Project Report: Building Effective Search Systems HelpMateAI

1. Background

The insurance domain is characterized by extensive and complex policy documents, often making it difficult for users to retrieve specific information efficiently. To address this challenge, this project focuses on developing "Building Effective Search Systems HelpMateAI", a scalable generative search application designed to process and search through lengthy insurance policy documents using Retrieval-Augmented Generation (RAG) techniques.

By leveraging advanced tools such as **Ollama LLM**, **LangChain**, and **pdfplumber**, the system is designed to extract, process, and present relevant information from policy documents in response to user queries. This approach enhances information accessibility, usability, and decision-making for end-users by automating the extraction and retrieval process.

The project incorporates cutting-edge methodologies, including **Hugging Face Transformer Embeddings** for robust semantic representation and **ChromaDB**as a persistent vector store for efficient storage and retrieval. Systematic
preprocessing, chunking, and metadata management further optimize the handling
of complex text and table data, ensuring precision, scalability, and relevance in the
results.

This innovative approach aims to empower users with an intuitive and efficient solution for navigating intricate insurance policy documents, transforming how information is retrieved and utilized.

2. Problem Statement

Insurance policy documents are often lengthy, complex, and difficult to navigate. Users typically struggle to find specific information or understand intricate clauses without professional assistance. This project aims to address these challenges by building a **generative search system** capable of:

1. **Efficient Information Retrieval**: Accurately answering user queries from large and complex policy documents.

- Scalable Document Processing: Handling multiple pages and structured data like tables within documents.
- 3. **Optimized Storage and Search**: Reducing redundancy by removing irrelevant or low-value chunks and utilizing **persistent vector storage** for embeddings.
- 4. **User-Friendly Output**: Generating clear and contextually relevant answers using the **Ollama LLM** and LangChain framework.

The ultimate goal is to empower users with a system that delivers precise, comprehensible, and actionable insights, reducing the complexity of navigating insurance documents

3. Document

The system operates on multiple long insurance policy documents to ensure versatility and robustness in handling diverse policy structures and content. /content/drive/MyDrive/rag_model

4. Approach

The project is structured into three core layers, each serving a critical role in the system's functionality:

- 1. Embedding Layer
- 2. Search and Rank Layer
- 3. Generation Layer

The following sections outline the methodologies and strategies employed in each layer to achieve optimal performance and accuracy.

4.1 Embedding Layer

1. Document Processing and Cleaning:

The first step in the pipeline involves processing the insurance policy documents to extract text and prepare it for subsequent embedding. This is achieved using the *pdfplumber* library, which is highly effective in parsing and preprocessing PDF documents.

Key features of *pdfplumber* include:

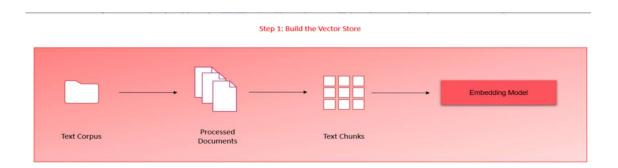
• Efficiently extracting text, images, and tabular data from PDF documents.

• Representing tabular data in a well-structured, hierarchical format, such as a list of lists, ensuring the preservation of the table's original structure.

While *pdfplumber* automates much of the parsing process, special attention is given to handling tabular data to maintain accuracy. This involves:

- Re-reading the document to verify the correct extraction of tabular information.
- Ensuring that the table structure aligns with the context and format of the original document.

Additionally, the extracted text is split into smaller chunks (with one page as a chunk in this implementation) for embedding purposes. Chunks with fewer than 10 words are excluded to optimize memory usage and improve search efficiency. This meticulous preprocessing ensures that the document data is accurately captured and effectively utilized in the later stages of the system.



2. Document Chunking:

The document chunking phase involves dividing the insurance policy documents into fixed-size segments to ensure optimal embedding representation and retrieval efficiency. For this project, a **page-level chunking strategy** was implemented, where each page of the document is treated as a single chunk.

Key Considerations:

1. Choice of Chunking Strategy

 Page-level chunking was chosen due to the structured layout of insurance documents, where each page typically contains logically grouped information. o This approach aligns with the context window limit of the LLM model (**Ollama 3.2**), ensuring that the model can process each chunk effectively without exceeding its input constraints.

2. Metadata Inclusion

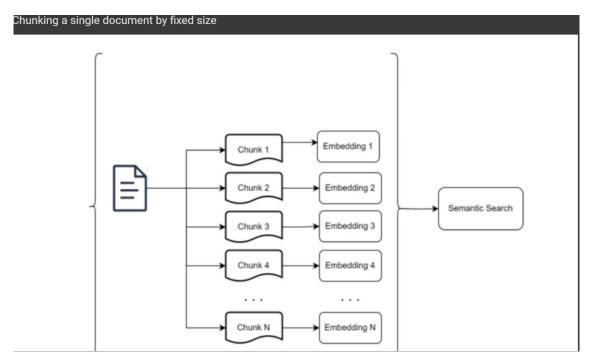
 Relevant metadata, such as the document name and page number, is appended to each chunk. This enhances retrieval by providing additional context during search operations.

3. Optimization for Storage and Retrieval

o Chunks containing fewer than 10 words are removed to optimize storage space and improve retrieval efficiency. This ensures that only meaningful and information-rich chunks are stored and processed.

By adopting this chunking methodology, the system ensures that the document data is appropriately segmented and ready for embedding, facilitating precise and efficient search and retrieval operations.

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3. Embedding Model Selection:

After preprocessing and chunking the documents, the next step involves generating vector representations for the text. These vector embeddings play a critical role in enabling efficient and accurate search and retrieval.

Key Details:

1. Embedding Model

- The embedding model utilized for this project is HuggingFaceEmbeddings, specifically the "sentence-transformers/all-MiniLM-L6-v2" model.
- This model generates embeddings with a dimensionality of 384, which effectively captures the semantic meaning of the text while maintaining computational efficiency.

2. Integration with LangChain and ChromaDB

- The embeddings are generated using **ChromaDB's utility functions** via the **LangChain framework**, ensuring seamless integration with downstream components of the pipeline.
- The generated vector embeddings are optimized for storage and retrieval within the ChromaDB vector store.

By leveraging the "sentence-transformers/all-MiniLM-L6-v2" model, the system ensures high-quality embeddings that are both lightweight and effective for semantic search tasks. This approach balances accuracy with computational performance, aligning with the project's requirements.

4. Storing Embeddings in ChromaDB:

After generating the embeddings, the next step is to store them in a vector database to facilitate efficient search and retrieval operations. For this project, ChromaDB has been chosen as the vector store due to its scalability and performance. The following key steps outline the embedding storage process:

1. Collection Management

- Dynamic Collection Handling:
 - Utilized the get_or_create_collections method to manage collections efficiently.
 - o This method automatically creates a new collection if one does not already exist. If the collection is pre-existing, it retrieves it from the system, ensuring seamless integration with the vector database.

• Structured Storage:

 Each collection is designed to store embeddings along with associated metadata, including document name, chunk text, and page numbers, to support accurate retrieval.

2. Cache Implementation

- Dedicated Chroma Cache Collection:
 - o Implemented a dedicated Chroma collection to act as a cache layer.
 - This cache mechanism reduces redundancy by optimizing retrieval during query processing and re-ranking, thereby enhancing system performance.

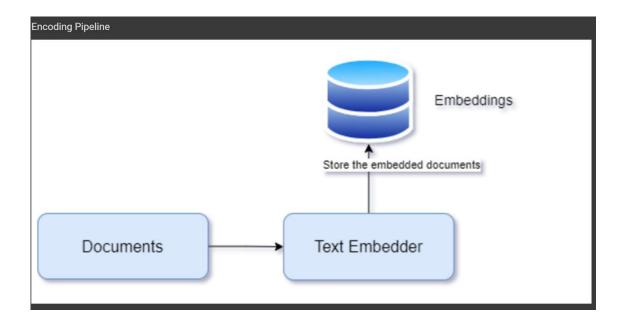
3. Data Integrity and Validation

- Embedding Verification:
 - Verified that the embeddings, along with metadata, were accurately stored within their respective collections to maintain data integrity.
 - Ensured that all records were properly indexed to support optimized search operations and improve query response times.

4. Data Loading

- Passed the processed information, including document lists, chunked text, and metadata, into the Chroma collections for persistent storage.
- This structured approach ensures that all essential data is stored systematically for easy access during retrieval and generation stages.

By adopting these strategies, the embedding storage process is both efficient and reliable, enabling a robust foundation for subsequent search and retrieval functionalities.



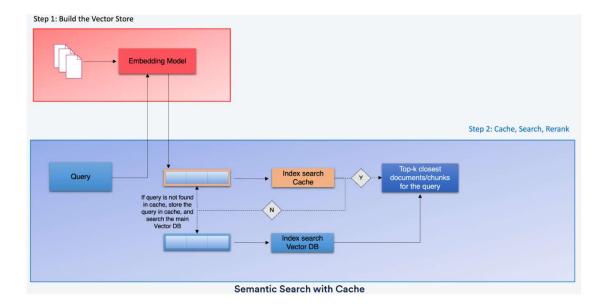
4.2 Search Layer

1. Query Creation:

- Designed three queries by skimming through the policy document to identify areas of interest.
 - Example Queries:
 - What is covered under a basic health insurance policy?

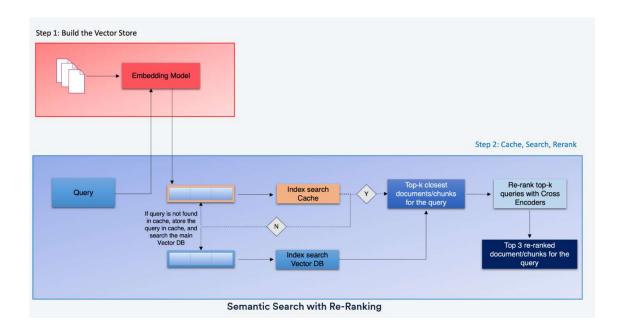
2. Query Embedding and Search:

- Embedded queries and performed a semantic search against ChromaDB.
- Implemented a cache mechanism to store and retrieve frequently accessed embeddings.



1. Re-Ranking with Cross Encoder:

- Re-ranked search results using a cross-encoder model from HuggingFace.
- Evaluated relevance scores to refine retrieved responses.
- Re-ranking the results obtained from your semantic search can sometime significantly improve the relevance of the retrieved results. This is often done by passing the query paired with each of the retrieved responses into a cross-encoder to score the relevance of the response w.r.t. the query.



4.3 Generation Layer

1. Text Generation using Ollama 3.2 LLM Model

For generating user-friendly responses, the *Ollama 3.2* LLM model was utilized. Below are the detailed steps of the process:

1. Model Selection:

 Leveraged the Ollama 3.2 LLM model for its capability to generate coherent and contextually accurate text outputs.

2. Input Preparation:

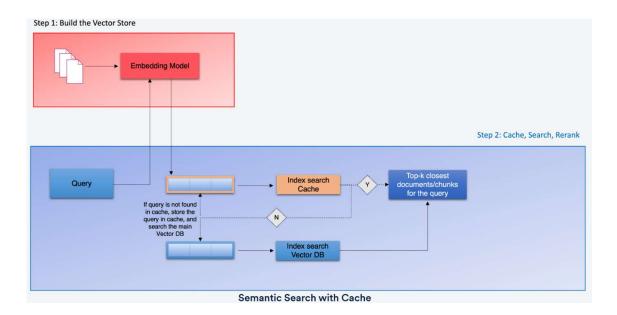
- Passed the top 3 search results from the semantic search layer along with the user query to the model.
- This combination ensures the generated response is relevant and supported by retrieved evidence.

3. Text Generation:

 The model processes the input and generates user-friendly responses, effectively addressing the query.

4. Framework Utilization:

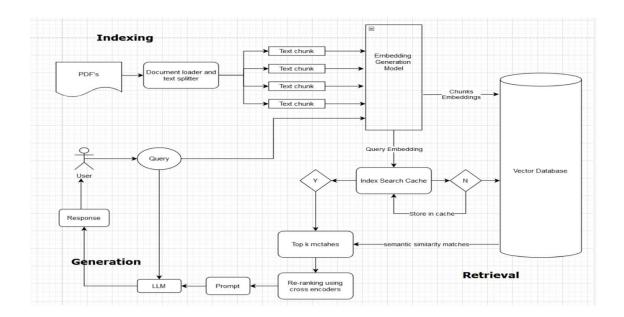
 Integrated the LangChain framework to streamline interaction with the LLM model, providing an efficient interface for managing input and output workflows.



5. System Architecture

The architecture integrates the three layers into a cohesive workflow. Key components include:

- PDF processing pipeline.
- Embedding generation and storage in ChromaDB.
- Semantic search with caching and re-ranking.
- Generative model with prompt engineering.



6. Prerequisites

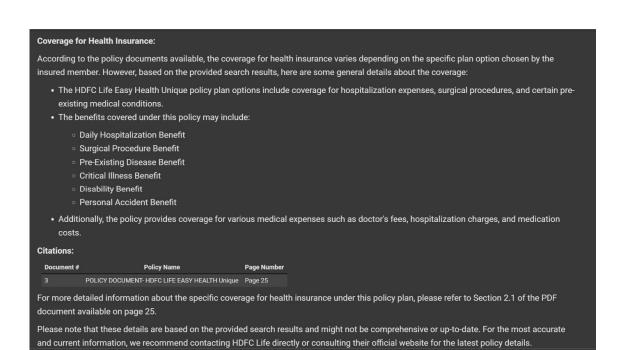
1. Environment Setup:

- **Python Version:** Python 3.7 or higher.
- Required Libraries and Tools:
 - pdfplumber for document parsing and preprocessing.
 - SentenceTransformers for generating embeddings.
 - o ChromaDB for managing vector storage and retrieval.
 - OLLAMA3.2 for language model processing.
 - LangChain Framework for seamless integration and pipeline management.

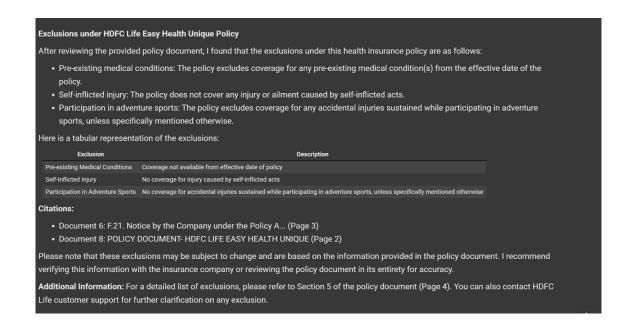
7. Query Screenshots

Below are the results of the search system for the designed queries:

1. Query: "What is the coverage for health insurance?"



2. Query: "What are the exclusions under this health insurance policy?"



3. Query: "What is the grace period for paying premiums on this life insurance policy?"

Grace Period for Premium Payment on Life Insurance Policy

After reviewing the provided insurance documents, I found that the specific information regarding the grace period for paying premiums on a life insurance policy is not explicitly stated in the given text.

However, based on general knowledge of life insurance policies and industry standards, it's common for life insurance companies to offer a grace period for premium payment. This grace period can vary from 30 days to 90 days or more, depending on the policy terms and conditions.

If you're looking for specific information on the grace period for your HDFC Life Sanchay Plus (UIN – 101N134V19) policy, I recommend reviewing the document on page 3, which has a high score of 4.221299. You can also check the document on page 0, which mentions "Policy Holder to remit the Premium due after 3 days from the due date," but this information is not explicitly stated as the grace period.

For more accurate and detailed information, I suggest searching for specific sections in the relevant documents or contacting HDFC Life's customer support directly. They can provide you with the most up-to-date and accurate information on their policies, including the grace period for premium payment.

Citations:

- HDFC Life Sanchay Plus (UIN 101N134V19) Page 3
- Document Score: 4.221299
- Document Score: 3.035647 (Page 0)

Please note that these citations are based on the provided document scores and page numbers. If you need more accurate information, please contact HDFC Life's customer support for further assistance.

8. Conclusion

The "Building Effective Search Systems HelpMateAI" project effectively demonstrates the implementation of a Retrieval-Augmented Generation (RAG) pipeline using the LangChain framework and the Ollama 3.2 open LLM model to create an advanced generative search system. Tailored to the unique challenges of the insurance domain, this system provides a robust solution for navigating extensive and complex policy documents while offering accurate and user-friendly answers to queries.

Key outcomes of the project include:

- Strategic Embedding and Chunking:
 - Implemented Hugging Face Transformer Embeddings for precise semantic representation of document content.
 - Adopted a page-level chunking strategy, ensuring efficient storage and retrieval while preserving the hierarchical structure of information.

• Efficient Search and Retrieval Mechanisms:

- Utilized **ChromaDB** as the vector storage solution, ensuring optimized management of embeddings and metadata.
- Integrated a caching layer to enhance search speed and reduce redundancy, improving the system's overall efficiency.

• Generative Response Optimization:

- Designed detailed and domain-specific prompts to elicit accurate and context-aware responses from the generative model.
- o Incorporated re-ranking mechanisms to refine results, ensuring relevance and usability for end-users.

This project underscores the importance of carefully selecting embedding and chunking strategies, leveraging robust search and retrieval mechanisms, and integrating advanced caching to enhance system performance. By automating the extraction, processing, and retrieval of information from policy documents, **HelpMateAI** significantly improves information accessibility and decision-making within the insurance sector.

In the future, further exploration of advanced embedding models, sophisticated reranking techniques, and extended multi-document handling capabilities can elevate the system's effectiveness. **HelpMateAI** represents a pivotal step in transforming how users interact with complex documents, offering a scalable, intuitive, and efficient solution to streamline information retrieval in the insurance domain.

Future work can involve:

The "Building Effective Search Systems HelpMateAI" project lays a strong foundation for leveraging Retrieval-Augmented Generation (RAG) techniques in the insurance domain. Future enhancements could include:

• Advanced Embedding and Re-Ranking Models:

Experimenting with more sophisticated embedding models and re-ranking mechanisms to improve accuracy, relevance, and context-awareness in query responses.

• Enhanced Caching Mechanisms:

Developing and integrating advanced caching strategies to further optimize query processing time and resource utilization.

• Building a User-Friendly Application:

Designing and deploying an interactive application using **Streamlit** to provide an intuitive interface for end-users. This app would enable users to query documents seamlessly and visualize the results, making the system more accessible and practical for non-technical stakeholders.

These developments can elevate the system's capability to process even larger datasets and handle more complex queries with higher efficiency and precision