Retrieval-Augmented Generation (RAG) Model for QA Bot

Overview

This document outlines the implementation of a Retrieval-Augmented Generation (RAG) model designed for a Question Answering (QA) bot that retrieves information from a given dataset and generates coherent answers. The model leverages a vector database to store and retrieve document embeddings efficiently and utilizes a generative AI model to create responses based on the retrieved information.

Model Architecture

Components

1. **Data Loader**: Responsible for loading documents here we are using PDFs and extracting text for processing.

2. **Text Cleaner**: Cleans the extracted text to remove unnecessary characters and whitespace.

3. **Text Splitter**: Splits the cleaned text into manageable chunks suitable for processing and embedding.

4. **Embedding Generator**: Creates embeddings for the text chunks using a generative AI model.

5. **Vector Database**: A storage solution for document embeddings that enables efficient retrieval. In this implementation, we use Chroma as the vector store.

6. **Retrieval Mechanism**: Retrieves relevant document embeddings based on the user's query.

7. **Response Generator**: Utilizes the google generative AI model to produce coherent answers from the retrieved information.

Flow of Information

1. **Data Loading**: Load PDF files and extract text.

2. **Text Processing**: Clean and split the text into chunks.

3. **Embedding Creation**: Generate embeddings for each text chunk and store them in the vector database.

4. **Query Handling**: Receive user queries, retrieve relevant embeddings, and generate responses using the generative model.

5. **Output**: Display the generated response to the user.

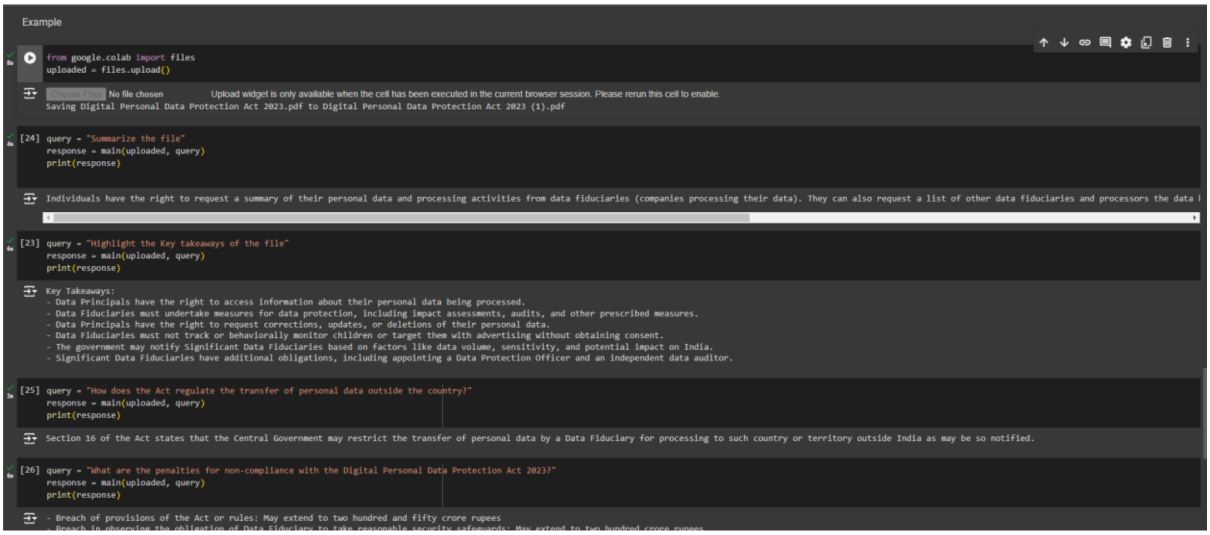
Implementation Steps

1. Data Loading and Preprocessing: In the Colab notebook, PDF files are uploaded, and the text is extracted using the `PyPDF2` library. The text is then cleaned to remove any unwanted characters.
2. Text Chunking: The cleaned text is split into chunks using the **RecursiveCharacterTextSplitter** class, which helps manage the length of the text segments for efficient processing.
3. Embedding Generation: Using **GoogleGenerativeAIEmbeddings** from the **langchain_google_genai** library, embeddings for the text chunks are created. The embeddings are stored in **Chroma**, a vector database designed for efficient similarity searches.
4. Query Handling and Response Generation:
   When a user submits a query:

- The relevant document chunks are retrieved based on the embeddings.
- The generative model processes the retrieved text to generate a coherent response.

Examples:

Below is the snippet of examples of queries and there response output



Conclusion

The implemented RAG model for the QA bot efficiently retrieves and generates answers from provided documents using a combination of text processing, embedding generation, and generative AI techniques. This solution can be adapted for various business use cases where quick and accurate information retrieval is required.