Simplifying AI Research Papers
– A One-Stop-Shop for Accessing and Understanding AI-ML Literature

A DATS 6303 Natural Language Processing Project

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Abstract

AI Research papers are available in abundance in today's time, with cutting edge development happening almost every day. One of the most popular destinations to access these scholarly articles and research papers is the arXiv platform which is an open-source archive for research papers in various fields.

The problem arises when we want to access articles pertaining to specific topics or a combination of topics, it is difficult to find the right resource without having to resort to a google search. Additionally, not everyone is equipped with the time, effort, and/or capability to fully dive into the details of the technical aspects of the research paper they are referencing and find answers to the exact question in mind.

Starting with the arXiv dataset, the final deliverable also expanded the built utility to offer a more comprehensive learning experience.

Outline of Project Components and Contribution

In this work, I have utilized arXive dataset, particularly AI-ML research papers as a starting point to create an interactive Topic Modelling page. The purpose of this page is for the user to leverage the utility of BERTopic to view some of the important words/topics that occur the most within papers relevant to the input prompt. The next page I worked on adds PDF-Upload-Q&A functionality as one of the utilities that we offer. The purpose of this page is to enable learners to upload a PDF file of a research paper or any technical article that they want to understand or fetch relevant information from, after doing so, they can interact with a chatbot that answers any question about the document.

A comprehensive list of all work done by me is –

- An interactive topic modelling page using BERTopic including visualizations.
- A Document Upload Chatbot page for users to interact with their document in a question-answering chatbot format.

Description of Contribution

Topic Modeling

Methodology: This page employs the arXiv dataset as a primary data source for generating visualizations through the implementation of a custom topic modeling approach. The key innovation lies in the development of a bespoke topic modeler, functioning on user-provided prompts related to various AI topics. The backend process involves conducting a search within the arXiv dataset through the functionality within arxiv package, extracting and presenting the top 10-20 most recent research papers pertinent to the specified topic.

To enhance the quality of the retrieved information, a cleaning step is integrated into the methodology, leveraging the Natural Language Toolkit (NLTK) package. This cleaning process is specifically tailored to retain only relevant words, as their significance is paramount for subsequent analysis and visualization.

Then we set up the BERTopic model and cleaned text is passed into this model object to perform topic modeling. The details of BERTopic model are discussed below. The results from fitting the cleaned data are visualized through several visualizations, providing us with insight into important topics in the relevant research papers.

BERTopic Model

BERTopic is a topic modeling technique that leverages transformers and c-TF-IDF to create dense clusters allowing for easily interpretable topics whilst keeping important words in the topic descriptions. You load in your documents as a list of strings and simply pass it to the fit-transform method.

There are two outputs generated, topics and probabilities. A value in topics simply represents the topic it is assigned to. Probabilities on the other hand demonstrate the likelihood of a document falling into any of the possible topics. A basic explanation of under-the-hood operations in BERTopic is explained below:

1. The very first step we have to do is converting the documents to numerical data. BERTopic is using sentence-transformers to create embeddings for the documents that are passed. Not only that, but there are also many pre-trained models available ready to be used.
2. Documents with similar topics are then clustered together such that we can find the topics within these clusters. Before doing so, we first need to lower the dimensionality of the embeddings as many clustering algorithms handle high dimensionality poorly. For this purpose, UMAP is arguably the best performing as it keeps a significant portion of the high-dimensional local structure in lower dimensionality.
3. After having reduced the dimensionality of the document’s embeddings, we can cluster the documents with **HDBSCAN**. HDBSCAN is a density-based algorithm

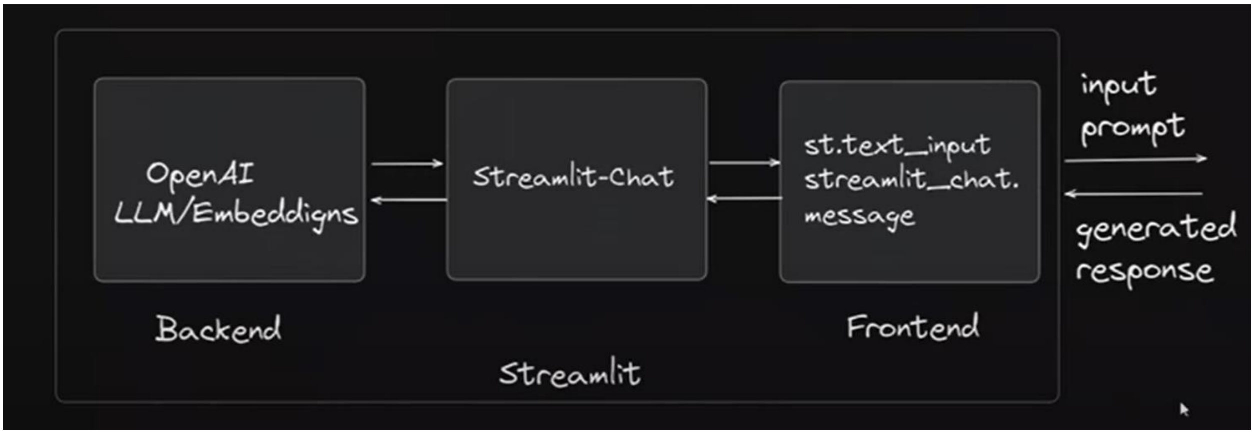
that works quite well with UMAP since UMAP maintains a lot of local structure even in lower-dimensional space. Moreover, HDBSCAN does not force data points to clusters as it considers them outliers.

4. The last step is utilizing a class-based variant of TF-IDF (c-TF-IDF), that would allow us to extract what makes each set of documents unique compared to the other. The intuition behind the method suggests that when you apply TF-IDF as usual on a set of documents, what happens is comparing the importance of words between documents. Instead, a single cluster is treated as a document. Now, we have a single **importance** value for each word in a cluster which can be used to create the topic. If we take the top 10 most important words in each cluster, then we would get a good representation of a cluster, and thereby a topic.

Document-Q&A

1. Conceptual Framework:
    - This part of the project exemplifies the paradigm of Retrieval-Augmented Generation.
    - The methodology integrates two core components: a retrieval system and a generative system.
2. Retrieval System:
    - The retrieval system is designed to extract relevant information from a specified database or document set.
    - LangChain, a language processing tool, facilitates the semantic search mechanism incorporated in its Vector Stores crucial for efficient information retrieval and embedding storage.
3. Generative System:
    - The generative system is responsible for producing human-like text based on the retrieved information.
    - LangChain API to connect with HuggingFace Models is leveraged to access Language Model (LLM), aiding in the generation of contextually relevant responses.
4. Langchain Integration:
    - LangChain plays a pivotal role in streamlining both retrieval and generation tasks.
    - The semantic search mechanism utilizes LangChain's vector store for efficient information retrieval.
    - The Language Model within HuggingFace Hub via API provided from LangChain is employed for generating coherent and contextually appropriate responses.

A Rough Sketch of the Workflow:



Workflow Implementation for Text-Based Question Answering System:

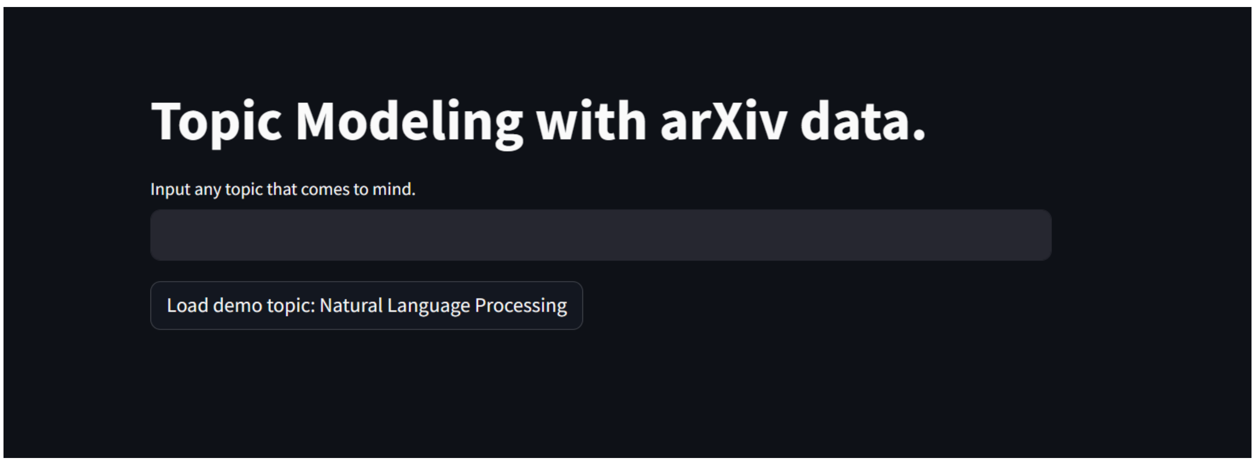
1. Document Ingestion:
   - Initiate the workflow by uploading a PDF file containing relevant information.
2. Text Extraction and Chunking:
   - Extract text from the PDF file.
   - Employ the recursive character text splitter feature within LangChain to divide the text into smaller chunks.
   - This step is crucial due to the limited context window of Language Models (LLMs) with attention mechanisms.
3. Embedding and Knowledge Base Creation:
   - Embed the segmented text chunks.
   - Utilize the Facebook AI Similarity Search (FAISS) library to create a vector store, serving as the knowledge base.
   - FAISS is chosen for its efficiency in similarity search and clustering of high-dimensional vectors.
4. User Interaction:
   - Users input questions related to the content within the PDF document.
5. Semantic Search:
   - Compute embeddings for the user's question.
   - Perform a semantic search within the vector store to retrieve relevant contexts associated with the input question.
6. Question-Answer Chain:
   - Employ the question-answer chain from LangChain.
   - Feed the retrieved context and the user's query into the Language Model (LLM) to generate a response. In this scenario, Google – Flan -T5 large is selected as the language model of choice owing to its fast and light performance in terms of computation.

Experimental Setup

Streamlit has been selected as the Web Application Python framework to create an interactive dashboard to showcase the Topic Modeling as well as the Document-Q&A pages. Streamlit is a free and open-source framework to rapidly build and share machine learning and data science web apps. It is a Python-based library specifically designed for machine learning engineers.

Results

Topic Modeling:
The page for the Topic Modeling looks like this –

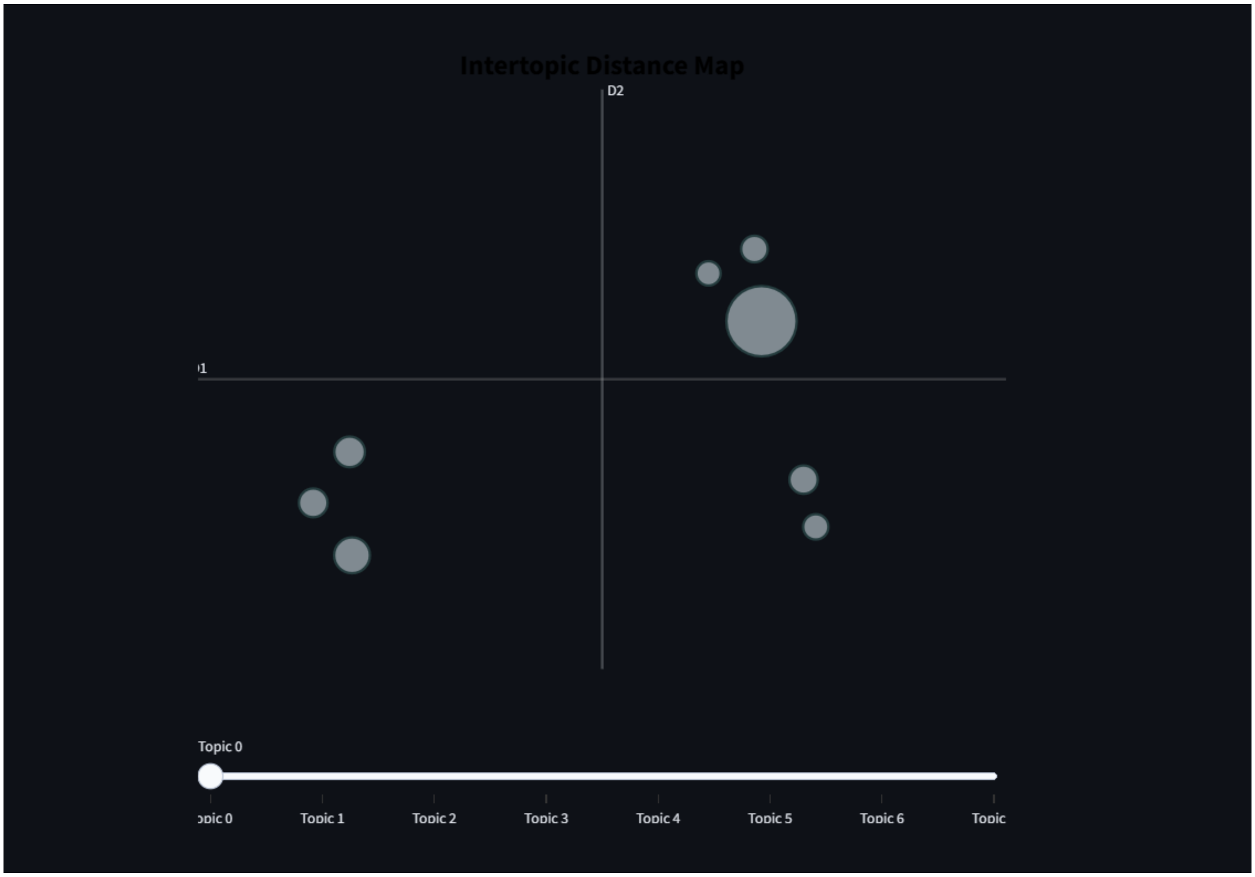


A sample prompt of Natural Language Processing is provided. This query is used to find relevant documents from arXive and the process is initiated. These are the visualizations provided as the output once the BERTopic is fit on the data.

	Topic	Count	Name	Representation
0	-1	1,063	-1_language_model_vector_neural	language model vector neural
1	0	655	0_function_network_neural_input	function network neural input
2	1	170	1_planning_natural_language_based	planning natural language bas
3	2	124	2_multilingual_languages_classification_text	multilingual languages classificat
4	3	109	3_language_translation_machine_understanding	language translation machine
5	4	106	4_word_words_vectors_vector	word words vectors vector
6	5	94	5_linguistics_computational_association_pp	linguistics computational associa
7	6	85	6_probability_sentence_conditional_given	probability sentence conditional
8	7	78	7_lexical_tokens_analysis_graph	lexical tokens analysis graph

This table provides a quick view of the top 10 topics identified by the models across arXive papers relevant to natural language processing.

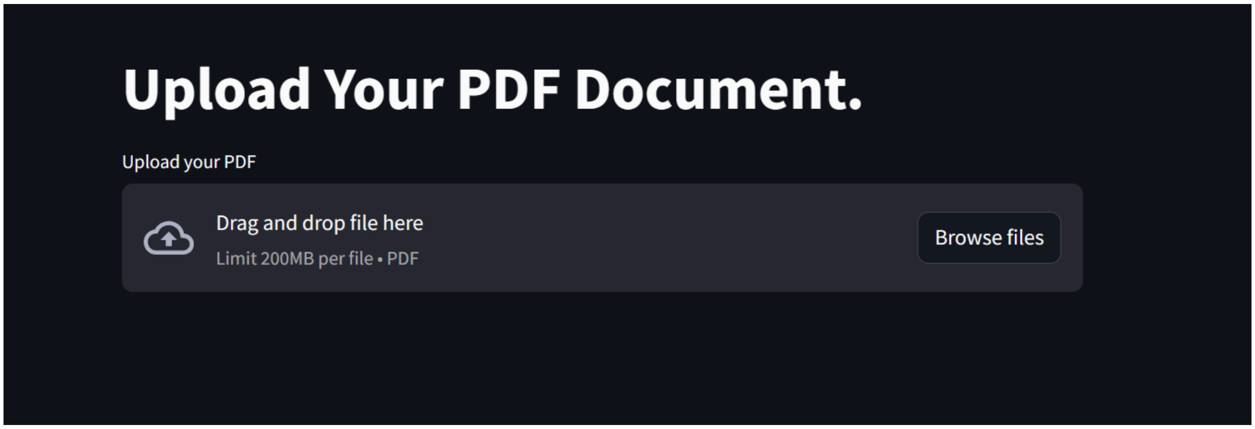
This is a visual representation of the same table above. The X-axis represents the c-TF-IDF score for each word that was unique to a particular topic. Each word in a topic describes the underlying theme of that topic and can be used for interpreting that topic. From a glance, the most frequent topics seem to have coherent and clear topic representations.

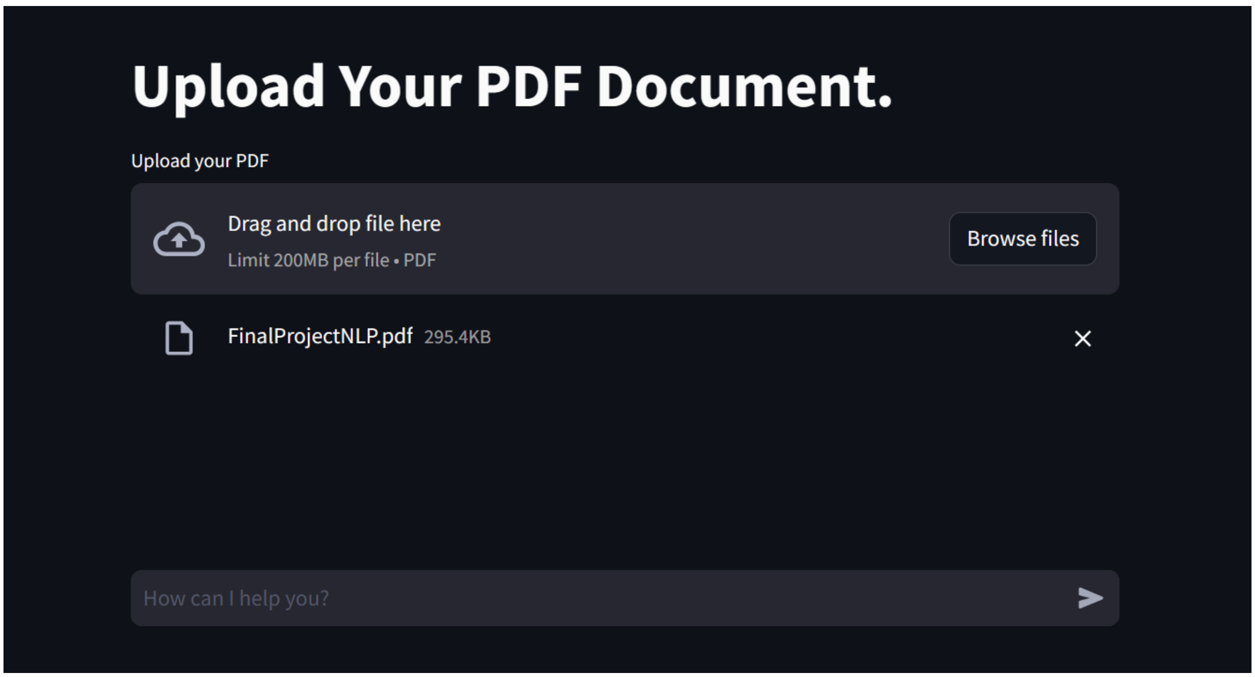


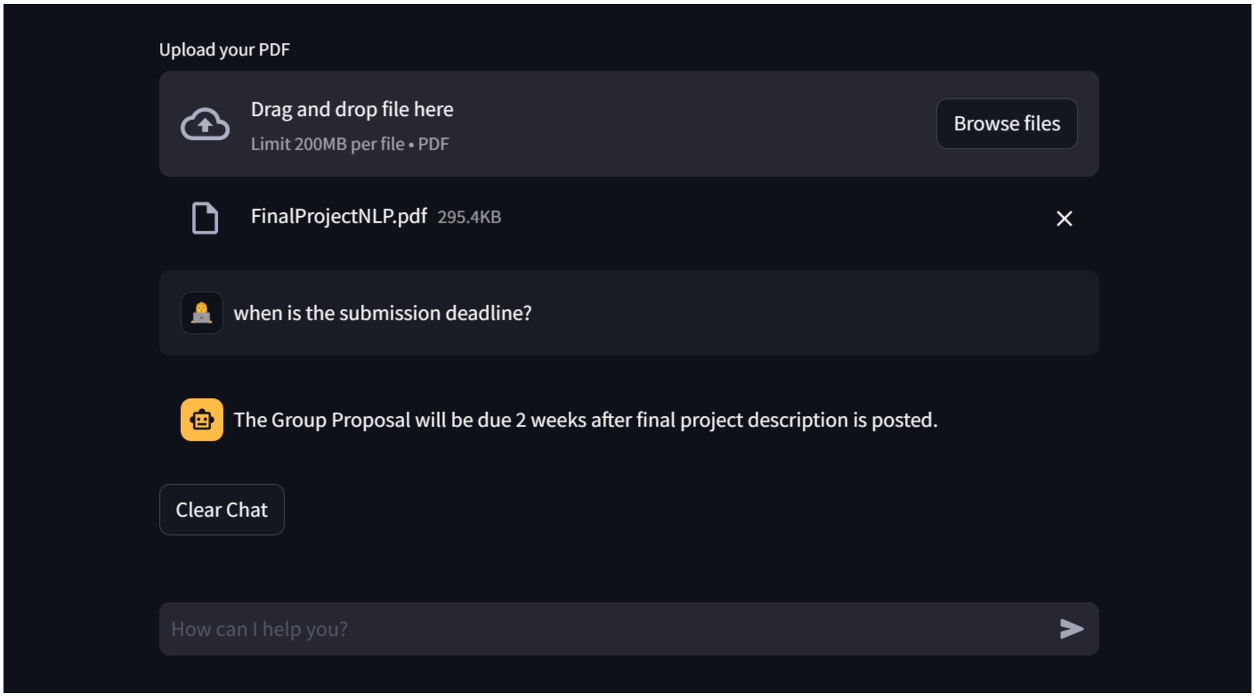
This plot gives us the inter-topic relationship between the identified key topics from the natural language related scientific papers. Embedded class-based TF-IDF representation of the topics in 2D using Umap is presented. Each circle indicates a topic, and its size is the frequency of the topic across all documents.

Document – Q&A:

The page for the Topic Modeling looks like this –







The document can be interacted with through the input option and a chatbot can be utilized to answer any questions about the document.

Conclusion

I have gained an in-depth understanding of Language Models and also explored new types of models like BERTopic which is designed for a specific task such as topic modeling. In addition to that, I got exposed to LangChain, Llama-index (although I didn't end up employing this, I learnt about it during my testing phase), HuggingFace, cutting-edge LLMs like Llama 2 which has given a lot of exposure to industry-level solutions and creating applications that seemed to be a complete mystery at the start of this course.

References

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- https://github.com/Unstructured-IO/unstructured/tree/main
- https://stackoverflow.com/questions/76990736/differences-between-langchain-llamaindex#:~:text=Langchain%20is%20also%20more%20flexible,LLMs%20and%20retrieving%20relevant%20documents.
- https://www.kaggle.com/code/bygbrains/dog-cat-pandas-image-classifier

Code Originality Index:

- For the Document-Upload-Q&A-Streamlit-V2.py → The calculation is as follows: (68 – 45) / (68 + 10) * 100 = 29.48%
- For arXiv-TopicModelling-Streamlit.py → The calculation is as follows: (100 – 30) / (100 + 20) * 100 = 58.33%