RAG-Based LLM for Radiation Oncology Patient Queries

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Presentation Outline

i. Business Statement and Proposed Solution
ii. Architecture Overview and Components
iii. Evaluation and Analysis
iv. Deployment and Tools
v. Live Demonstration

i. Problem Context – Oncology Patient Questions

1. Radiation process involves high-energy X-rays, precision treatments, **technical information processes**.
2. Impact on patient well being: body image, sexual health, emotional well being.
    - **Patients lack accessible, empathetic information.**
    - **Clinicians face burnout, repetitive patient queries.**

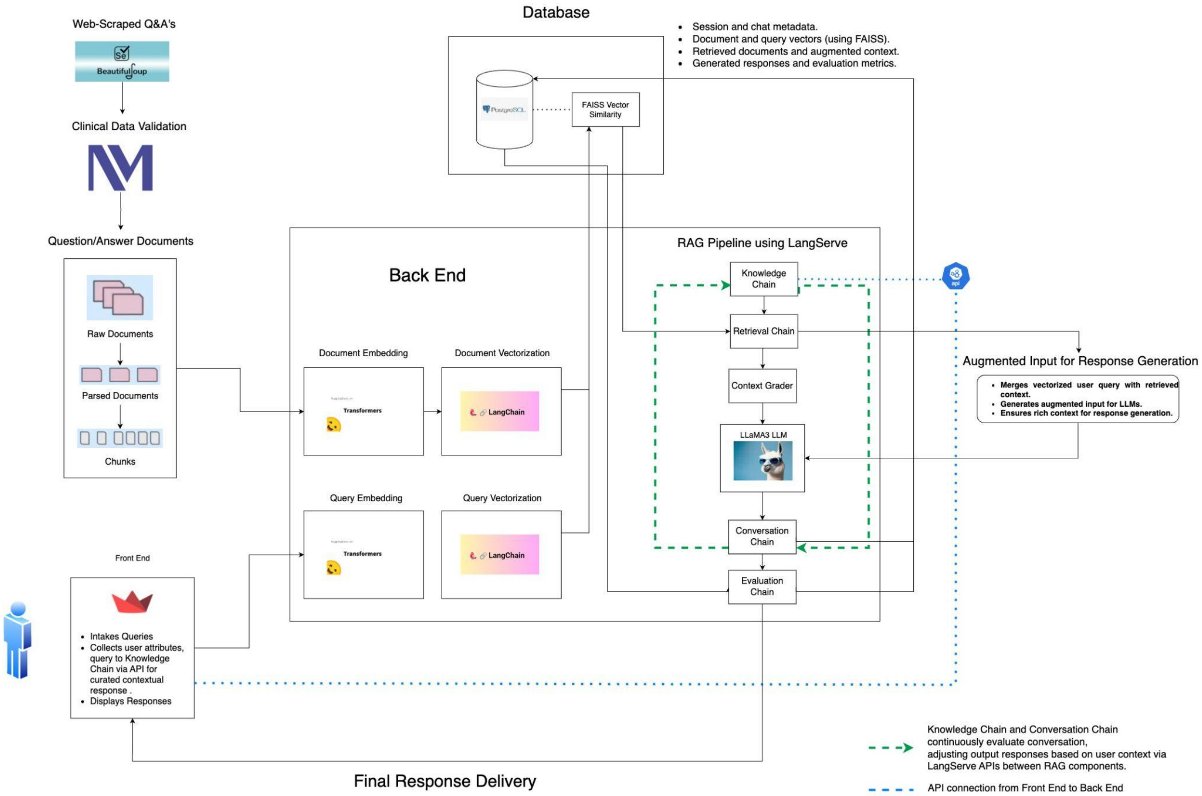
Solution: AI chatbot to complement clinical care, providing real-time, personalized responses.

i. Core Objectives and Features

Build RAG-based LLM chatbot: to provide personalized, accurate, and empathetic responses based on the patient questions.

- **Depth of RAG database:** Increase from 115 to >500 QA pairs
- **Dynamic Retrieval Pipeline:** Facebook AI Similarity Search for embedding-based similarity search.
- **LLM-Driven Response Generation:** LLaMA3.1 8B
- **Grading and Evaluation:** LangChain Grader Chain
- **User Profile Tailoring:** patient demographics for personalization.
- **Data Management System:** Store user queries, generated responses, evals, vector embeddings.
- **Feedback Loop:** Collection of user feedback to improve model performance.
- **Preprocessing Pipeline:** consistent embeddings, accuracy in retrieval, response.

ii. System Architecture Overview



Real-Time Query Processing: Supports fast vectorized retrieval and response generation within milliseconds.
Dynamic Retrieval with F.AI.S.S.: Top-K similarity search with fallback to general knowledge base for ambiguous queries.
Modular Microservices Architecture: Independent components to ensure scalability through lightweight architecture.
Personalized User Experience: Tailors responses based on user demographics: age, gender, and education level.
Evaluation and Feedback Loop: Scores responses for relevance, trustworthiness, and empathy. Stores clinician feedback for continuous refinement.

ii. Data Collection and Processing

Data Sources: Cancer.org, RTAnswers.org from 115 to >500 QA pairs.

Data Collection Process:

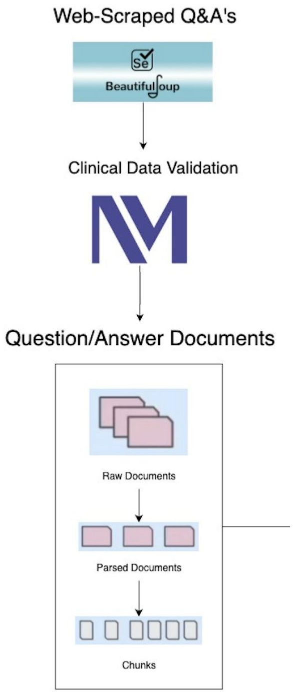
- Web Scraping: *BeautifulSoup* and for Q&A Extraction
- Text Cleaning: HTML tags, special characters, stop words.
- Normalization: lowercase for consistency.

Extraction:

- Use *Llama3.1:8b LLM* to generate directed questions from non-question format sources and validate from NU Medicine Team

Vectorization Pipeline:

- Two Vector Stores: 1. based on Question as Index; 2. based on Answers as Index
- Both Question and Answer are vectorized by *huggingFace*-"transformers/all-mpnet-base-v2"
- The vectorized Embeddings are stored in *Faiss Vector Store* locally



ii. Database

PostgreSQL database stores:

- User metadata and queries,
- Session conversation, chatbot generated responses
- Q&A dataset
- Evaluation scores for analysis.

Scalability for large interaction: Database supports multiple user sessions and real time data retrieval by engaging between backend chains and stored data.

- Embedding vectors stored as an extension to SQL database.
- Supports Facebook AI similarity search for relevance scoring.

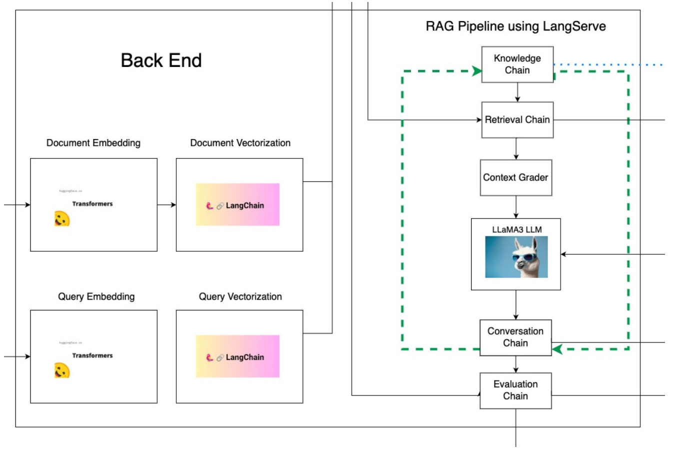
session			
INTEGER	id	PK	Auto-incrementing primary key
VARCHAR	username		Username of the session
INTEGER	age		Age of the user (nullable)
VARCHAR	gender		Gender of the user (nullable)
VARCHAR	disease_site		Disease site (nullable)
VARCHAR	education_level		Education level (nullable)

has many

session_chat			
INTEGER	id	PK	Auto-incrementing primary key
INTEGER	session_id	FK	Foreign key to session
TEXT	user_question		Original user question
TEXT	parsed_question		Parsed representation of the question
TEXT	response		System's response
BOOLEAN	is_verified		Whether the response is verified
FLOAT	retrieval_similarity		Similarity score (nullable)
FLOAT	retrieval_relevancy		Relevancy score (nullable)
JSON	response_eval_scores		Evaluation scores in JSON format (nullable)
JSON	response_analytics		Additional response analytics (nullable)

ii. Backend Design and Components

1. **Embeddings**: HuggingFace Transformers-sentence-transformers/all-mpnet-base-v2- create dense vector representations of text for both document and query inputs. Uses ClinicalBERT for embeddings of technical, domain-specific data to ensure medical accuracy.
2. **RAG Pipeline**: Combines knowledge retrieval, context grading, and LLM input to deliver precise and relevant responses.
3. **Evaluation Chains:** use predefined metrics (e.g., relevance, accuracy, empathy) and LLMs to systematically assess and ensure the quality, reliability, and domain alignment of generated responses.

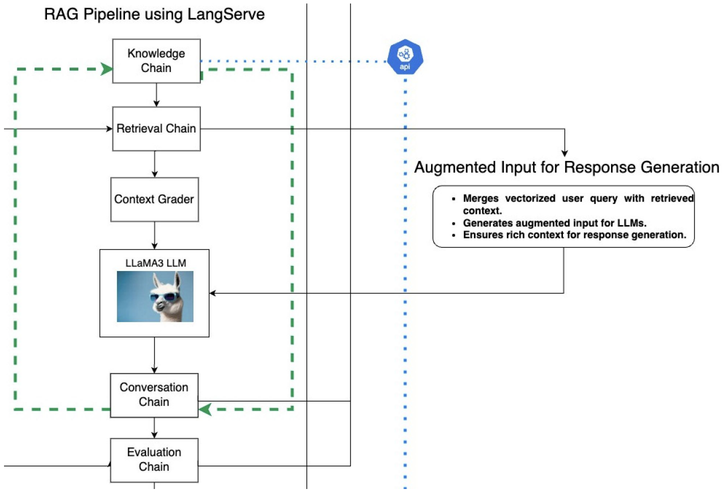


Lightweight architecture:

- Connecting the backend directly to the database.
- Connecting frontend to the backend (and not database) via API to ensure a scalable system.

ii. RAG Pipeline

Knowledge Chain: Learns about the user and integrates conversational context to ensure consistency and relevance in ongoing dialogue.
Retrieval Chain: Handles document retrieval by identifying and re-ranking the most relevant documents from the vector store based on relevance thresholds.
Augmentation: Merges user queries and retrieved documents to prepare rich contextual inputs for the LLMs.
Generation: Converts augmented inputs into fluent, informative responses using LLaMA3 LLM.
Context Grader: Evaluates the quality and trustworthiness of retrieved documents to refine the input for response generation.
Conversation Chain: Manages interactive dialogues, ensuring logical flow and leveraging user-specific insights for a tailored experience by working with Knowledge Chain.
Evaluation Chain: Scores responses for empathy, readability, completeness, and overall quality assurance.



ii. Knowledge and Retrieval Chain

Knowledge Chain:

- **User Information Management:** Stores essential user details such as name, age, gender, education level, and cancer location.
- **Personalized Query Framing:** Generates personalized user queries by incorporating details like disease site and conversation history.
- **Dynamic Summary Creation:** Continuously updates a running summary of the conversation, capturing user inputs and chatbot responses.
- **Contextual Adaptation:** Ensures tailored responses by using stored user data (e.g., age, education level) to guide the LLM in crafting appropriate, context-sensitive replies.
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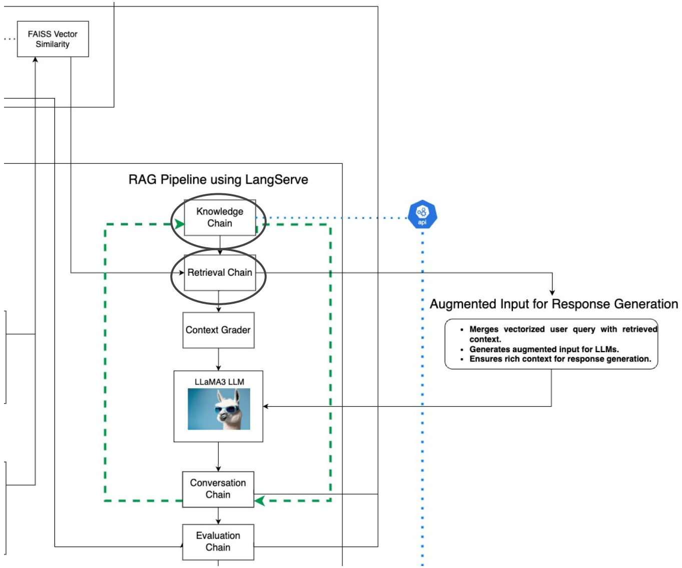
Retrieval Chain:

- **Vector-Based Matching:** Retrieves the most relevant documents from the vector store using advanced vector similarity algorithms.
- **Dynamic Re-Ranking:** Ranks retrieved results based on relevance thresholds to prioritize the most applicable responses.
- **Pre-Processing for Context:** Prepares retrieved documents for downstream components like augmentation and response generation.

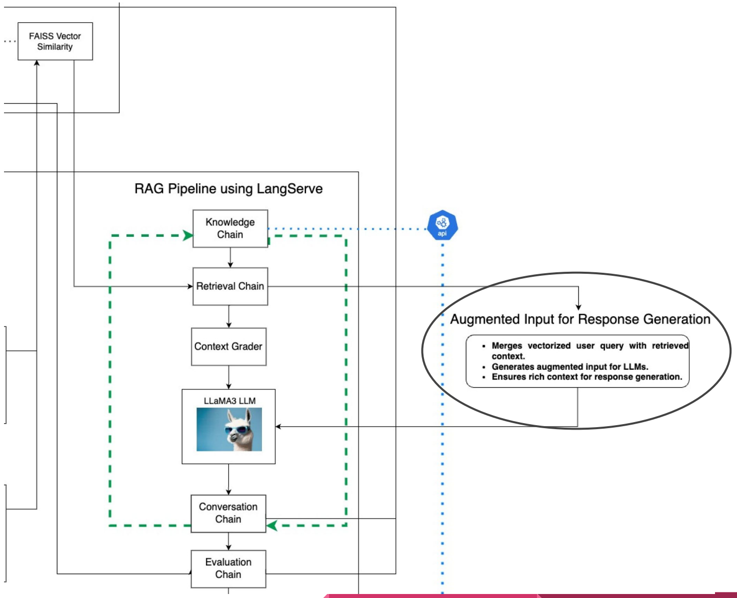


ii. Augmentation: Enriching Input for Precision

Context Integration: Combines vectorized user queries with retrieved documents to create a unified and contextually rich input.

Alignment Refinement: Tailors the input prompt to align with oncology-specific or general-purpose objectives, ensuring accurate and relevant responses.

Optimized Input for LLMs: Enriches retrieved context for seamless processing by next-stage LLMs, enhancing the precision and reliability of generated responses.



ii. Generation and Large Language Model Integration

LLaMa 3.1 (Primary LLM)

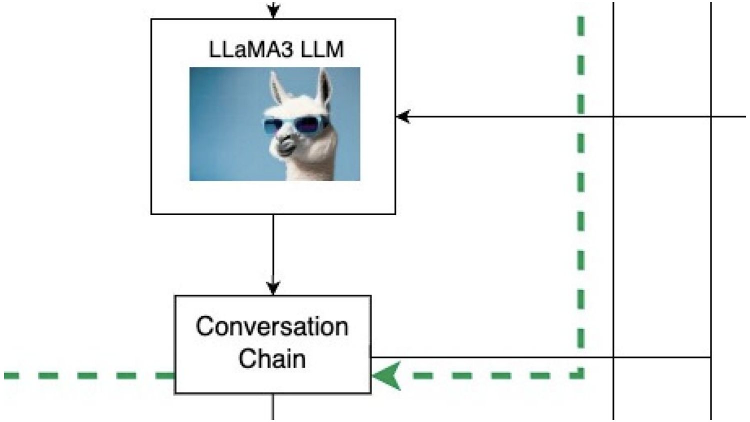
- **Purpose**: Handles all patient inquiries, ranging from general to highly specific oncology-related questions.
- **Capabilities**:
    - Ensures **multi-turn conversational continuity**, maintaining context across complex queries.
    - Balances technical depth and accessibility for diverse patient education levels.
    - **Adapts responses** to align with the system's contextual inputs from the Knowledge Chain and Retrieval Chain.

Augmented Input

- **Enhanced Contextualization**: Combines patient query, retrieved documents, and system-generated context to provide nuanced responses.
- **Optimized Precision**: Tailors outputs to address both technical and personal aspects of oncology queries.

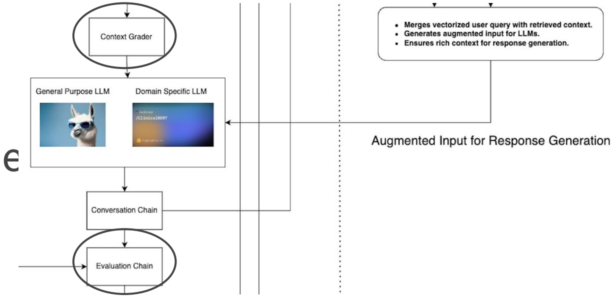
Storage

- LLaMa-generated responses pass through the **Conversation Chain** for consistency and are stored in **PostgreSQL**, enabling review, auditing, and iterative improvements.



ii. Context Grader and Evaluation Chain

Context Grader evaluates and ranks **relevance, accuracy and trustworthiness of retrieved documents**. Ensuring appropriate and high-quality content is selected for the response generation pipeline
Occurs along side Augmentation Phase



Evaluation Chain framework includes both **automated** and **human validation** processes to ensure that responses from the system are **highly reliable**.

- Relevance, trustworthiness, and empathy of responses by llama3.1:8b.
- Provides actionable feedback for continuous system improvement.
- Comparability of LLM-generated responses to authoritative data and experts for reliability.

1. Factual Correctness
2. Completeness
3. Conciseness
4. Coherence
5. Relevance
6. Potential Harm

ii. Streamlit User Interface

Query Input: Users can input queries related to radiation oncology. Interface validates input to avoid incomplete/irrelevant queries.

Collects Demographic Data: age, gender, and education level used to tailor responses for better understanding.

Displayed response includes retrieved context, LLM-generated answer, and evaluation scores: trustworthiness, relevance, empathy.

Feedback Mechanism allows the user to rate the quality and helpfulness of the response and stored for iterative improvement by researchers/developers.

iii. Robustness Analysis

Robustness testing covers diverse oncology-related queries derived from patient needs and clinical contexts, spanning 10 cancer types.

Focused on assessing the system's ability to handle patient-centric and technical questions.

Core Inquiry Domains:

1. **Technical Understanding:** Delves into treatment mechanisms and therapeutic interventions.
2. **Personal Impacts:** Covers quality of life concerns, side effects, and daily disruptions.
3. **Adaptation Needs:** Evaluates interest in recurrence possibilities and emerging therapies.

Strategic Insight: Patient questions indicate a deep need for nuanced, reliable, and empathetic information on their treatment journey.

Patient-Centered Information Dynamics - Robustness in Response Evaluation

Depth of Testing:

- Evaluated generated responses against metrics of **semantic similarity**, **key point alignment**, and **message consistency.**
- Utilizes a weighted scoring model (40% semantic, 30% alignment, 30% consistency).

Adaptive Query Handling processes responses to:

- Lexical and grammatical variations (e.g., typos).
- Contextual nuances specific to patient history and disease site.

Automated Evaluation Pipeline:

- Integrates **LangChain** and **Ollama LLM** with structured prompts for generating reliable and detailed evaluations.
- Ensures scalability and accuracy for large datasets of patient queries, enabling comprehensive robustness analysis.

iv. Backend Implementation and other connections

APIs and Modular Architecture

- Built with **FastAPI** to establish seamless and modular connections between components.
- Serves as the backbone for managing **sessions, chat interactions, and feedback loops.**

Key Connections

- **Front-End ↔ Back-End:**
  The front-end interacts with the RAG pipeline using **API calls for query submissions and response retrieval.**
- **Back-End ↔ Database:**
  The back end communicates with the PostgreSQL database via Facebook AI Similarity Search extension, to store and retrieve document and query embeddings efficiently.

LangServe and RAG Pipeline

- LangServe powers the RAG system by wrapping **LangChain chains as APIs,** ensuring dynamic communication across components.
- Facilitates **real-time updates of Q&A pairs** and context sharing between the Knowledge Chain, Retrieval Chain, and downstream models.

iv. Dockers Role in the RAG System

Backend Dockerization:

- Backend services, including the RAG pipeline, are containerized for scalability and portability.
- Configured with **Ollama Server to run LLMs efficiently within Docker**.

Database Integration:

- Database **mounted dynamically in Docker**, avoiding the need to copy database files during container build.
- Ensures faster build times and simplifies updates.

Optimized Backend Performance:

- Docker Compose manages multi-container applications, linking the backend, database, and APIs.

iv. Model Deployment and Configuration

Deployment Strategy:

- Modular deployment pipeline separates frontend, backend, and database components.
- Designed for both **on-premise and cloud-based scalability.**
- Hosted on **Northwestern Medicine's on-premise servers.**

Environment Configuration:

- Utilizes Docker containers to ensure **consistent and isolated environments** across development, testing, and production.
- Optimized deployment instructions created to align with institutional infrastructure.

Live Demonstration