RAG-System-for-Research-Paper-Discussions-arXivBot

***Abstract*—The rapid growth of research publications on platforms such as arXiv has made it increasingly difficult for researchers to stay updated with recent advancements. Traditional search engines and summarization tools often lack contextual reasoning and factual grounding. In this work, we present arXivBot, an advanced Retrieval-Augmented Generation (RAG) system designed for research paper discussions. The system integrates dense vector-based retrieval with a fine-tuned Falcon-7B language model using LoRA and 4-bit quantization. Our system achieves a RAGAS Faithfulness score of 0.82, demonstrating strong contextual grounding and minimal hallucination. The results show that integrating retrieval with fine-tuned generation significantly improves reliability and response quality in academic query answering.**

I. Introduction

Over 20,000 research papers are published monthly on arXiv, making information extraction increasingly challenging. Researchers often spend significant time searching, summarizing, and interpreting literature. Traditional retrieval systems lack contextual reasoning, while standalone Large Language Models (LLMs) may hallucinate when generating responses.

To address these challenges, we propose arXivBot, a Retrieval-Augmented Generation (RAG) system that combines semantic retrieval with fine-tuned language generation to provide accurate and context-aware responses to research queries.

II. Related Work

Recent advancements in NLP have introduced large language models capable of summarization and question answering. Retrieval-Augmented Generation (RAG) improves factual consistency by integrating document retrieval before response generation.

While prior work has explored dense retrieval and summarization, many systems lack robust grounding evaluation and domain adaptation. Our work integrates fine-tuning with systematic evaluation using RAGAS metrics to improve reliability.

III. Methodology

A. System Architecture

The arXivBot system consists of two main components:

1) **Retriever Module:** Uses dense vector embeddings to retrieve relevant research paper segments.
2) **Generator Module:** Fine-tuned Falcon-7B model generates responses grounded in retrieved context.

B. Document Processing and Indexing

- Research papers were parsed into structured text segments (nodes).
- Each segment was embedded using HuggingFace embedding models.
- Nodes were indexed in a vector store using LlamaIndex.

C. Model Selection and Fine-Tuning

We selected Falcon-7B due to its performance-efficiency balance. Fine-tuning was performed using:

- LoRA (Low-Rank Adaptation)
- 4-bit quantization
- Dataset of 500 curated research papers
- Single epoch training due to hardware constraints

D. RAG Workflow

The RAG pipeline follows:

1) User submits query.
2) Retriever fetches top relevant document nodes.
3) Retrieved context is passed to the fine-tuned LLM.
4) Model generates context-aware response.

IV. Experimental Setup

A. Dataset

- 500 research papers from computer science domains.
- Structured parsing into semantic chunks.

B. Training Configuration

- LoRA fine-tuning with 4-bit quantization.
- Training on Google Colab.
- One epoch training (approx. 3 hours).

C. Evaluation Metrics

We evaluated performance using:

- Final Training Loss
- Inference Speed
- RAGAS Faithfulness metric

Faithfulness measures whether generated responses are fully supported by retrieved context.

V. Results

A. Fine-Tuning Performance

- Final Training Loss: 1.54
- Inference Speed: 1422 tokens per second

The low loss indicates successful domain adaptation, while inference speed demonstrates scalability.

Metric	Score
Faithfulness	0.82

TABLE I
RAGAS EVALUATION RESULTS

B. RAGAS Evaluation

We evaluated grounding using the RAGAS framework.

A Faithfulness score of 0.82 indicates that generated answers were largely grounded in retrieved documents with minimal hallucination.

C. Qualitative Observations

- Responses were context-aware and domain-specific.
- Retrieval effectively reduced hallucination.
- The system handled complex research queries reliably.

VI. CHALLENGES AND SOLUTIONS

A. Hardware Constraints

Limited GPU resources restricted training to one epoch. We addressed this using LoRA and 4-bit quantization to reduce memory usage.

B. Model Selection

Due to hardware limitations, Mistral could not be used. Falcon-7B provided a suitable balance between efficiency and performance.

C. RAG Integration

The RAG architecture was implemented from scratch, requiring careful integration between retriever and generator modules.

VII. FUTURE WORK

Future improvements include:

- Multi-language support
- Interactive web interface
- Multi-agent reasoning extensions
- Expanded evaluation with additional RAGAS metrics

VIII. CONCLUSION

arXivBot demonstrates the effectiveness of combining Retrieval-Augmented Generation with fine-tuned large language models for research paper discussions. The system achieved strong domain adaptation and a RAGAS Faithfulness score of 0.82, indicating reliable contextual grounding. Despite hardware limitations, the system successfully provides accurate and scalable research query assistance.

REFERENCES

1) LlamaIndex Documentation. https://github.com/jerryjliu/llama_index
2) RAGAS Evaluation Framework. https://github.com/explodinggradients/ragas