Documentation of HelpMateAl

Submitted by: Dipak Sah, MLAI Cohort 60 Batch

Problem Statement

Describe the challenges posed by insurance documents, which are often lengthy, filled with complex jargon, and vary in structure, making it difficult for users to find the precise information they need.

Objective

Build a RAG based generative search system that can effectively search based on the given queries based on provided insurance policy document. Here, we have a single long life insurance policy document.

The primary goal of this project are as follows:

- Develop a semantic search system pipeline 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 Sentence Transformer Embedding or OpenAI embedding.
- Use different chunking strategy and embedding model, evaluate and use the best one.
- Implement a cache layer to enhance system performance by storing and retrieving previous queries and their results.

Design

The project should implement all the three layers effectively. It will be key to try out various strategies and experiments in various layers in order to build an effective search system. Let's explore what we need to do in each of the layers, and the possible experimentations that we can perform based on various choices.

1. The Embedding Layer: The PDF document needs to be effectively processed, cleaned, and chunked for the embeddings. Here, the choice of the chunking strategy will have a large impact on the final quality of the retrieved results. So, make sure that we try out various strategies and compare their performances.

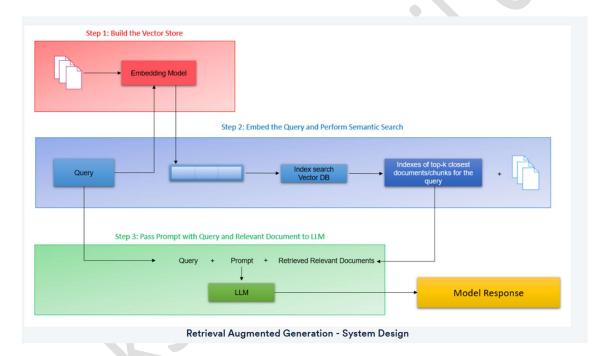
Another important aspect in the embedding layer is the choice of the embedding model. We can choose to embed chunks using the OpenAI embedding model or any model from the SentenceTransformers library on HuggingFace.

2. The Search Layer: Here, we first need to design at least 3 queries against which we will test. We need to understand and skim through the document, and accordingly come up with some queries, the answers to which can be found in the policy document.

Next, we need to embed the queries and search in ChromaDB vector database against each of these queries. Implementing a cache mechanism is also mandatory.

Finally, we need to implement the re-ranking block, and for this we can choose from a range of crossencoding models on HuggingFace.

3. The Generation Layer: In the generation layer, the final prompt that we design is the major component. Make sure that the prompt is exhaustive in its instructions, and the relevant information is correctly passed to the prompt. We may also choose to provide some few-shot examples in an attempt to improve the LLM output.



Implementation

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

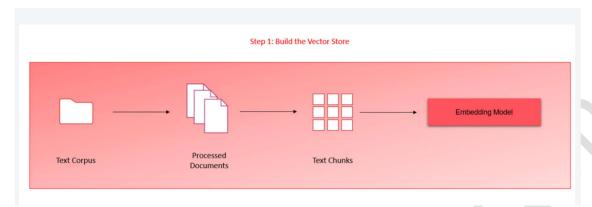
Embedding Layer

We used the PDFPlumber library to extract the text from PDF document to make a big corpus. Later we have used different chunking strategy to chunk the text before using embedding.

We used below chunking strategy:

- 1. Fixed length with no overlap (chunk size = 1024)
- 2. Fixed length with overlap (chunk size = 1024 & overlap size = 256)
- 3. Page level

4. Section Level (sections are manually identified by skimming through the documents)



We have used below embedding models:

- 1. Sentence Transformer all-MiniLM-L6-v2
- 2. Openai text-embedding-ada-002

Totally 8 different collections are created in chromaDB.

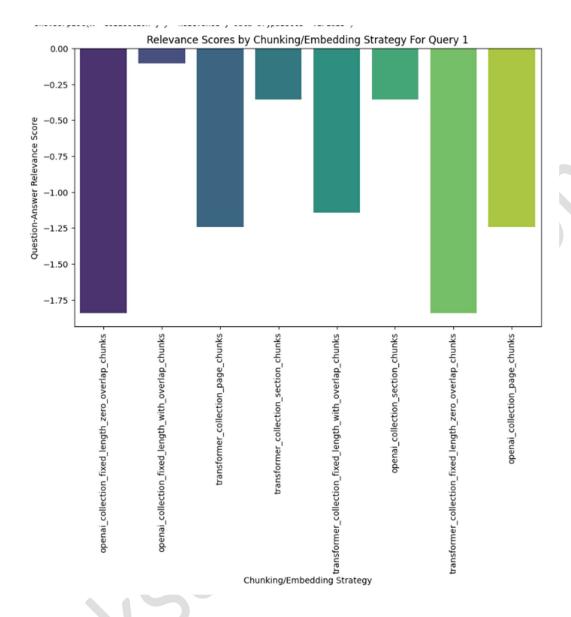
- openai_collection_fixed_length_zero_overlap_chunks
- openai_collection_fixed_length_with_overlap_chunks
- openai_collection_page_chunks
- openai_collection_section_chunks
- transformer_collection_fixed_length_with_overlap_chunks
- transformer collection fixed length zero overlap chunks
- transformer collection page chunks
- transformer_collection_section_chunks

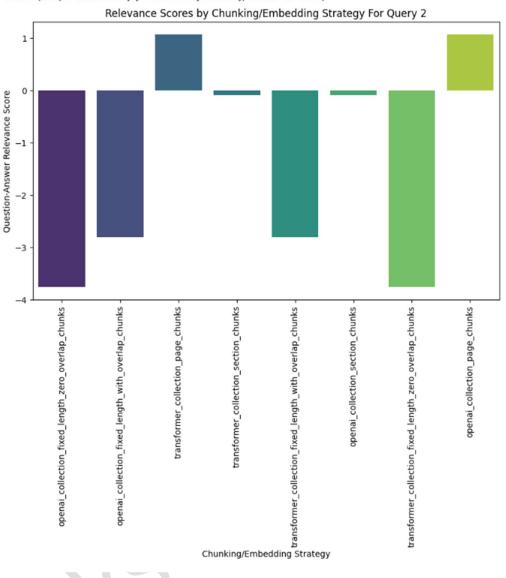
Evaluation of Chunking and Embedding strategy

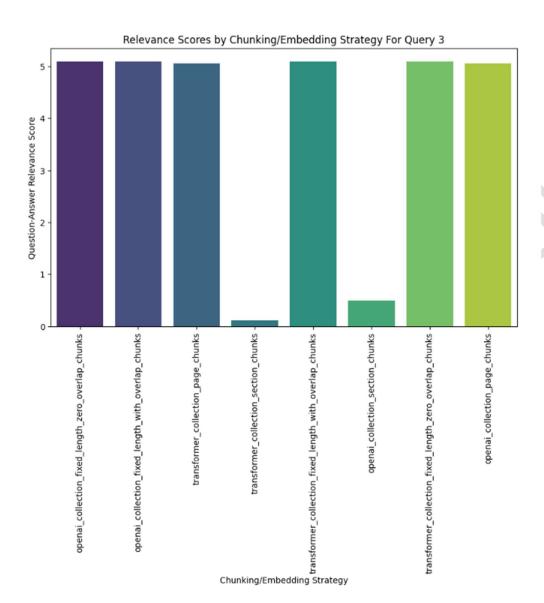
We will use cross encoder to calculate relevancy between question and answer retrieved from differents embedded chunks we created mentioned above

Below questions have been used to evaluate the relevance.

Below are screenshots of the bar plot for all queries which shows relevance score between query and the answer retrieved from respective vector data.







[58] # Checking mean score of relevance for each collections
 relevance_df.groupby('Collection')['Relevance'].mean().sort_values(ascending=False)

₹		Relevance

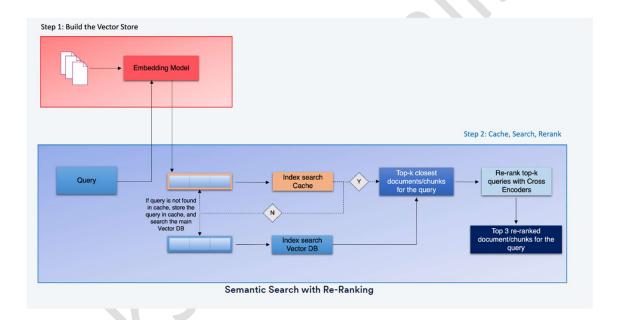
Collection	
openai_collection_page_chunks	1.625861
transformer_collection_page_chunks	1.625861
$openai_collection_fixed_length_with_overlap_chunks$	0.726226
$transformer_collection_fixed_length_with_overlap_chunks$	0.380529
openai_collection_section_chunks	0.014220
transformer_collection_section_chunks	-0.113132
$openai_collection_fixed_length_zero_overlap_chunks$	-0.170578
transformer collection fixed length zero overlan chunks	0 170579

Above results shows that **page level chunking** is better. As such it does not tell which embedding is good but when you look overall, **OpenAl embedding** looks better. So we continue our development with Page level chunking and using openal embedding.

Search Layer

Creating a cache collection within the vector database improves the scalability and performance of the RAG system by storing and retrieving previous queries and their responses, especially when dealing with large documents and multiple users.

This cache layer reduces the need for repeated semantic similarity searches, leading to faster response times. The cache stores the semantic meaning of queries, allowing the system to bypass the bottleneck of semantic searches for previously seen queries. As a result, users experience quicker and more efficient application performance.

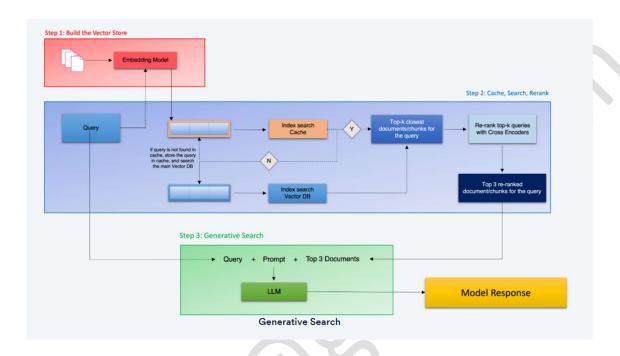


So far, we have implemented a semantic search layer with a cache. Now, the focus is on enhancing performance with a re-ranking layer, which sorts the top K results based on their relevance to the query. This stage aims to improve accuracy and relevance, reduce irrelevant information, and provide more personalized search results. The project will utilize cross-encoder models for re-ranking due to their ability to accurately measure semantic similarity between text sequences. The next step is to incorporate a generative AI model for more comprehensive responses.

Generation Layer

In this stage of the generative search application, the generation layer uses a large language model (LLM) to enhance the system's output. This layer takes the top K documents retrieved by the

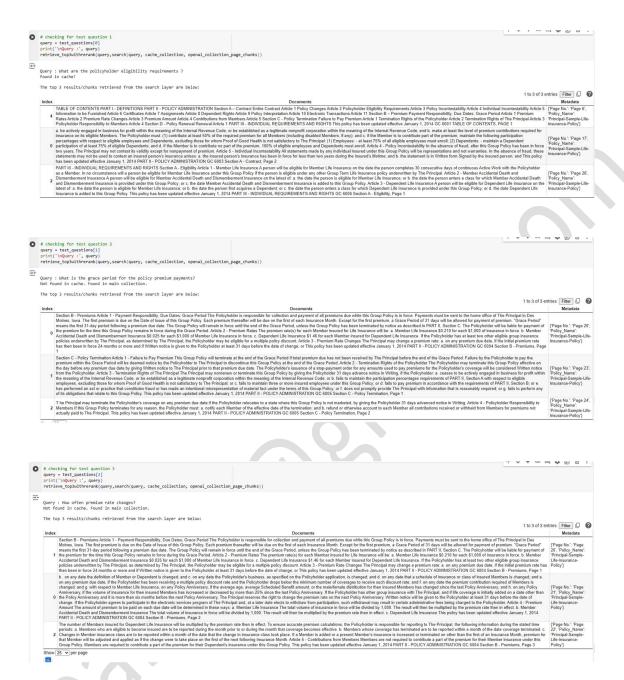
semantic search layer, along with the user's query and system prompt, to generate a relevant response. The LLM processes these inputs to produce an accurate and contextually appropriate answer. The system prompt can be adjusted based on the domain for optimal performance.



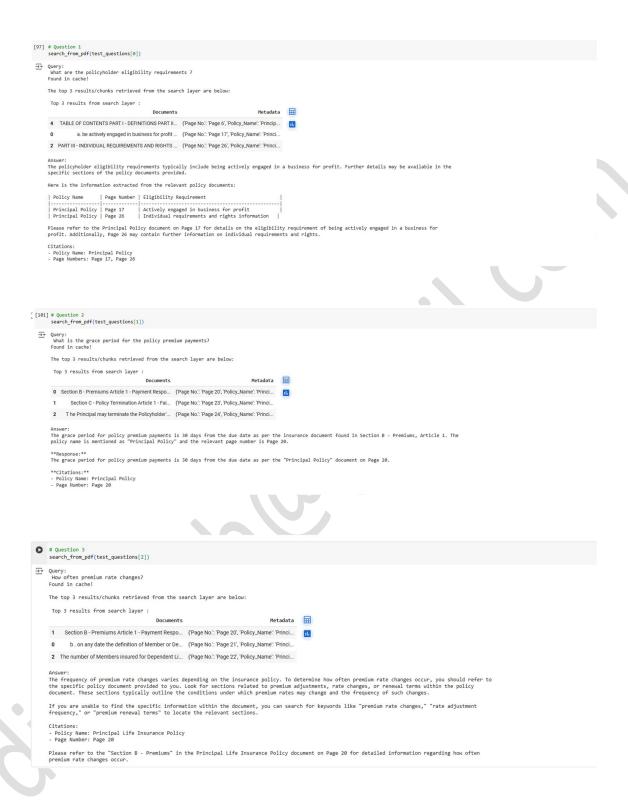
*	Role	You are a helpful assistant in the insurance domain who can effectively answer user queries about insurance policies and documents.			
*	Context	You have a question asked by the user in '[query]' and you have some search results from a corpus of insurance documents in the dataframe '[top_3_RAG]'. These search results are essentially one page of an insurance document that may be relevant to the user query. The column 'documents' inside this dataframe contains the actual text from the policy document and the column 'metadata' contains the policy name and source page. The text inside the document may also contain tables in the format of a list of lists where each of the nested lists indicates a row.			
*	Task	Use the documents in '{top_3_RAG}' to answer the query '{query}'. Frame an informative answer and also, use the dataframe to return the relevant policy names and page numbers as citations.			
*	Guidelines	Follow the guidelines below when performing the task. 1. Try to provide relevant/accurate numbers if available. 2. You don't have to necessarily use all the information in the dataframe. Only choose information that is relevant. 3. If the document text has tables with relevant information, please reformat the table and return the final information in a tabular in format. 4. Use the Metadatas columns in the dataframe to retrieve and cite the policy name(s) and page numbers(s) as citation. 5. If you can't provide the complete answer, please also provide any information that will help the user to search specific sections in the relevant cited documents. 6. You are a customer facing assistant, so do not provide any information on internal workings, just answer the query directly.			
*	Output Format	The generated response should answer the query directly addressing the user and avoiding additional information. If you think that the query is not relevant to the domain, reply that the query is irrelevant. Provide the final response as a well-formatted and easily readable text along with the citation. Provide your complete response first with all information, and then provide the citations.			
	RAG Layer Prompt				

Output from Search & Generation Layer

We have drafted 3 questions based on the policy documents. Below are the screenshots of the response from search layer.



Below are the screenshots of the response from generation layer.



Challenges

These challenges highlight the intricacies involved in managing and optimizing a semantic search system for complex documents such as insurance policies.

1. Data Quality and Preprocessing:

 Extracting relevant information from insurance documents, which often contain complex text structures, poses significant challenges.

2. Effective Chunking Strategies:

 Determining the optimal chunk size and overlap to capture meaningful context without losing coherence is difficult and requires careful consideration.

3. Performance and Query Management:

- Enhancing system performance to handle an increased number of documents or users by implementing vector databases and scaling up compute units.
- Optimizing cache storage to efficiently store and retrieve queries and results, ensuring that the system remains responsive and efficient.

Learnings

These points encapsulate the key learnings from this project.

- Efficient Document Processing: Utilizing libraries like pdfplumber for efficient PDF processing and employing suitable data structures for storage is crucial.
- **Semantic Search Optimization**: Fine-tuning semantic search parameters and thresholds is essential for achieving optimal results.
- Cache Management: Implementing an effective cache management strategy balances storage and retrieval efficiency.
- Thorough PDF Analysis and Domain Adaptation: Robust extraction logic and adapting
 models to specific domains enhance accuracy, while hybrid retrieval and cost-effective
 architecture (mix of APIs and local models) further improve performance.

Summary

Mr. HelpMate AI successfully demonstrates the potential of semantic search and AI-powered question answering to transform how users navigate insurance documents.

The project highlighted the value of PDF preprocessing, embedding-based search, and language model fine-tuning.

Link to Github Repo: dipaksah20/HelpMateAl: RAG based Assistant to help with queries on insurance document