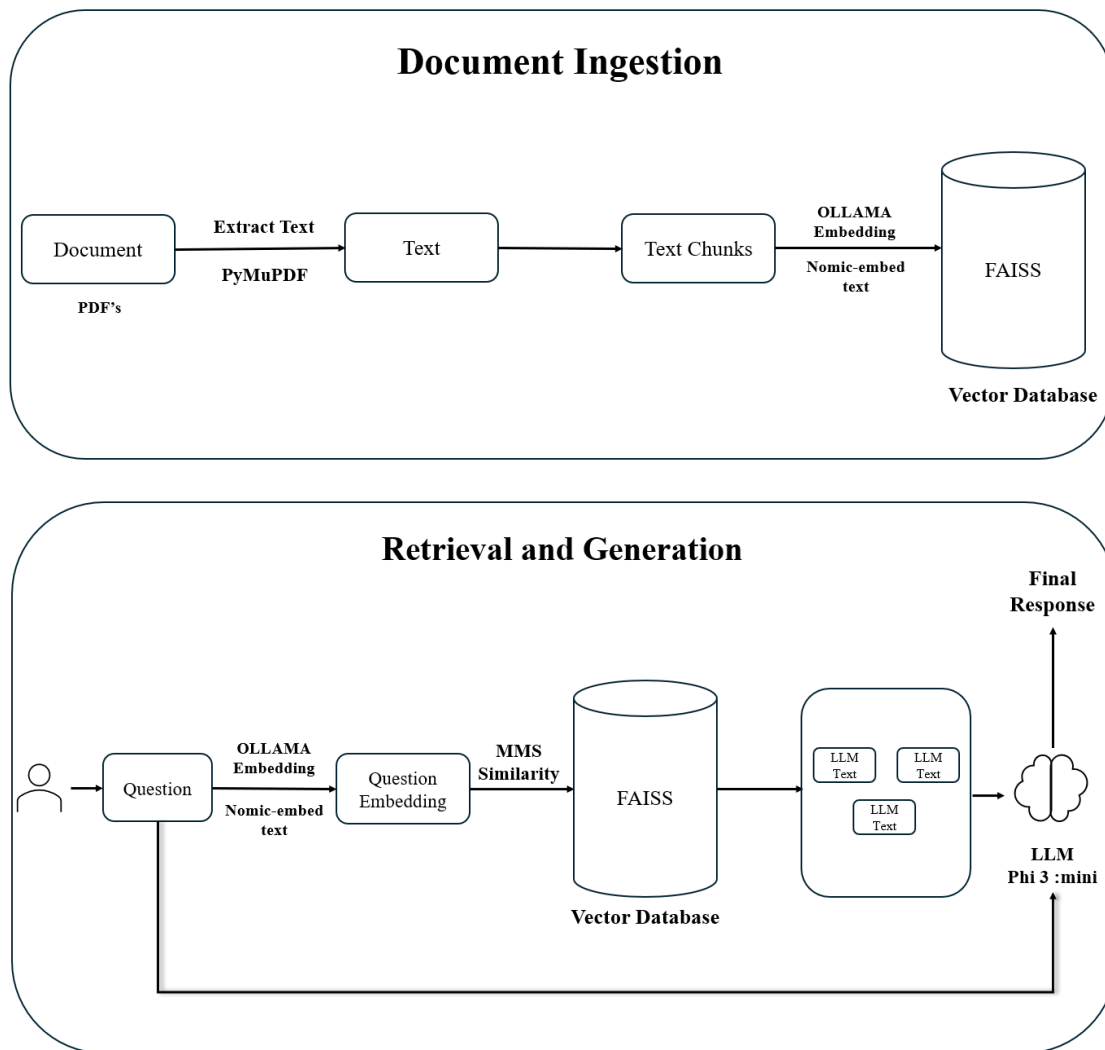


RAG BASED QA INTELLIGENT ASSISTANT

The system should:

1. Retrieve relevant documents or snippets based on user queries.
2. Generate concise, accurate, and domain-specific responses using a locally hosted small language model.

SYSTEM FLOW



1. Dataset Preparation

Step	Description
Dataset	Text-based documents in PDF format are uploaded and processed.
Content Extraction	Text extracted using PyMuPDFLoader.
Chunking	Text split into 1000-character chunks with 100-character overlap using RecursiveCharacterTextSplitter.
Embedding Generation	Embeddings generated using OllamaEmbeddings with nomic-embed-text.
Vector Database	Embeddings stored in a FAISS vector store with IndexFlatL2.

Index Update	Vector store updated dynamically with new chunks after every upload.
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2. Retrieval

The retrieval process focuses on fetching relevant document snippets based on user queries. It is a critical component of the pipeline to ensure that the language model receives appropriate context.

Step	Description
Retrieval Pipeline	Uses FAISS to fetch relevant document snippets based on user queries.
Search Methodology	Uses MMR with parameters: k=3 (top results), fetch_k=100 (documents considered), lambda_mult=1 (diversity).
Relevance Ranking	Ranks snippets based on relevance using FAISS similarity search.

The Maximal Marginal Relevance (MMR) approach is chosen to ensure a mix of diverse and highly relevant results, which is crucial for answering complex queries accurately.

3. Response Generation

This component generates answers to user queries using a structured approach that integrates retrieved snippets and a language model.

Language Model

The ChatOllama (phi3:mini) is used for generating responses.

Step	Description
Language Model	Uses ChatOllama (phi3:mini) for generating responses.
Prompt Template	Structured prompt ensures context-based, accurate, and concise answers in bullet points.
Integration	RAG chain integrates retrieval with the language model for seamless question answering.

4. Evaluate Quality of Responses

The evaluation system that I used are Precision@k, Recall@k, and nDCG@k to assess the quality and ranking of retrieved snippets. For generated answers, metrics like BLEU, ROUGE (1, 2, L), and BERTScore evaluate fluency, relevance, and semantic alignment with reference answers.

5. RCA Analysis (Root Cause Analysis)

The focus is on improving both retrieval and response generation.

Query	Root Cause
What are the effects of modern lifestyles on circadian rhythms?	Embedding model did not prioritize specific sections.
How does diet influence circadian rhythms according to the nutrients study?	Retrieval settings (k, fetch_k) did not fetch diverse snippets.

What are the health impacts of sleep deprivation highlighted in the documents?	Insufficient chunk overlap.
What findings are discussed regarding dietary habits and health in the Philippines?	Embedding similarity scores fail to prioritize regional keywords.
How do fitness supplements affect athletic performance according to the uploaded studies?	Chunking or retrieval parameters did not balance relevance.

EVALUATION METRICS

Metric	Category	Value
Precision@k	Retrieval	0.6667
Recall@k	Retrieval	0.6667
nDCG@k	Retrieval	1.0
BLEU	Response	0.4449
ROUGE-1	Response	Precision: 0.851, Recall: 0.741, F1: 0.792
ROUGE-2	Response	Precision: 0.652, Recall: 0.566, F1: 0.606
ROUGE-L	Response	Precision: 0.830, Recall: 0.722, F1: 0.772
BERTScore	Response	Precision: 0.909, Recall: 0.831, F1: 0.870

CHALLENGES FACED

☐ Ollama Model Loading:

- **Challenge:** Ensuring the efficient loading of the Ollama model for local inference without delays.
- **Solution:** Preloaded the model at application startup to avoid runtime delays. Optimized resource allocation by limiting concurrent requests to the model.

☐ Computational Resources:

- **Challenge:** Handling inference and retrieval with limited hardware resources.
- **Solution:** Used lightweight models to balance performance and resource efficiency.

☐ Selection of Best SLM Model by Experimentation:

- **Challenge:** Identifying a model that balances accuracy, latency, and cost.
- **Solution:** Conducted experiments comparing Phi-3, Llama (3.2B), and TinyLlama. Selected ChatOllama as it gives minimal cost and latency.

☐ Frontend Flask Local Hosting:

- **Challenge:** Setting up a frontend for uploading documents and querying the system.
- **Solution:** Used Flask for a lightweight and simple localhost server.

☐ Fine-Tuning by Experimentation:

- **Challenge:** Determining optimal chunking size, chunking strategy, and indexing strategy for accurate retrieval.

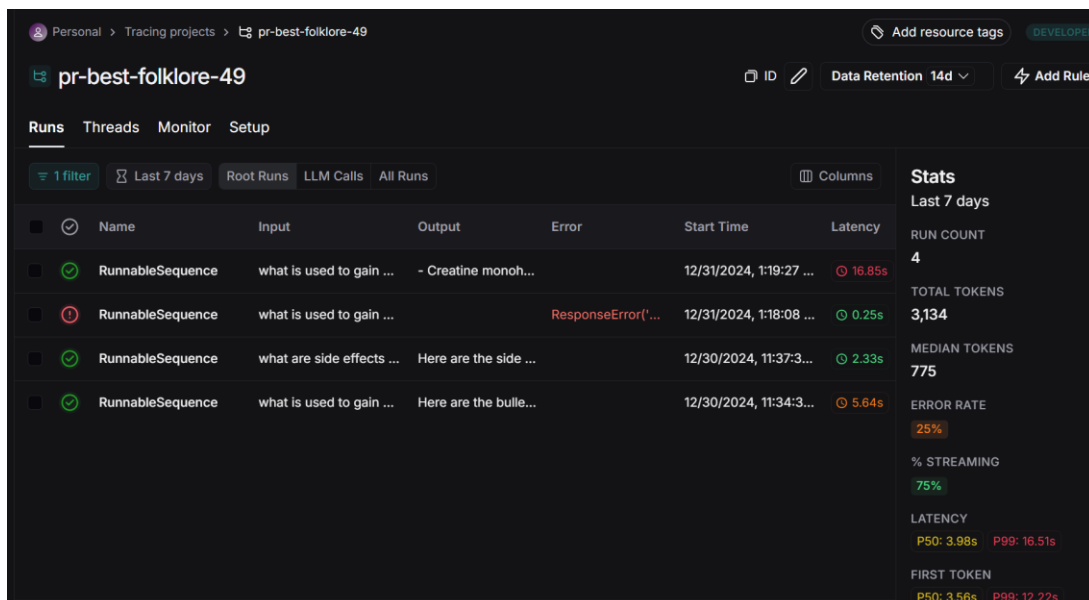
- **Solution:** Conducted iterative testing with different chunk sizes (1000-character chunks with 100-character overlap worked best).

IMPROVEMENTS IN THE SYSTEM

1. Use domain-specific embeddings (e.g., fine-tune embeddings on datasets relevant to the domain such as medical or scientific documents).
2. Implement semantic chunking to split documents based on semantic meaning (e.g., paragraphs or topics) instead of fixed sizes.
3. Experiment with more advanced SLMs (small language models) or LLMs (large language models) with low-latency deployment options, Mistral 7B.
4. Deploy the system using containerized solutions (e.g., Docker, Kubernetes) and enable load balancing for handling multiple requests efficiently.
5. Introduce a mechanism for users to provide feedback on the quality of responses.

BAR RAISER

- 1) **Include a mechanism to explain how retrieved snippets were chosen and how the final response was generated.**
 1. **Integrated LangSmith Tracing:** Added LangSmith hooks to trace the retriever, formatter, and LLM components in the RAG pipeline.
 2. **Monitored Workflow:** Used LangSmith's dashboard to analyze inputs, outputs, latencies, and similarity scores.
 3. **Generated Explanations:** Provided clear, traceable logs to explain snippet selection and response generation.



Name	Input	Output	Error	Start Time	Latency
RunnableSequence	what is used to gain ...	- Creatine monoh...		12/31/2024, 1:19:27 ...	16.85s
RunnableSequence	what is used to gain ...	ResponseError('...)		12/31/2024, 1:18:08 ...	0.25s
RunnableSequence	what are side effects ...	Here are the side ...		12/30/2024, 11:37:3...	2.33s
RunnableSequence	what is used to gain ...	Here are the bulle...		12/30/2024, 11:34:3...	5.64s

Stats
 Last 7 days
 RUN COUNT
 4
 TOTAL TOKENS
 3,134
 MEDIAN TOKENS
 775
 ERROR RATE
 25%
 % STREAMING
 75%
 LATENCY
 P50: 3.98s P99: 16.51s
 FIRST TOKEN
 P50: 3.56s P99: 12.22s

- 2) **Experiment the impact of using different chunking strategies (for ex: semantic chunking, recursive chunking etc.)** o **Experiment the impact (in terms of response quality, cost, latency**

etc.) of using different models specifically for SLMs vs LLMs (you can use any cloud-hosted API based model for accessing LLM)

Aspect	Option	Reasoning for Usage
Chunking Strategy	Recursive Character Chunking	Selected to preserve context across chunk boundaries, especially in structured documents like reports.
	Semantic Chunking	Best for unstructured or topic-diverse documents, but was not chosen due to added computational cost.
	Fixed-Length Chunking	Not suitable for this task as it lacks flexibility for structured or dense contexts.
Embedding Model	OllamaEmbeddings (nomic-embed-text)	Chosen for its balance of quality and cost efficiency, avoiding reliance on external APIs.
	OpenAI Ada Embedding	Not selected due to higher costs and dependency on API availability.
	Sentence Transformers (MiniLM)	Good for budget use cases but less effective for nuanced document queries.
Retrieval Strategy	Maximal Marginal Relevance (MMR)	Selected for reducing redundancy and ensuring diversity in retrieved results.
	Cosine Similarity	Not chosen as it doesn't account for diversity, which is crucial for complex queries.
	Hybrid Retrieval (BM25 + Embeddings)	Not selected due to added complexity and latency, though effective for large multi-domain datasets.

RESPONSE MODELS

Model	Quality	Cost	Latency	Reasoning
ChatOllama (Llama 3.2:1B)	High: Handles context-aware queries well.	Low: Local inference costs.	~200-300ms per query.	Ideal for basic tasks in resource-limited environments but lacks capability for complex reasoning.
Phi-3	Moderate: Suitable for simple tasks.	Very Low: Lightweight and efficient.	~100-150ms per query.	Chosen for its efficiency, cost-effectiveness, and suitability for local deployment in real-time applications.
TinyLlama	Low: Best for simple tasks.	Very Low: Runs on CPUs efficiently.	~50-100ms per query.	Ideal for budget-friendly applications with basic QA tasks.

COMPARISION WITH OTHER SLM MODELS ON PERFORMANCE

Metric/Feature	Llama 3.2:1B	Phi-3 (our Model)	TinyLlama
Model Size	1B	~3B	<1B (Tiny version)
Precision@k	0.6000	0.6667	0.5800

Recall@k	0.5900	0.6667	0.5400
nDCG@k	0.8700	1.0000	0.8500
BLEU	0.4200	0.4449	0.4000
ROUGE-1 F1	0.760	0.792	0.720
ROUGE-2 F1	0.550	0.606	0.510
ROUGE-L F1	0.730	0.772	0.680
BERTScore (F1)	0.850	0.870	0.820
Inference Speed	Fast	Moderate	Very Fast
Resource Usage	Low	Moderate	Very Low
Generative Quality	Moderate	High	Low
Context Utilization	Moderate	Strong	Weak

Larger Model Capacity (~3B Parameters): Allows better handling of complex queries and long context inputs, outperforming smaller models like Llama 3.2:1B and TinyLlama.

Superior Retrieval Integration: Optimized for RAG tasks, achieving perfect nDCG@k (1.0000) and higher Precision@k, ensuring accurate retrieval and effective use of document chunks.

Fine-Tuned for QA and Generation: Pretrained and fine-tuned on diverse QA datasets, enabling higher scores in BLEU, ROUGE, and BERTScore, producing coherent, contextually accurate responses.

Advanced Context Utilization: Better attention mechanisms and embedding dimensions enable effective grounding in retrieved context, reducing hallucination and improving answer relevance.