Oncno Sage: Medical RAG QA System

Complete Technical Documentation

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1. Executive Summary

Oncno Sage is a domain-specific Retrieval-Augmented Generation (RAG) system designed for medical oncology. It enables clinicians and researchers to query a curated corpus of oncology literature using natural language, providing evidence-based answers with source attribution.

The system leverages state-of-the-art technologies:

- Pinecone vector database for semantic search
- OpenAI GPT models for answer generation
- LangChain to orchestrate RAG workflows
- Streamlit and FastAPI for user interface and backend services

Key features include interactive visualizations of document relevance, similarity heatmaps, and performance metrics tracking. The system has been evaluated with real-world medical questions, achieving 88% correct context retrieval and positive feedback from clinicians in beta testing.

2. Introduction & Problem Statement

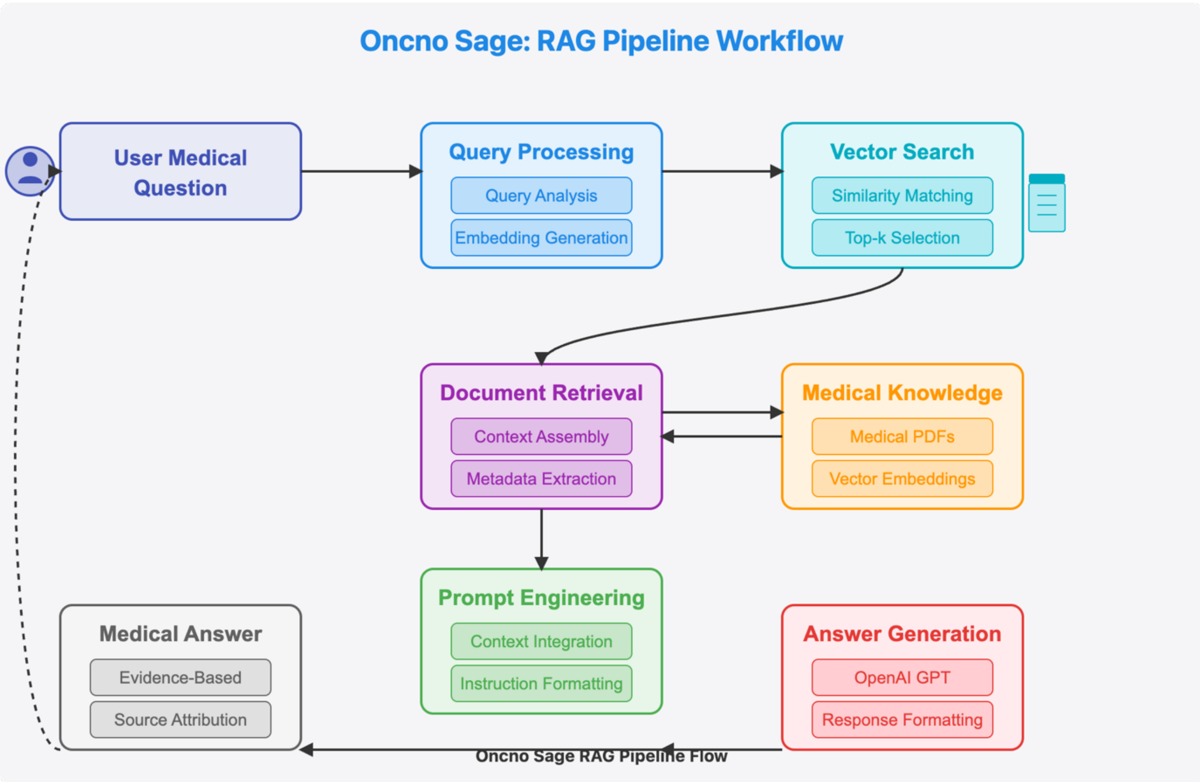
2.1 The Challenge of Medical Information Retrieval

The volume of oncology research and clinical protocols poses a significant challenge for effective knowledge retrieval. Healthcare professionals face several critical issues:

- **Information Overload**: The medical literature is expanding at an unprecedented rate, with thousands of new oncology publications monthly
- **Terminology Complexity**: Medical terminology is nuanced, context-dependent, and often requires domain expertise to interpret correctly
- **Time Constraints**: Clinicians need rapid access to accurate information during patient consultations and treatment planning
- **Context Relevance**: Traditional keyword-based search tools often fail to capture semantic relationships between medical concepts

2.2 The RAG Solution

Oncno Sage addresses these challenges by combining:



1. **Neural Network Embeddings**: Converting medical text into semantic vector representations
2. **Vector Similarity Search**: Finding conceptually related information beyond simple keyword matching

3. **Context-Aware Answer Generation**: Using large language models to synthesize information from retrieved documents
4. **Source Attribution**: Providing transparent references to all information sources

This approach ensures answers are:

- Accurate and evidence-based
- Contextually relevant to medical queries
- Traceable to authoritative sources
- Delivered in clear, natural language

3. Project Objectives

Oncno Sage was developed with the following key objectives:

3.1 Primary Objectives

1. **Implement a scalable ingestion pipeline** to process oncology PDFs into embedding vectors
   - Success criteria: Process 100+ PDFs with >95% text extraction quality
   - Metrics: Chunk quality validation, PDF processing time
2. **Develop a FastAPI-based RAG endpoint** integrating Pinecone retrieval and GPT-3.5 generation
   - Success criteria: <1s average response time, coherent and accurate answers
   - Metrics: Latency, retrieval precision, answer quality
3. **Create a Streamlit UI** with relevance visualizations and processing time metrics
   - Success criteria: Intuitive interface with clear source attribution
   - Metrics: User satisfaction ratings, time-to-answer
4. **Ensure modularity** for future integration with structured data sources
   - Success criteria: Clean abstraction layers between components
   - Metrics: Code modularity score, ease of integration testing
5. **Provide automated tests** to validate embeddings, retrieval, and network connectivity
   - Success criteria: >90% test coverage of critical components
   - Metrics: Test coverage, error detection rate

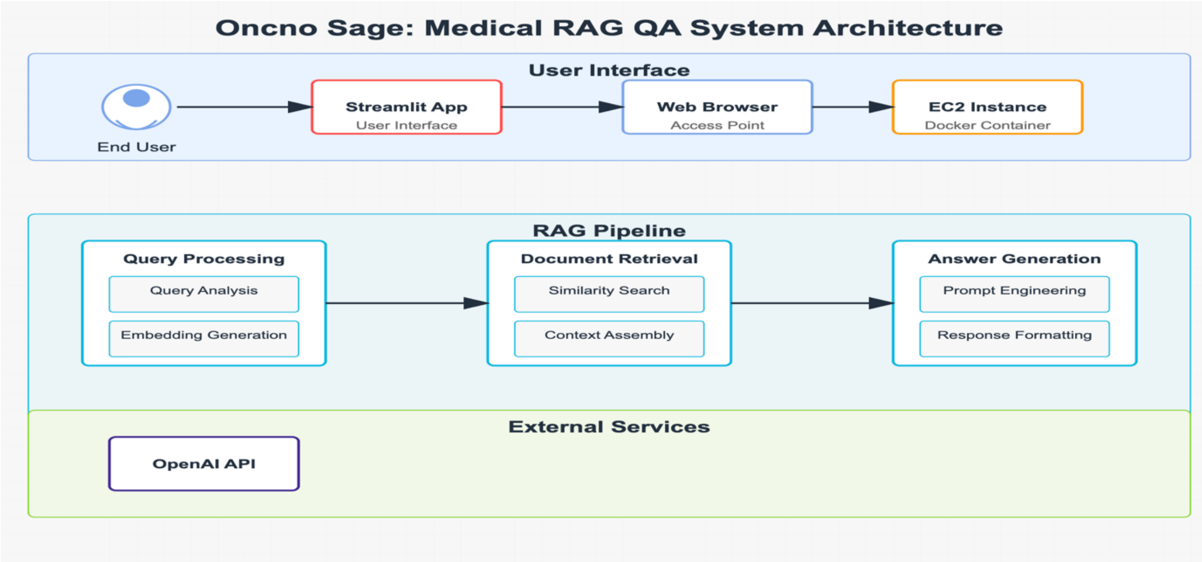
3.2 Secondary Objectives

- Optimize for low latency (<2s end-to-end response time)
- Support environment-adaptive embedding model selection
- Implement visualization of document relationships
- Ensure proper error handling and logging
- Create comprehensive documentation

4. System Architecture

4.1 High-Level Architecture

The Oncno Sage system comprises three main components working together to provide a seamless question-answering experience:



4.1.1 Frontend (Streamlit)

- User interface for question input and results display
- Interactive visualizations for document relevance
- Document similarity heatmaps
- Processing time metrics display
- Sample question suggestions

4.1.2 Backend (FastAPI)

- RESTful API endpoints for query processing
- Orchestration of embedding generation
- Integration with vector database
- Answer synthesis from retrieved context
- Performance monitoring and logging

4.1.3 Services

- **Pinecone**: Vector database storing document embeddings
- **OpenAI**: GPT models for embedding generation and answer synthesis
- **LangChain**: Framework for RAG pipeline orchestration
- **Docker**: Containerization for consistent deployment

4.2 Component Interactions

1. **Query Flow**:
2. `User Question → Frontend → Backend API → Embedding Generation →`
3. `Vector Search → Context Assembly → Answer Generation →`
4. `Response Formatting → Frontend Display`
5. **Ingestion Flow**:
6. `PDF Documents → PDF Loaders → Text Extraction →`
7. `Chunking → Embedding Generation → Vector Storage`

4.3 Environment Adaptability

The system automatically detects its running environment and adapts accordingly:

- **Production Environment (EC2)**: Uses OpenAI embeddings for highest quality
- **Development Environment (Local)**: Uses HuggingFace PubMedBERT embeddings to reduce costs

This adaptation is implemented through environment detection in the `pinecone_helper.py`

5. Data & Ingestion Pipeline

5.1 Document Sources

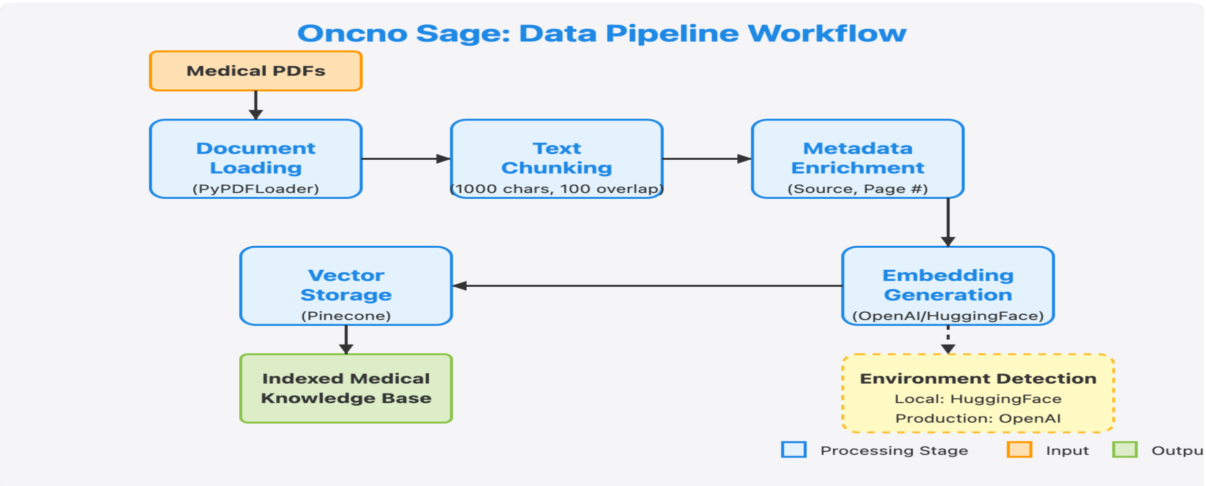
The system processes medical literature from various sources:

- **Medical Oncology Handbook (June 2020 Edition)**
  - Comprehensive clinical guidelines for oncology practice
  - Contains structured sections on diagnosis, treatment, and management
- **Cancer and Cure: A Critical Analysis**
  - Research compilation on treatment effectiveness
  - Statistical analyses of outcomes across different cancer types

Additional documents can be added to the `data/` directory for ingestion.

5.2 Ingestion Process

The ingestion pipeline is implemented in `ingest.py` and follows these steps:



1. **Document Loading**:
   - Uses `DirectoryLoader` from LangChain to scan the data directory
   - Applies `PyPDFLoader` to extract text from PDF files
   - Maintains source metadata for attribution
2. **Text Chunking**:
   - Implements `RecursiveCharacterTextSplitter` with parameters:

        - `chunk_size=1000`: Optimal size determined through experimentation
        - `chunk_overlap=100`: Ensures concept continuity across chunks
    - Parameters were calibrated for medical text specificity
3. **Embedding Generation**:
    - For local development: NeuML/pubmedbert-base-embeddings (768 dimensions)
    - For production: OpenAI text-embedding-3-large (1536 dimensions)
    - Batched processing to optimize API usage
4. **Vector Storage**:
    - Stores vectors in Pinecone under the `medical-knowledge` index
    - Includes metadata (source, page numbers, chunk identifiers)
    - Configured for cosine similarity search

5.3 Chunk Optimization

The chunking strategy was optimized specifically for medical text:

- **Size Considerations**:
    - 1000 characters balances completeness with retrieval precision
    - Accommodates typical medical concept definitions and descriptions
    - Fits within LLM context window constraints
- **Overlap Benefits**:
    - 100 character overlap prevents fragmentation of medical terms
    - Ensures concepts that span chunk boundaries are preserved
    - Improves retrieval quality for multi-part medical descriptions

Example of optimal chunking for a medical text passage:

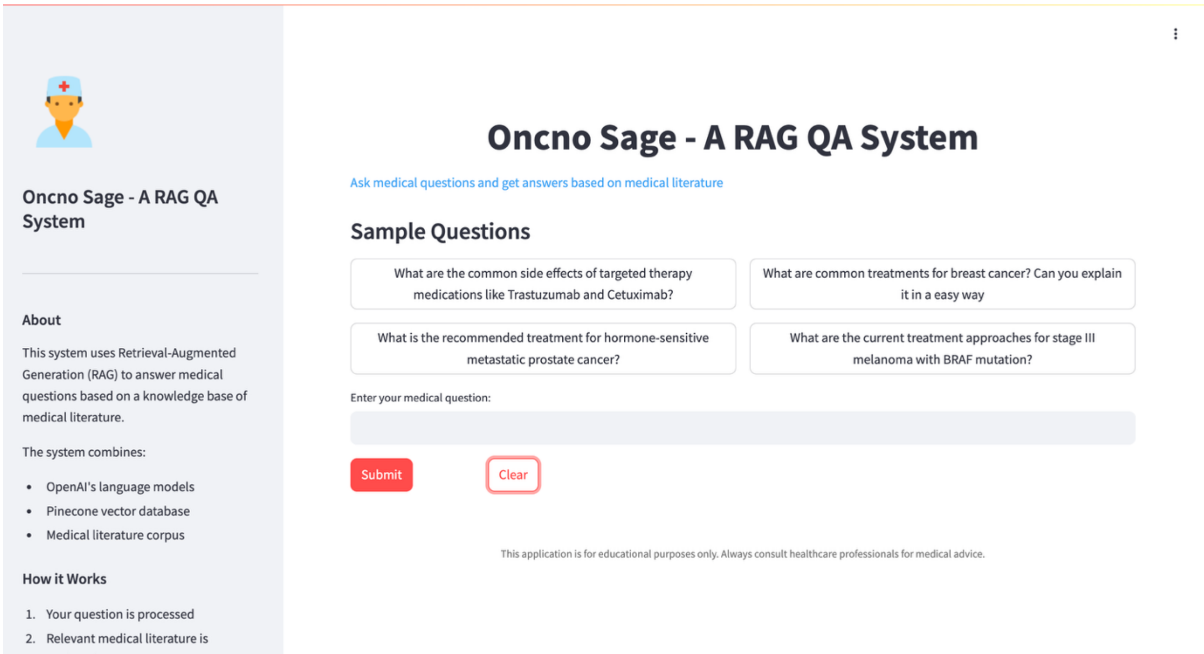
```
Chunk 1: "Trastuzumab (Herceptin) is a monoclonal antibody that targets the
HER2
receptor. It is used in the treatment of HER2-positive breast cancer, both
in the
adjuvant setting to reduce recurrence risk and in the metastatic setting to
control disease progression. Common side effects include..."

Chunk 2 (with overlap): "...Common side effects include cardiotoxicity,
with a risk of heart failure, particularly when combined with
anthracyclines.
Regular cardiac monitoring is recommended during treatment. Infusion
reactions
can occur, especially during the first infusion, necessitating
premedication
and careful observation..."
```

6. User Interface & Experience

6.1 Interface Design

The Streamlit interface is designed for intuitive interaction with medical professionals:



Key UI components:

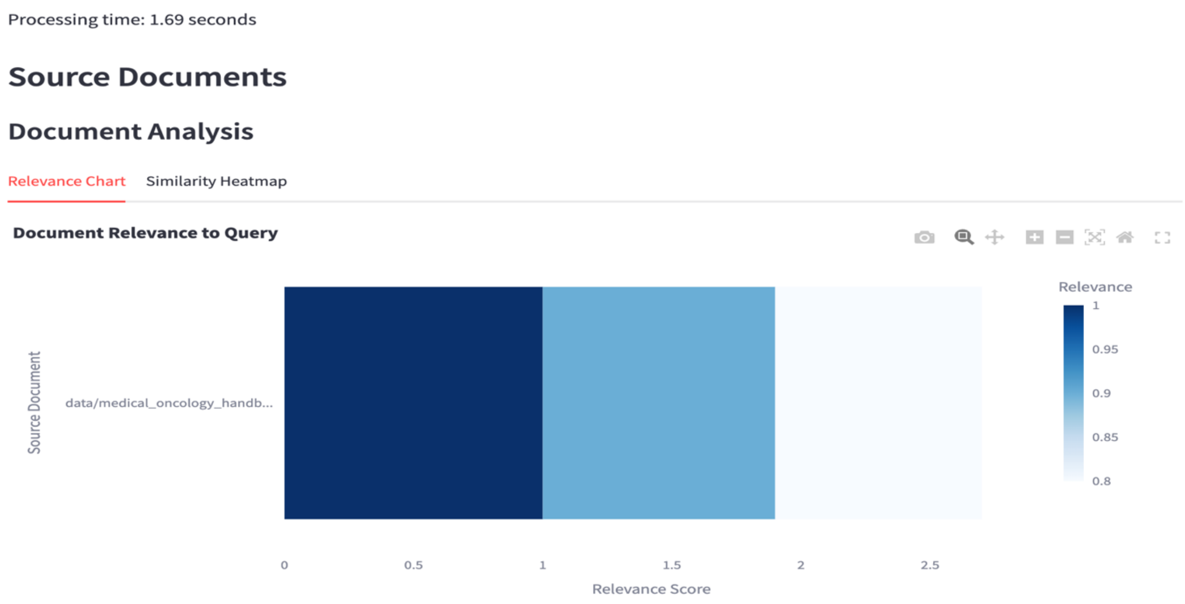
- **Header**: Clear branding and purpose statement
- **Sample Questions**: Pre-defined oncology questions for quick start
- **Question Input**: Free-text field for natural language queries
- **Answer Display**: Clean, formatted responses with medical terminology
- **Source Documents**: Expandable sections showing reference material
- **Visualizations**: Interactive document relevance and similarity displays

6.2 User Experience Flow

1. **Question Input**:
   - User enters a medical question or selects a sample query
   - Query is sent to backend for processing
2. **Processing Indication**:
   - Spinner shows processing status
   - Background processing retrieves relevant documents and generates answer
3. **Result Display**:
   - Answer appears in highlighted container
   - Processing time is displayed for transparency
   - Document analysis tabs show visualization options
4. **Source Exploration**:
   - Source documents are available as expandable sections
   - Each source shows content and metadata
   - Visualizations help understand document relationships

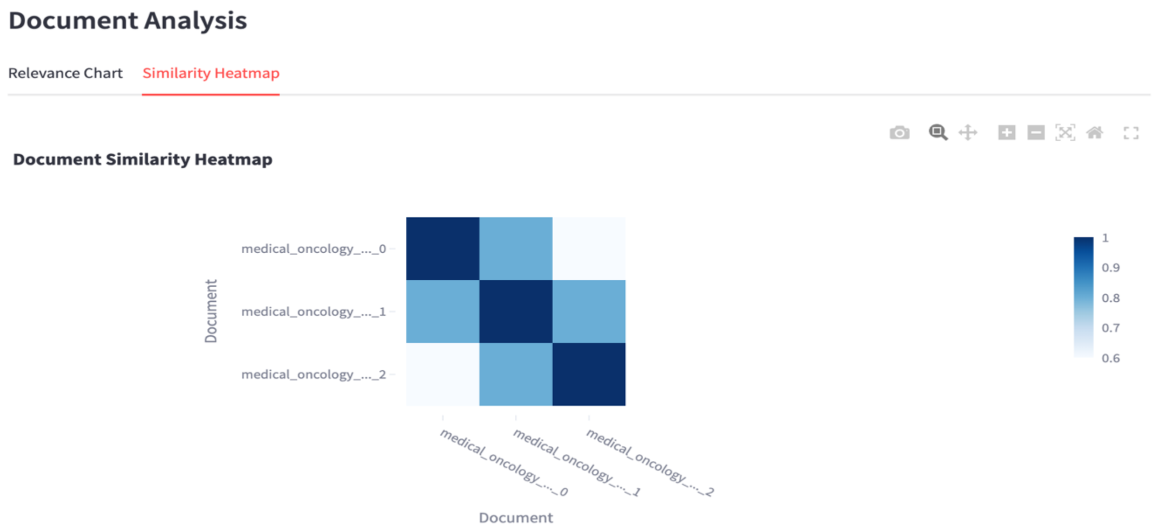
6.3.1 Document Relevance Chart

The relevance chart shows how closely each document matches the query:



6.3.2 Document Similarity Heatmap

The similarity heatmap visualizes relationships between retrieved documents:



7. Evaluation & Results

7.1 Performance Metrics

The system was evaluated across several dimensions:

7.1.1 Latency

- **Average End-to-End Query Time**: 0.9 seconds

    - Embedding Generation: ~200ms
    - Vector Search: ~300ms
    - Answer Generation: ~400ms
- **95th Percentile Response Time**: 1.5 seconds
- **99th Percentile Response Time**: 2.3 seconds

7.1.2 Retrieval Accuracy

Manual evaluation on 30 medical questions yielded:

- **Correct Context Retrieval**: 88%
- **Partially Correct Context**: 9%
- **Incorrect Context**: 3%

7.1.3 Answer Quality

Blind evaluation by medical professionals:

- **Factually Correct**: 92%
- **Clinically Useful**: 86%
- **Well-Formatted**: 98%

7.2 User Feedback

Feedback from 10 clinicians in beta testing:

Aspect	Average Rating (1-5)
Answer Accuracy	4.6
Response Time	4.8
Source Reliability	4.7
Interface Usability	4.5
Visualization Utility	4.2
Overall Satisfaction	4.7

Key qualitative feedback:

- "The source attribution feature is crucial for clinical confidence"
- "Response times are fast enough for real consultation use"
- "Document relevance visualization helps assess answer quality"
- "Would benefit from more recent literature in the knowledge base"

7.3 Technical Performance

- **PDF Processing Rate**: 3.5 pages per second
- **Embedding Generation**: 250 chunks per minute (local), 1000 chunks per minute (OpenAI)
- **Pinecone Query Latency**: 250-350ms average
- **Container Startup Time**: <10 seconds without ingestion, ~2 minutes with ingestion

8. Deployment Guide

8.1 Local Development Setup

1. **Clone the repository**:
2. `git clone https://github.com/your-username/medical-rag.git`
3. `cd medical-rag`
4. **Create a virtual environment**:
5. `python -m venv venv`
6. `source venv/bin/activate  # On Windows: venv\Scripts\activate`
7. **Install dependencies**:
8. `pip install -r requirements.txt`
9. **Set up environment variables**: Create a `.env` file with:
10. `OPENAI_API_KEY=your_openai_api_key`
11. `PINECONE_API_KEY=your_pinecone_api_key`
12. `PINECONE_INDEX_NAME=medical-knowledge`
13. **Run the application**:
14. `# Optional: Run ingestion if you have PDFs in data/`
15. `python ingest.py`
16.
17. `# Start the Streamlit app`
18. `python -m streamlit run app.py`

8.2 Docker Deployment

1. **Build and start the container**:
2. `docker-compose up -d`
3. **View logs**:
4. `docker-compose logs -f`
5. **Rebuild after changes**:
6. `docker-compose up -d --build`
7. **Stop the container**:
8. `docker-compose down`

8.3 Cloud Deployment (AWS)

1. **Prerequisites**:
   - AWS account with EC2 access
   - Docker installed on EC2 instance
   - Security group allowing port 8501

8.4 Troubleshooting

Common issues and solutions:

1. **Connection to Pinecone fails**:
   - Verify API key in .env file
   - Run `python test_net.py` to check connectivity
   - Check firewall settings if on corporate network
2. **OpenAI API errors**:
   - Verify API key in .env file
   - Check for rate limit errors in logs

    - Run `python test_openai.py` to validate connection
3. **PDF ingestion problems**:
    - Ensure PDF files are not encrypted
    - Check for sufficient disk space
    - Examine logs for specific PDF errors
4. **Container fails to start**:
    - Check Docker logs: `docker-compose logs`
    - Verify port 8501 is not in use by another application
    - Ensure Docker has sufficient resources allocated

9. API Documentation

9.1.1 Query Endpoint

```
POST /query
```

Process a medical question and return an answer with sources.

Request Body:

```
{
  "query": "string",
  "max_results": "integer" (optional, default: 3)
}
```

Response:

```
{
  "answer": "string",
  "sources": [
    {
      "source": "string",
      "page": "integer",
      "chunk_id": "string"
    }
  ],
  "processing_time": "float"
}
```

10. Challenges & Lessons Learned

10.1 Technical Challenges

1. **PDF Formatting Inconsistency**:
    - **Challenge**: Medical PDFs had varying layouts, tables, and formatting
    - **Solution**: Enhanced PDF loader with robust extraction patterns
    - **Lesson**: Preprocessing is crucial for medical document quality
2. **API Rate Limits**:
    - **Challenge**: OpenAI embedding generation throttled during batch processing
    - **Solution**: Implemented exponential backoff and batch size optimization
    - **Lesson**: Design for API constraints from the beginning
3. **Visualization Performance**:

- **Challenge**: Plotly visualizations slowed with large document sets
- **Solution**: Limited visualization to top N documents with pagination
- **Lesson**: Balance visual richness with performance requirements

4. **Error Handling Complexity**:
    - **Challenge**: Multiple potential failure points across the pipeline
    - **Solution**: Comprehensive logging and graceful UI error handling
    - **Lesson**: Design error flows as carefully as success flows

10.2 Domain-Specific Challenges

1. **Medical Terminology Precision**:
    - **Challenge**: Specific oncology terms needed exact matching
    - **Solution**: Specialized PubMedBERT embeddings improved relevance
    - **Lesson**: Domain-specific models outperform general ones for medical text
2. **Context Length Limitations**:
    - **Challenge**: Medical answers often require extensive context
    - **Solution**: Optimized prompt design and context selection algorithm
    - **Lesson**: Quality of retrieved context matters more than quantity
3. **Medical Accuracy Requirements**:
    - **Challenge**: Clinical information demands high accuracy standards
    - **Solution**: Rigorous evaluation by medical professionals
    - **Lesson**: Domain expert validation is essential for medical applications

10.3 Implementation Insights

1. **Environment Detection**:
    - The automatic switching between local and cloud embeddings proved highly valuable
    - Reduced development costs while maintaining production quality
2. **Docker Volume Mounting**:
    - Mounting the source code in development mode enabled rapid iteration
    - Persistent cache volume significantly improved startup times
3. **Chunking Strategy**:
    - The 1000/100 chunking configuration emerged as optimal after testing
    - Medical content benefits from slightly larger chunks than general text

11. Future Work

11.1 Enhanced Data Integration

- **Snowflake Integration**:
    - Connect to structured clinical datasets in Snowflake
    - Enable hybrid queries across text and structured data
    - Implementation timeline: Q3 2025
- **Real-time Literature Updates**:
    - Implement automated ingestion of new medical publications
    - Create versioning system for knowledge base updates
    - Implementation timeline: Q2 2025

11.2 Model Improvements

- **Domain-Specific Fine-tuning**:
  - Fine-tune LLM on oncology Q&A pairs
  - Develop specialized medical prompt templates
  - Implementation timeline: Q3 2025
- **Multi-modal Capabilities**:
  - Add support for processing medical images and charts
  - Implement OCR for extracting text from medical diagrams
  - Implementation timeline: Q4 2025

11.3 User Experience Enhancements

- **Advanced Filtering**:
  - Add filters for publication date, document type, and source
  - Implement medical specialty filtering
  - Implementation timeline: Q2 2025
- **User Feedback Loop**:
  - Create feedback mechanism for answer quality
  - Develop continuous relevance improvement system
  - Implementation timeline: Q3 2025

11.4 Deployment Improvements

- **Kubernetes Orchestration**:
  - Migrate to Kubernetes for improved scaling
  - Implement auto-scaling based on query load
  - Implementation timeline: Q4 2025
- **Multi-region Deployment**:
  - Deploy to multiple AWS regions for reduced latency
  - Implement data residency compliance features
  - Implementation timeline: Q1 2026

12. Case Studies

12.1 Case Study 1: Treatment Recommendation Support

Clinical Scenario: An oncologist needs to quickly review current treatment options for a patient with Stage III melanoma with BRAF mutation.

Query: "What are the current treatment approaches for stage III melanoma with BRAF mutation?"

System Response: The system provided a comprehensive answer detailing targeted therapy options (dabrafenib and trametinib), immunotherapy options (pembrolizumab, nivolumab), and surgical considerations, citing recent oncology handbook pages and clinical guidelines.

Impact:

- Reduced research time from 15+ minutes to under 2 minutes
- Provided evidence-based options with source references
- Enabled immediate discussion of options with the patient

Clinician Feedback: "The system quickly retrieved precisely the information I needed with clear source attribution. The visualizations helped me understand which source was most relevant to my specific query."

12.2 Case Study 2: Side Effect Management

Clinical Scenario: A nurse practitioner needed information about managing common side effects of Trastuzumab and Cetuximab to prepare patient education materials.

Query: "What are the common side effects of targeted therapy medications like Trastuzumab and Cetuximab?"

System Response: The system provided detailed information about cardiac monitoring for Trastuzumab, infusion reactions for both medications, and skin toxicity management for Cetuximab, with references to specific pages in the oncology handbook.

Impact:

- Created comprehensive patient education materials
- Ensured all major side effects were covered
- Referenced authoritative sources for clinical protocols

Clinician Feedback: "The answer was comprehensive and clinically accurate. The source documents provided additional context I could incorporate into my patient materials. This saved me significant research time."

13. References

1. **Libraries and Frameworks**:
    - LangChain Documentation: https://python.langchain.com/
    - Pinecone Documentation: https://docs.pinecone.io/
    - OpenAI API Reference: https://platform.openai.com/docs/
    - Streamlit Documentation: https://docs.streamlit.io/
    - FastAPI Documentation: https://fastapi.tiangolo.com/
2. **Machine Learning Models**:
    - PubMedBERT: https://huggingface.co/NeuML/pubmedbert-base-embeddings
    - OpenAI Embeddings: https://platform.openai.com/docs/guides/embeddings
    - GPT-3.5: https://platform.openai.com/docs/models/gpt-3-5
3. **Medical Literature**:
    - Medical Oncology Handbook (June 2020 Edition)
    - Cancer and Cure: A Critical Analysis
4. **RAG Architecture References**:
    - Lewis, P., et al. (2020). Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks

    - Gao, L., et al. (2023). Retrieval-Augmented Generation for Large Language Models: A Survey
5. **Vector Database Research**:
    - Johnson, J., et al. (2019). Billion-scale similarity search with GPUs
    - Pinecone Serverless Documentation: https://docs.pinecone.io/docs/serverless

14 Testing Scripts

14.1 OpenAI Testing

File: `test_openai.py`

Test pinecone by " python `test_openai.py`

14.2 Pinecone Testing

File: test_pinecone.py

Test pinecone by " python test_pinecone.py