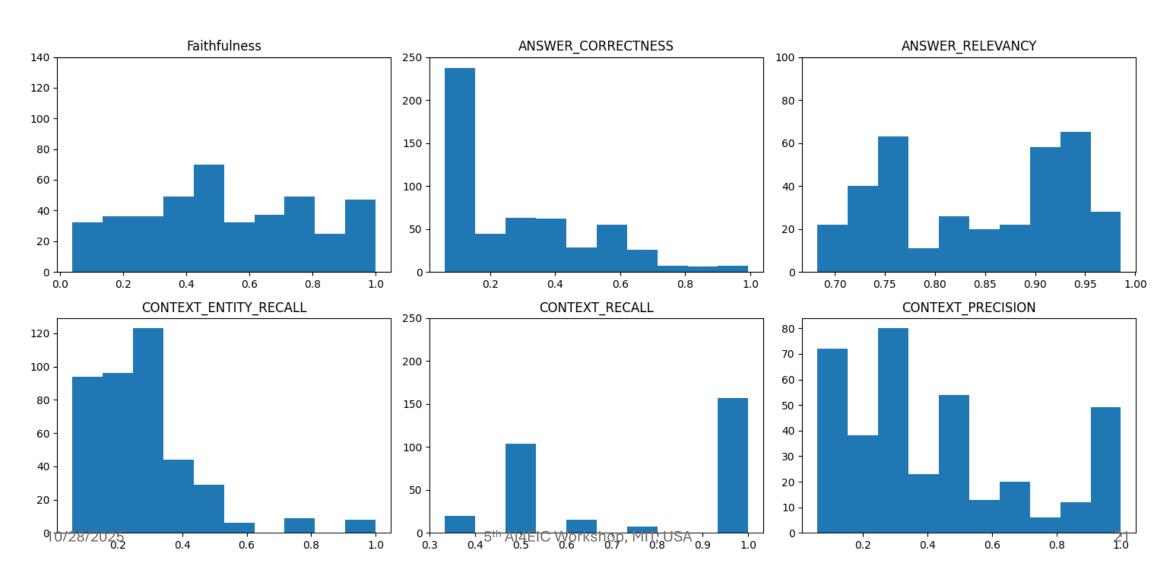
Results:

Chunk Size: 120 Similarity Metric: Cosine



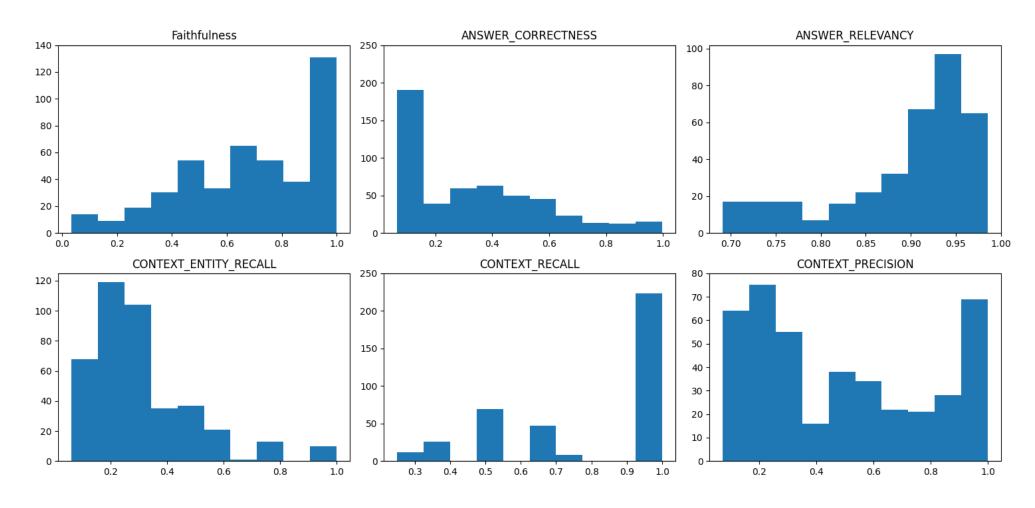
Results:

Chunk Size: 120 Similarity Metric: MMR



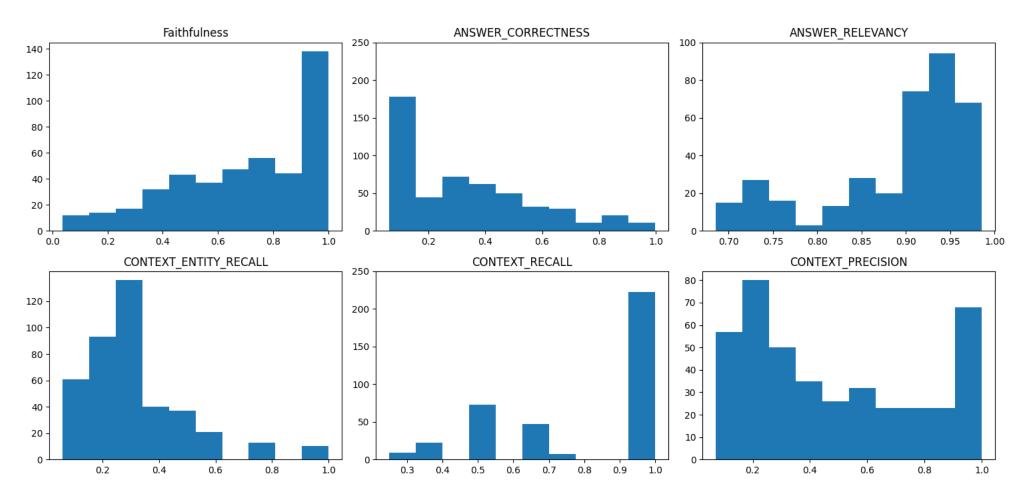
Evaluation:





Evaluation:





Results: Latency in sec (26 Gb GPU)

Statistic	Llama 3.2	Llama 3.3
Mean	14.30	226.46
Standard Deviation	9.36	75.54
Minimum	2.95	90.91
25% (Q1)	8.30	175.14
Median	11.33	215.88
75% (Q3)	17.31	266.66
Maximum	59.78	568.20