HelpMateAI: RAG based search system with Cache and reranking Project Report

1. Introduction:

HelpMateAI is an intelligent assistant designed to provide support and automate tasks for users in various domains such as customer service, technical support, and personal assistance. The project aims to leverage advanced natural language processing (NLP) and machine learning (ML) techniques to deliver a seamless and efficient user experience.

2. Objectives:

The primary objectives of the project are as follows:

- Develop a semantic search system using the RAG (Embedding Layer, Search and Rank Layer, Generation Layer) pipeline for efficient document retrieval.
- Extract relevant information from PDF documents, store them in a structured format, and generate vector representations using SentenceTransformerEmbedding's.
- Implement a cache layer to enhance system performance by storing and retrieving previous queries and their results.

3. Design:

3.1. RAG Pipeline:

Embedding Layer: Extract text and tables from PDFs, convert them to a dataframe, and generate vector representations using OpenAI's text-embedding-ada-002 model. Store these embeddings in ChromaDB.

Search and Rank Layer: Perform a semantic similarity search on the knowledge bank based on user queries, retrieving the top K closest documents or chunks.

Generation Layer: Utilize the results from the previous layer, including the original user query and a well-constructed prompt, to generate coherent answers using a language model.

3.2. Cache Implementation:

Set a threshold of 0.2 for semantic similarity.

Store queries and results in a cache_collection in ChromaDB for easy embedding and searching.

Use ChromaDB's utility functions to add documents, ids, and metadata to the cache_collection.

4. Implementation:

Use Google Colab for development and leverage libraries such as pdfplumber, tiktoken, openai, chromaDB, and sentence-transformers for document processing, embedding, and caching.

Implement functions to extract text and tables from PDFs, create a dataframe, generate vector embeddings, and perform semantic searches using the RAG pipeline.

Develop a cache system using ChromaDB to store and retrieve previous queries and their results.

The three layers for RAG pipeline are:

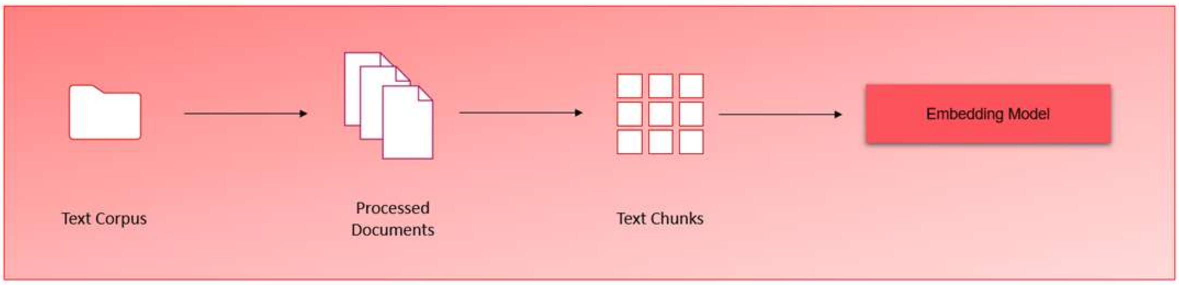
1. Embedding Layer
2. Search Layer
3. Generation Layer

Embedding Layer:

Processing and Chunking: Explore and compare various strategies for effective PDF document processing, cleaning, and chunking. Evaluate the impact of different chunking strategies on the quality of the retrieved results.

Embedding Model Choice: Choose between OpenAI's embedding model and SentenceTransformers from HuggingFace. Assess the impact of the selected model on the quality of vector representations.

Step 1: Build the Vector Store

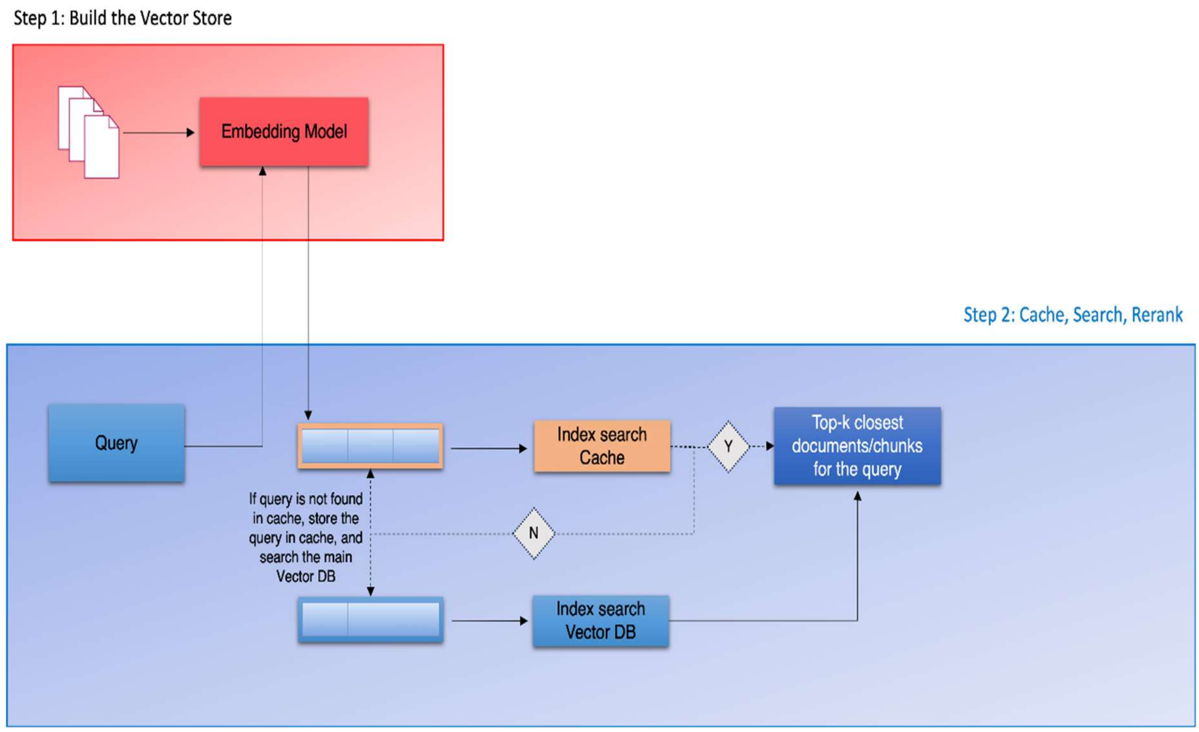


Search Layer:

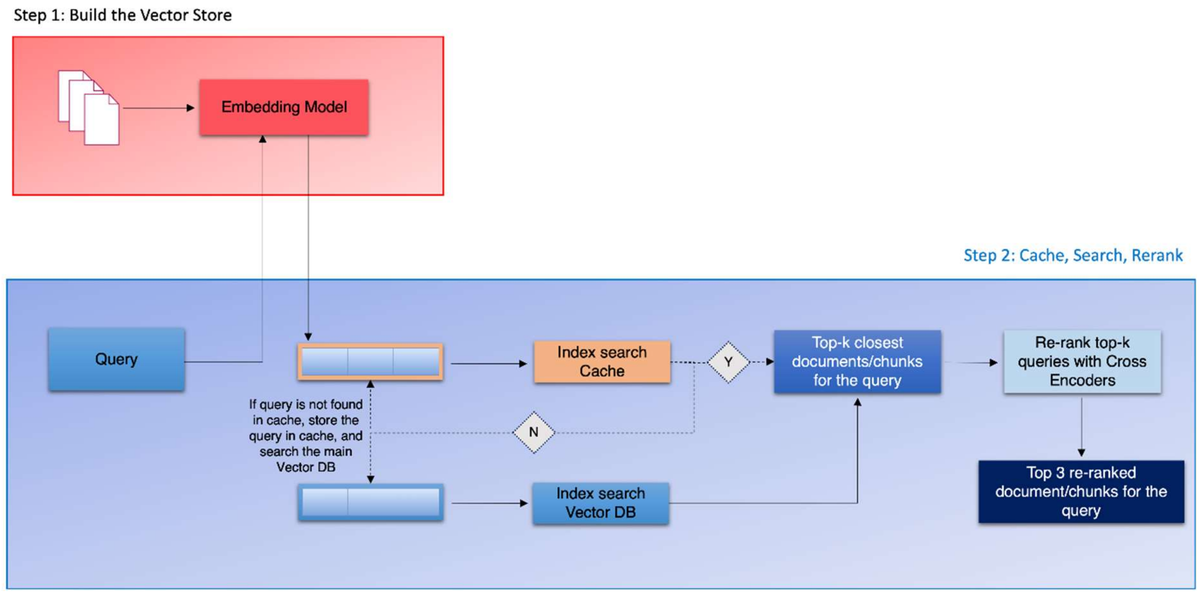
Query Design: Design a minimum of three queries that reflect information seekers' potential questions in the policy document. Ensure queries cover diverse aspects of the document to thoroughly test the system.

Vector Database Search: Embed queries and perform searches against the ChromaDB vector database. Implement a cache mechanism to store and retrieve previous queries and their results.

Re-ranking Block: Integrate a re-ranking block utilizing cross-encoding models from HuggingFace to enhance the relevance and accuracy of search results.



When using cross_encoder:



Generation Layer:

Prompt Design: Focus on designing a comprehensive and instructive prompt for the Language Model (LM) in the generation layer. Ensure the prompt effectively conveys relevant information to the LM for coherent answer generation.

Few-shot Examples: Enhance LM performance by providing few-shot examples in the prompt to guide the model in generating more contextually accurate responses.

Overall Project Insights:

Performance Evaluation: Conduct thorough evaluations for each layer, considering the impact of different strategies, models, and components on the system's performance.

Scalability: Address concerns about system scalability by considering potential increases in document numbers or user queries. Implement measures such as vector database scaling and compute unit adjustments.

Documentation and Codebase: Ensure a well-documented codebase that includes detailed explanations of implemented strategies, models, and mechanisms. Provide clear instructions for potential future developers or collaborators.

5. Technologies Used:

- **Programming Languages**: Python
- **Frameworks**: Open AI, HuggingFace
- **Databases**: Croma Vector DB

6. Challenges:

Performance Scaling: Address concerns about system performance with an increased number of documents or users by implementing vector databases and scaling up compute units.

Cache Storage: Optimize the cache collection to efficiently store and retrieve queries and results.

7. Lessons Learned:

Efficient Document Processing: Processing PDFs efficiently is crucial; libraries like pdfplumber and suitable data structures for storage play a vital role.

Semantic Search Optimization: Fine-tune semantic search parameters and thresholds for optimal results.

Cache Management: Implement an effective cache management strategy to balance storage and retrieval efficiency.

8. Conclusion:

The project successfully implements a semantic search system with the RAG pipeline and cache layer. The objectives are met, and the challenges are overcome with lessons learned for future improvements. The system provides a scalable and efficient solution for document retrieval and information extraction.