Help Mate AI- RAG Project

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Goal:

Build a robust generative search system capable of effectively and accurately answering questions from a policy document, by using RAG (Retrieval augmented generation) concept.

Data Source: Policy document present in PDF form as below:

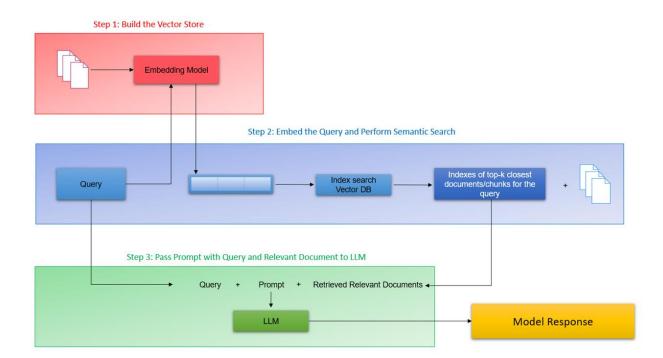
https://github.com/arunksinghbuee/helpmate-ai/blob/main/insurance-document/Principal-Sample-Life-Insurance-Policy.pdf

Collab Notebook PDF: https://github.com/arunksinghbuee/helpmate-ai/blob/main/Mr.HelpMate%20Al%20Project.pdf

System Design:

RAG pipeline mainly consists of 3 layers:

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



Embedding Layer

This layer is a crucial component of RAG models, serving as the first layer. It contains an embedding model trained on extensive text and code datasets to learn word and phrase relationships. This layer enables systems to understand text meaning and its semantic relation to queries, crucial for tasks like question answering, summarization, and machine translation. It generates embeddings for text corpora, aiding the RAG model in comprehending queries and generating relevant responses.

Embedding generation code -> Refer https://github.com/arunksinghbuee/helpmate-ai/

There are multiple types of chunking methods which can be used as per nature of data.

| Chunking Method | Description | Advantages | Disadvantages |
|--------------------------------------|--|--|---|
| Use entire document without chunking | The entire document is treated as a single chunk. | Simple and easy to implement. | The chunk may not always fit within the context window. This may result in extraneous contexts, thereby affecting the quality of the embedding. |
| Fixed-size chunking | The document is split into fixed-size windows with each window representing a separate document chunk. | Simple and easy to implement. Having a consistent chunk size will make the system consistent. | May cut off the context in between chunks, resulting in information loss. |
| Chunking on natural delimiters | Natural delimiters in the document are used to determine the boundaries of each chunk (sentence, paragraph, etc.). | Can result in more meaningful chunks as it utilises the structure of the document and the natural breaks within it. | May be time-consuming to find the right delimiters. |
| Overlapping chunks | The document is split into fixed-size overlapping windows. | Simple and easy to implement. Redundancy is offset by higher accuracy and latency. | May result in information redundancy across different chunks. |

By looking at provided document, most of the similar context data is present on each page and it is further divided into sections & paragraphs on each page.

Word length in each page varies up to maximum of 418 words which is suitable for creation of embedding using **text-embedding-ada-002** OpenAI embedding model.

```
insurance_pdf_data['Text_Length']
       30
1
         5
2
      230
3
         5
4
      110
      . . .
59
      285
      418
60
      322
61
62
         5
         8
63
Name: Text_Length, Length: 64, dtype: int64
```

Embedding models

OpenAl offers two powerful third-generation embedding model (denoted by -3 in the model ID). You can read the embedding v3 announcement blog post for more details.

Usage is priced per input token, below is an example of pricing pages of text per US dollar (assuming ~800 tokens per page):

| MODEL | ~ PAGES PER DOLLAR | PERFORMANCE ON MTEB EVAL | MAX INPUT |
|------------------------|--------------------|--------------------------|-----------|
| text-embedding-3-small | 62,500 | 62.3% | 8191 |
| text-embedding-3-large | 9,615 | 64.6% | 8191 |
| text-embedding-ada-002 | 12,500 | 61.0% | 8191 |

Search & Rank Layer

This layer ensures that the retrieved text is accurate, relevant, and contextually appropriate. This layer consists of two main components: a search component that retrieves relevant documents using semantic similarity techniques, and a re-rank component that ranks the retrieved documents based on relevance, popularity, and freshness. The search and re-rank layer is crucial for tasks like question answering, summarization, and machine translation, as it helps in retrieving and ranking relevant information efficiently. It plays a key role in enhancing the performance of AI tasks and is an integral part of the project's RAG models.

Embeddings are generated using OpenAI and stored in ChromaDB. Embeddings of search query is generated using the same model and top 3 most matching results are obtained based on its cosine similarity.

```
# Set up the embedding function using the OpenAI embedding model
model = "text-embedding-ada-002"
embedding function = OpenAIEmbeddingFunction(api key=openai.api key,
model name=model)
# Initialise a collection in chroma and pass the embedding function to it
so that it used OpenAI embeddings to embed the documents
insurance collection = client.get or create collection(name='RAG on Insur-
ance', embedding function=embedding function)
# Convert the page text and metadata from your dataframe to lists to be
able to pass it to chroma
documents list = insurance pdf data["Page Text"].tolist()
metadata list = insurance pdf data['Metadata'].tolist()
# Add the documents and metadata to the collection alongwith generic inte-
ger IDs. You can also feed the metadata information as IDs by combining
the policy name and page no.
insurance collection.add(
   documents = documents list,
    ids = [str(i) for i in range(0, len(documents list))],
   metadatas = metadata list
```

Caching mechanism is also implemented to optimize search performance. Search query embedding and search result metadata is stored in Vector DB (ChromaDB in this case) whenever any search is performed.

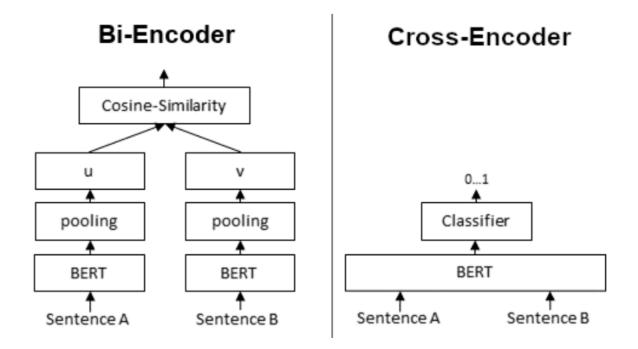
If new search query is found similar to already existing query in cache embeddings, depending on variance factor defined, then corresponding cached search results are used, rather than searching on whole document imbedding's.

```
# Implementing Cache in Semantic Search
# Set a threshold for cache search
threshold = 0.2
ids = []
documents = []
distances = []
metadatas = []
results df = pd.DataFrame()
# If the distance is greater than the threshold, then return the results
from the main collection.
if cache results['distances'][0] == [] or cache results['distances'][0][0]
> threshold:
      # Query the collection against the user query and return the top 10
results
      results = insurance collection.query(
      query_texts=query,
      n results=10
      )
      # Store the query in cache collection as document w.r.t to ChromaDB
so that it can be embedded and searched against later
      # Store retrieved text, ids, distances and metadatas in
cache collection as metadatas, so that they can be fetched easily if a
query indeed matches to a query in cache
      Keys = []
     Values = []
      for key, val in results.items():
        if val is None:
          continue
        for i in range(10):
          Keys.append(str(key)+str(i))
          Values.append(str(val[0][i]))
      cache collection.add(
          documents= [query],
          ids = [query], # Or if you want to assign integers as IDs
0,1,2,..., then you can use "len(cache_results['documents'])" as will
```

Re-ranking:

Re-ranking the results obtained from 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.

There are several cross-encoders available. We are using **cross-encoder/ms-marco-MiniLM-L-6-v2** from **sentence_transformers**



```
# Import the CrossEncoder library from sentence_transformers
from sentence_transformers import CrossEncoder, util

# Initialise the cross encoder model

cross_encoder = CrossEncoder('cross-encoder/ms-marco-MiniLM-L-6-v2')

# Input (query, response) pairs for each of the top 20 responses received from the semantic search to the cross encoder
# Generate the cross_encoder scores for these pairs

cross_inputs = [[query, response] for response in results_df['Documents']]
cross_rerank_scores = cross_encoder.predict(cross_inputs)

# Store the rerank_scores in results_df
results_df['Reranked_scores'] = cross_rerank_scores
```

Semantic Search Result Code:

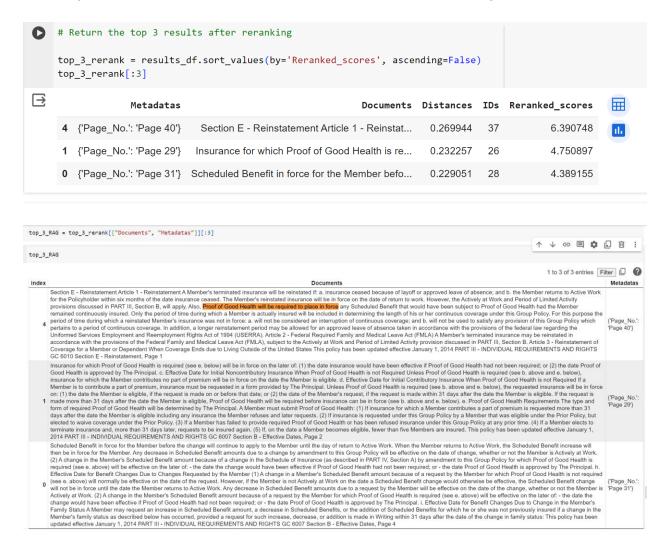
```
# Return the top 3 results after reranking

top_3_rerank = results_df.sort_values(by='Reranked_scores',
ascending=False)
top_3_rerank[:3]

top_3_RAG = top_3_rerank[["Documents", "Metadatas"]][:3]
```

Search Queries

1. Que: What are the requirements for placing in force any Scheduled benefit that would have been subject to Proof of Good Health has the member remained continuously insured?



Answer is clearly found in first result which is mentioned on page no 40 of the document.

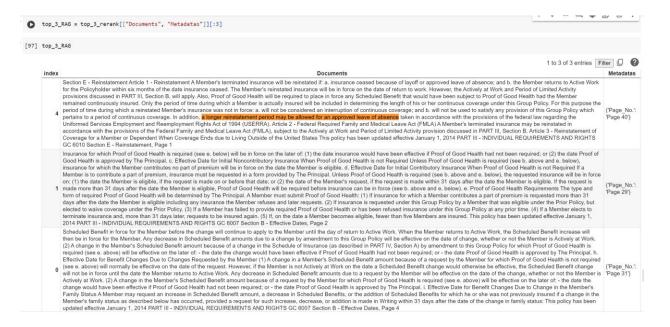
2. Que: How is the peroid of time during which a reinstated Member's insurance was not in force treated for the purpose of determining the length of continuous coverage under the Group Policy?



Answer is clearly found in first result which is mentioned on page no 40 of the document.

3. What provisions may allow for a longer reinstatement period for an approved leave of absence taken in accordance with the Uniformed Services Employment and Reemployment Rights Act of 1994 (USERRA)?





Answer is clearly found in first result which is mentioned on page no 40 of the document.

Generation Layer

This is the final stage of the RAG model, featuring a large language model trained on extensive text and code datasets. It enables the model to produce new text in response to user queries. This layer synthesizes retrieved information, shaping it into coherent and contextually relevant responses. Crucial for tasks like question answering, summarization, machine translation, and generative search, the generation layer excels in providing context and natural language capabilities for such searches.

Find below prompt used. This also mentioned **Few Shots Prompts** for better results.

```
# Define the function to generate the response. Provide a comprehensive
prompt that passes the user query and the top 3 results to the model
def generate response (query, results df):
    11 11 11
    Generate a response using GPT-3.5's ChatCompletion based on the user
query and retrieved information.
    ** ** **
    messages = [
                {"role": "system", "content": "You are a helpful assis-
tant in the insurance domain who can effectively answer user queries about
insurance policies and documents." },
                {"role": "user", "content": f"""You are a helpful assis-
tant in the insurance domain who can effectively answer user queries about
insurance policies and documents.
                                                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' in-
side this dataframe contains the actual text from the policy document and
the column 'metadata' contains 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.
                                                 Use the documents in
'{top 3 RAG}' to answer the query '{query}'. Frame an informative answer
and also, use the dataframe to return page numbers as citations.
                                                 Examples:
                                                 ####
                                                 User Message: Under what
four conditions may a member's insurance be continued if Active work ends
due to layoffs or approved leave of absence?
                                                Assistant: Based on the
provided documents, the four conditions under which a member's insurance
may be continued if Active work ends due to layoffs or approved leave of
```

for a specific period if the member is on an approved leave of absence.

1. Continuation coverage

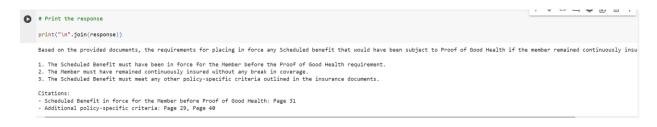
2. Continuation coverage

absence are:

for a specific period if the member is laid off.

Query Outputs:

Query 1: What are the requirements for placing in force any Scheduled benefit that would have been subject to Proof of Good Health has the member remained continuously insured?



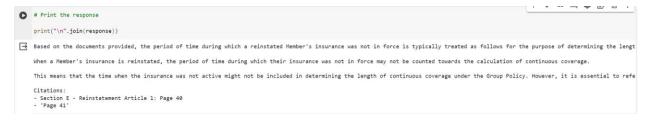
Based on the provided documents, the requirements for placing in force any Scheduled benefit that would have been subject to Proof of Good Health if the member remained continuously insured are as follows:

- 1. The Scheduled Benefit must have been in force for the Member before the Proof of Good Health requirement.
- 2. The Member must have remained continuously insured without any break in coverage.
- 3. The Scheduled Benefit must meet any other policy-specific criteria outlined in the insurance documents.

Citations:

- Scheduled Benefit in force for the Member before Proof of Good Health: Page 31
- Additional policy-specific criteria: Page 29, Page 40

Query 2: How is the period of time during which a reinstated Member's insurance was not in force treated for the purpose of determining the length of continuous coverage under the Group Policy?



Based on the documents provided, the period of time during which a reinstated Member's insurance was not in force is typically treated as follows for the purpose of determining the length of continuous coverage under the Group Policy:

When a Member's insurance is reinstated, the period of time during which their insurance was not in force may not be counted towards the calculation of continuous coverage.

This means that the time when the insurance was not active might not be included in determining the length of continuous coverage under the Group Policy. However, it is essential to refer to the specific details outlined in the insurance policy document to understand the exact treatment of this period.

Citations:

- Section E Reinstatement Article 1: Page 40
- 'Page 41'

Query 3: What provisions may allow for a longer reinstatement period for an approved leave of absence taken in accordance with the Uniformed Services Employment and Reemployment Rights Act of 1994 (USERRA)?



Based on the provided documents, the provisions that may allow for a longer reinstatement period for an approved leave of absence taken in accordance with the Uniformed Services Employment and Reemployment Rights Act of 1994 (USERRA) can be found in the Section E - Reinstatement. The detailed explanation regarding the reinstatement period extension, any specific conditions or criteria for eligibility, and the process for reinstatement after an approved leave of absence under USERRA would be specified in this section.

Citations:

- Section E - Reinstatement, Page 40