CSE 4/535 - Introduction to Information Retrieval - Fall 2024
Project 3

Team:

Sai Venkat Reddy Sheri (ssheri, 50545752)
Praneeth Posina (leelasat, 50540667)
Swetha Reddy Ganta (sganta3, 50539689)

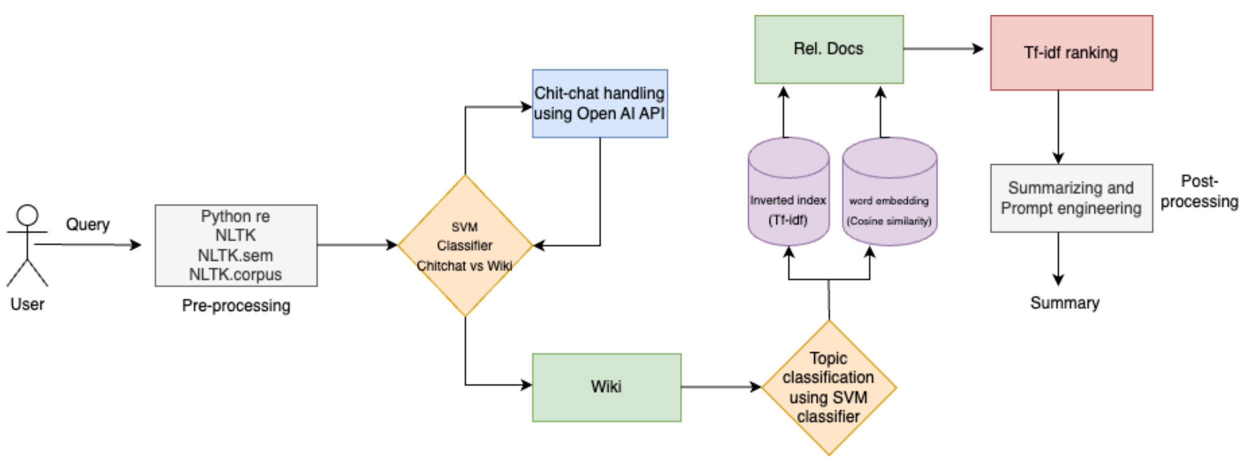
Introduction:

The project is about creating an end-to-end Information Retrieval chatbot that can intelligently answer user queries using information from Wikipedia scraped documents. It can handle diverse conversations across various topics like health, technology, travel etc. by integrating web scraping, indexing and query handling It can also perform general conversations or casual talks..

To build this chatbot, we developed a web scraper that gathers and indexes a dataset of more than 60,000 documents and classifies the topics to give accurate query responses. In addition, the chatbot includes strong exception handling to handle mistakes seamlessly and provide analytical insights through visualizations based on the conversations in the user interface.

Methodology:

This architecture outlines the process of building a chatbot capable of handling both general conversations (chit-chat) and answering questions using information from Wikipedia documents. Each step in the system plays an essential role in ensuring the chatbot works smoothly and accurately. Here's how it works:



1. Preprocessing

The preprocessing stage prepares user queries for classification and retrieval. The following methods were used:

Tokenization, Stemming, and Lemmatization using Natural Language Toolkit (NLTK): This involves breaking the text into smaller parts, reducing words to their base forms, and standardizing them for analysis.

Stop-word Removal: In this step, we filter out most common words like "the" and "is" that don’t add much meaning.

Python Regular Expressions (re): Further, we used the re model in Python to clean and normalize text by identifying specific patterns, such as removing special characters or formatting inconsistencies.

Semantic Analysis (NLTK.sem): This includes using advanced tools to analyze the meaning of the text and reference large language databases. It is useful for understanding relationships and context within the text.

Access to Linguistic Corpora (NLTK.corpus): The corpus module in NLTK provides access to a collection of precompiled text datasets, such as word lists, dictionaries, and linguistic corpora. These datasets are valuable for tasks like language modeling and text analysis.

This step ensures the query is clean and structured, laying the foundation for accurate classification and document retrieval.

2. Chit-chat vs. Wiki Classification

A **Support Vector Machine (SVM)** classifier, trained on labeled datasets, determines if the query is for chit-chat or informational (Wiki) purposes.

For instance, some queries were marked as chit-chat (like "How’s the weather today?") and others as Wiki-based (like "Tell me about balanced diet”- coms under health topic). By learning the patterns and differences in these queries, the SVM can classify new, unseen queries into one of these two categories.

Additionally, a dropdown menu is added through User Interface (UI) for selection between General Conversation (Chit-chat), Self-Operating Classifier (Classifier predicts the type of query whether chitchat or not), Multi Topic (Can answer muti topic queries), and all the topics . This allows us to manually select among multiple options provided.

3. Chit-chat Handling

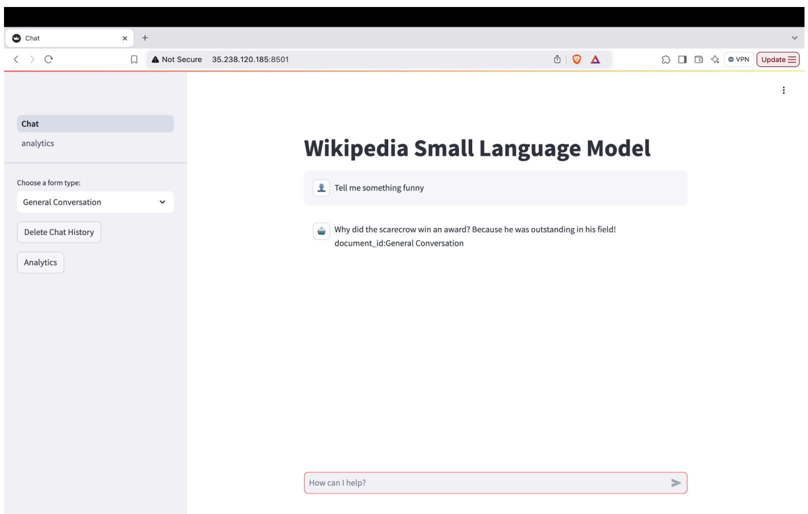
After the system processes the user’s query and determines it’s a chit-chat request through the SVM classifier, or by manual selection in UI it moves on to the **chit-chat handling module**.

The system's first major task after preprocessing the query is to figure out whether the user wants to have a general conversation (chit-chat) or is looking for factual information (Wiki-based query). To achieve this, a Support Vector Machine (SVM) classifier is used.

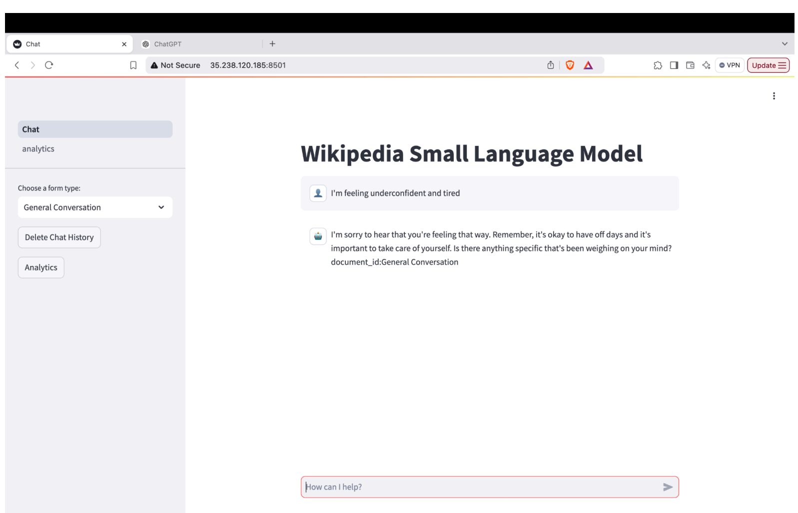
This module is designed to manage casual, open-ended conversations with the user, such as answering questions like, "How's your day?" or "What's your favorite book?"

To handle these types of conversations, the chatbot relies on the **OpenAI API**, which is well-known for its advanced language generation capabilities. The API enables the chatbot to provide responses that feel natural, friendly, and engaging, making smooth interactions.

For example, if the user says something like, "Tell me a joke," the chatbot uses the OpenAI API to generate a witty and humorous reply.



Similarly, it can respond thoughtfully to statements like, "I'm feeling tired today."



This approach's ability to generate dynamic and context-aware responses is one of its main advantages. The OpenAI API may produce a huge number of responses that seem customized for the discussion. But in rule-based systems that may rely on pre-written responses. This shows the chatbot is versatile and able to adapt to different styles of user interaction.

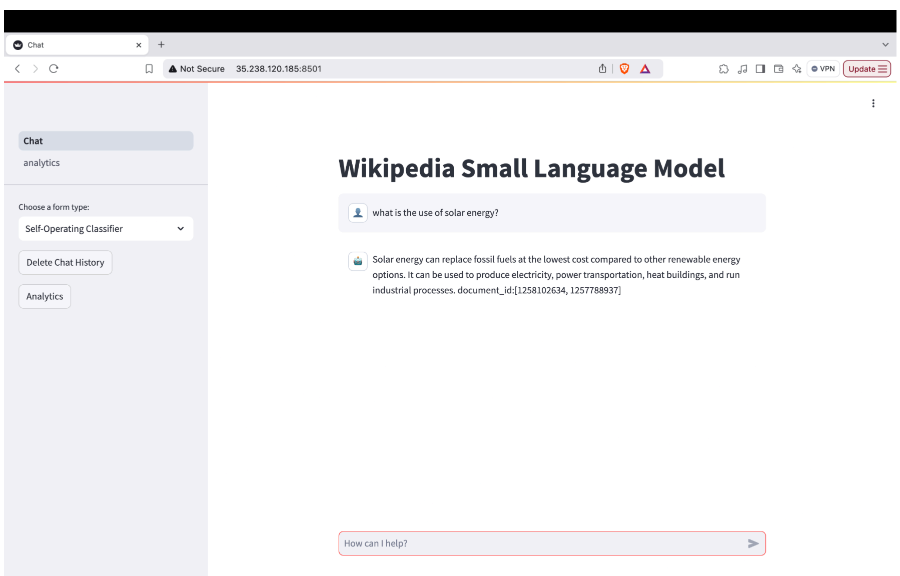
With this, the users who want to have a general and fun conversation with chatbot can have a seamless experience.

4. Topic Classification

If the system determines that a query is informational and related to Wikipedia content (through the chit-chat vs. Wiki classifier), it needs to further narrow down what the query is about. This is where **Topic Classification** comes in.

In this step, the system uses the same **Support Vector Machine (SVM) classifier** to identify the specific topic of the query.

For example, if a user asks, “What is the use of solar energy?”, the classifier would recognize this as related to the **Environment** topic.



The associated document IDs:


```
"revision_id": 1258102634,
"title": "Sustainable energy",
"summary": "Energy is sustainable if it  meets the needs of the present without compromising the ability of future gener
"url": "https://en.wikipedia.org/wiki/Sustainable_energy",
"topic": "World Health Organization"
```

```
"revision_id": 1257788937,
"title": "Climate change mitigation",
"summary": "Climate change mitigation  or decarbonisation  is action to limit the greenhouse gases in the atmosphere tha
"url": "https://en.wikipedia.org/wiki/Climate_change_mitigation",
"topic": "global inflation"
```


Similarly, a query like, “What are the symptoms of Migraine?” would be categorized under **Health**. But in our experiments, we got an accuracy of 80% while choosing the ‘self-operating classifier’. To get better results, choosing the topic directly helps.

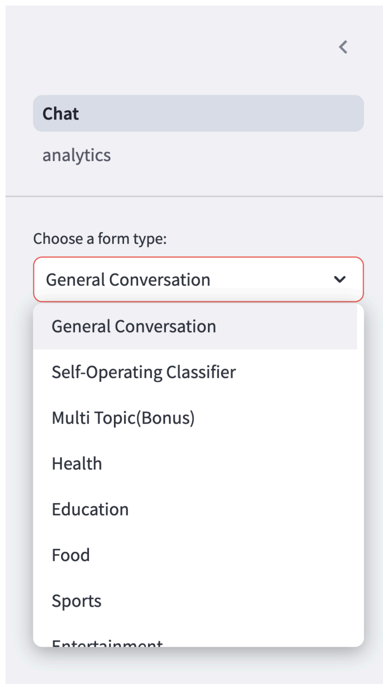


Fig: List of topics to choose from

This classification process is important because Wikipedia contains vast amounts of information on countless topics. By narrowing the query to a specific category, the system can focus on retrieving documents that are highly relevant to the user’s question. This saves time and ensures that the retrieved information is accurate and specific, rather than being too broad or unrelated.

The SVM classifier used here was trained on labeled datasets that include queries categorized by topics like **Health**, **Environment**, **Technology**, **Food etc**. During the training phase, the system learned the patterns in these queries — for instance, recognizing that terms like “medicine” or “disease” often relate to **Health**, while words like “software” or “AI” are more likely to belong to **Technology**.

By accurately identifying the topic, the system can streamline the next steps, such as document retrieval. Instead of searching through all available data, it searches only within the subset of documents that match the topic. This not only improves the speed of the process but also enhances the quality of the final answer provided to the user.

Ultimately, this step ensures that the chatbot delivers targeted, topic-specific responses, making the user experience more efficient and satisfying. Whether the query is about health advice, environmental issues, or technological advancements, the system is equipped to handle it with precision.

5. Document Retrieval with Inverted Index

We used two techniques—**TF-IDF** and **Cosine Similarity**—to find the most relevant documents based on their queries.

1. TF-IDF (Term Frequency-Inverse Document Frequency):

This technique is all about identifying the importance of words (terms) in a document relative to the entire collection of documents (corpus).

- **Term Frequency (TF):** It measures how often a term appears in a document. Words that occur frequently are assumed to be important within that document.
- **Inverse Document Frequency (IDF):** It reduces the weight of terms that are common across many documents, like "the" or "is," because such terms are less helpful in distinguishing one document from another. By combining TF and IDF, the system assigns a weight to each term, emphasizing words that are both frequent in a document and rare across the corpus. This helps the system rank documents by their relevance to the query.

2. Cosine Similarity:

Once the system has represented documents and the query as numerical vectors (using Sbert or sentence transformers library), it calculates **Cosine Similarity** to determine how closely the query matches each document:

- Cosine Similarity measures the angle between the query vector and document vectors. If the vectors point in the same direction (i.e., the angle is small), the similarity is high, meaning the document is more relevant.
- This method ensures that documents with terms closely aligned to the query are ranked higher, even if the query and document lengths differ.

3. The Role of the Inverted Index:

An **inverted index** acts as the backbone of the retrieval process. During preprocessing, the system creates this data structure, which maps each term in the corpus to a list of documents where the term appears. Think of it as a reverse lookup table for words:

- When a user submits a query, the system can instantly identify which documents contain the query terms by consulting the inverted index.
- This dramatically speeds up the retrieval process, as the system doesn't need to scan every document—it only focuses on those linked in the index.

6. Re-ranking Retrieved Documents

After the initial retrieval of documents using TF-IDF and Cosine Similarity, the system doesn't stop there. It takes the extra step of **re-ranking** the documents to refine their relevance scores. This involves recalculating and combining TF-IDF scores and Cosine Similarity measures for each document in relation to the user's query.

- **Why re-rank?** The first pass might bring in documents that are roughly relevant but not perfectly ordered by relevance. Re-ranking allows the system to fine-tune the priority of documents, ensuring the most pertinent ones are pushed to the top.
- **How it works:** Each document is assigned a new composite score based on its initial retrieval metrics. The system applies additional weighting or filters during this step to better align results with the query context or user preferences.

This ensures that the most meaningful documents are presented first, setting the stage for effective post-processing.

7. Post-processing

Once the most relevant documents are identified and ranked, the system shifts its focus to delivering a final response that's user-friendly and actionable. This stage involves two key tasks:

A. Document Summarization

The system uses **generative techniques** to condense large volumes of text into concise summaries. Instead of confusing the user with raw data, it highlights the essential points from the top-ranked documents.

Open AI API (GPT Model) extracts the main ideas and presents them in a coherent summary. This saves users time by cutting through the clutter and providing a digest of the key information.

B. Prompt Engineering for Precise Answers

In some cases, users need direct answers rather than summaries. For this, we introduced **prompt engineering** into the project which involves carefully designed prompts to extract specific, contextually accurate responses from the retrieved content.

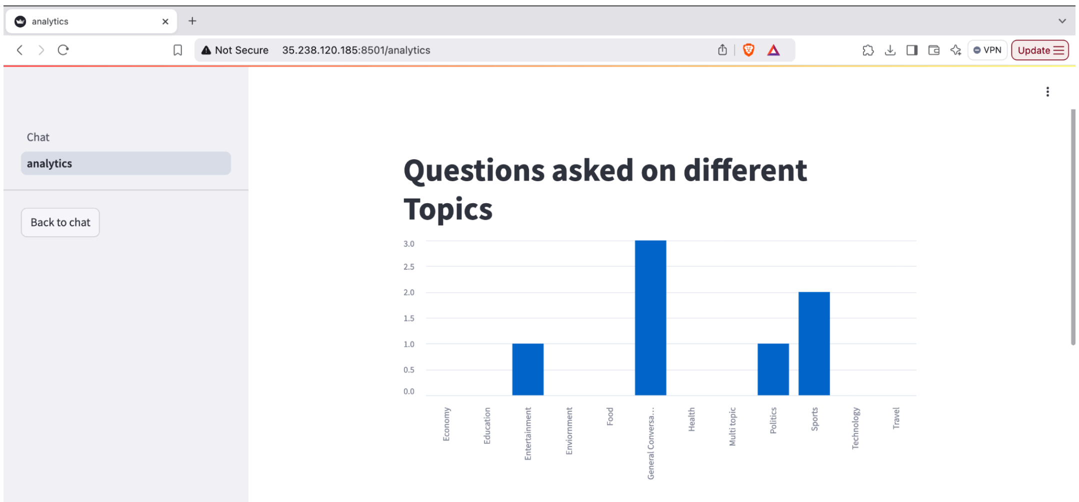
- For instance, if a user asks, "What is the capital of France?", the system bypasses general summaries and directly pinpoints "Paris" from the retrieved documents.

- This process ensures that answers are tailored to the user's query and presented in a way that's easy to understand.

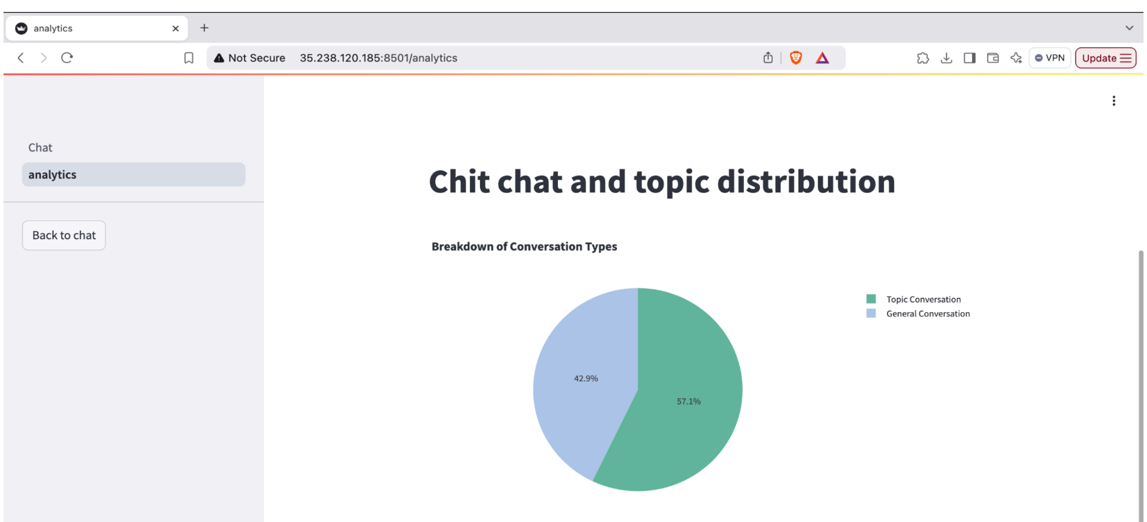
Analytics:

The following images depict the real-time analytics of the chatbot through three visualizations:

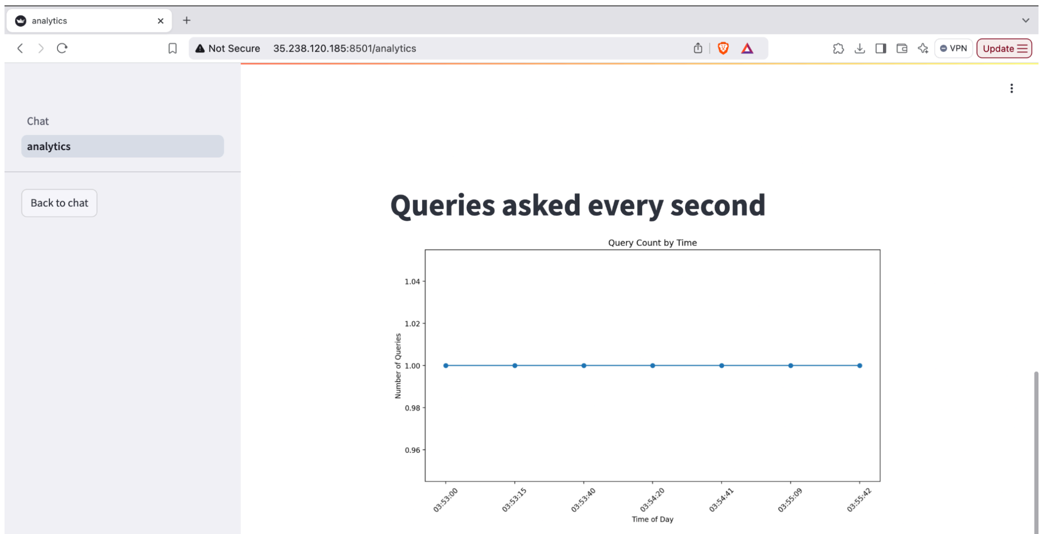
1. Questions asked on different Topics provide a graphical representation in the form of a bar graph about the number of queries made on each topic in the corpus.



2. Chit Chat and Topic distribution pie chart depicts General conversation vs Topic Conversations which represents queries made on each segment.



3. Queries asked every second show a line graph on the number of queries made per each second, with more traffic the values of queries increases which can be used to monitor the traffic.



Conclusion:

To simply put, the system tokenizes and pre-process the query, and searches it in the tf-idf index and gets 2-3 documents. If the given query doesn't have the tokens that directly matches with the documents then it goes to cosine similarity and finds the most similar documents using cosine similarity score and then gets the the document. If there are multiple documents which match the query in TF IDF, those multiple documents are fetched and they are ranked according to the TF IDF scores. The top two documents are taken and these documents are either from TF IDF inverted index or cosine similarity will be given to the summarizer and that summarizer will find out the exact answer only within the document and returns the answer.

Team contribution:

Sai Venkat Reddy Sheri	**Praneeth Posina**	**Swetha Reddy Ganta**
TF-IDF	Scraping - Indexing	SVM Classifier
Open AI Integration for Chitchat model	Vector Embeddings and Cosine Similarity	Document Summarization
User Interface	Analytics	Prompt Engineering
Documentation	Documentation	Documentation