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

A DATS 6303 Natural Language Processing Project report by Team – 2

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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

In this work, we 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 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. The next page utilizes a similar arXive retrieval mechanism to work with textual data input provided by a user about a topic of their interest that they wish to learn more about. An input is again taken from the user to address their question and an answer is provided by utilizing LangChain and Deeplake vector database. The last page of the work completes all the functionalities and enables user to paste a link to any Medium/TowardsDataScience etc. article and we have utilized a web scraping mechanism to retrieve the text and provide the user with a summary for quick understanding of these long articles.

A comprehensive list of all work done 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.
- The next page utilizes the question answering feature with a different approach, by prompting both the topic and question from the user.
- The last page enables user to build a summary of Medium articles by just pasting the link in an input field.

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.

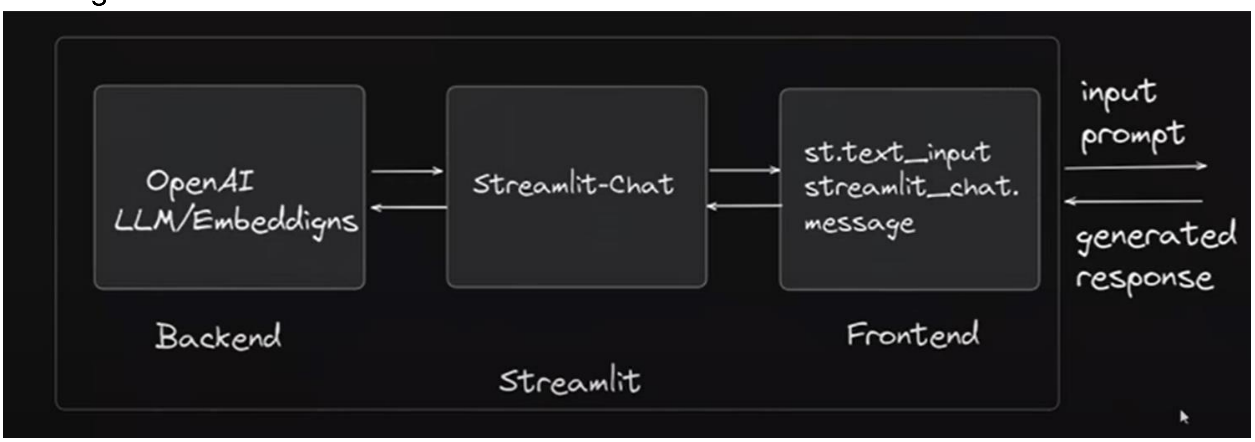
Document-Q&A

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 all the work that is done in this work in the form of multiple 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.

MediumBlink: The Rapid Insight & Web Weaver

Why Longformer?

The Longformer, a breakthrough in natural language processing, emerges as a superior tool for text summarization, specifically designed to overcome the limitations faced by earlier transformer models like BERT and GPT in handling extended documents. This proficiency can be attributed to several key aspects of its design and functionality, which are intrinsically linked to the challenges of processing long text sequences.

Longformer was primarily developed to handle longer sequences, a critical requirement for summarizing complex documents like academic papers, legal documents, or extensive articles. Traditional transformer models are limited to processing about 512 tokens, a constraint stemming from the memory-intensive nature of their self-attention mechanisms.
Longformer extends this limit substantially, allowing the processing of documents with

thousands of tokens. This extended processing capacity is crucial for summarization, as it enables the model to comprehend the full breadth of a lengthy document, ensuring that key themes and details spread across the text are accurately captured in the summary.

Another significant advancement in Longformer is its efficiency in the attention mechanism. Standard transformers exhibit a quadratic increase in computational complexity with longer sequences, making them inefficient for lengthy texts. In contrast, Longformer introduces an attention mechanism that scales linearly with the length of the sequence. This efficiency is paramount for summarization tasks, as it allows for quick and resource-effective processing of large volumes of text.

Longformer's enhanced performance on specific tasks like document summarization is also noteworthy. Its ability to process and understand extended context makes it particularly well-suited for summarizing long documents, where understanding the entire narrative and its nuances is essential for generating coherent and comprehensive summaries.

Moreover, the model's resource optimization feature is a critical factor in its practical application. By efficiently processing longer texts, Longformer optimizes the use of computational power and memory, making it a viable option for large-scale deployments and real-world applications.

In summary, Longformer's design, characterized by its capability to handle extended text sequences, its efficient attention mechanism, and its optimized resource usage, makes it exceptionally well-suited for summarization tasks. Its ability to process long documents in their entirety, balancing detail and overview, ensures that summaries are not only accurate and comprehensive but also coherent, encapsulating the essential elements of the original text.

Transfer Learning with Longformer:

In this project report, my focus was to apply transfer learning in natural language processing (NLP) by using a fine-tuned Longformer model from Hugging Face. The concept of transfer learning revolves around utilizing a model trained on one type of data or task and adapting it to another. This approach is particularly advantageous in NLP, where large-scale language models require extensive computational resources and time for training.

My project capitalized on a Longformer model already fine-tuned for machine learning article summarization. The original Longformer model, developed by the Allen Institute for AI, excels in handling long text sequences, a common limitation in traditional models like BERT and GPT-2. Its architecture, featuring a sliding window attention mechanism, allows for efficient processing of long documents. However, while the base Longformer is proficient in general language tasks, its application to domain-specific tasks like summarizing machine learning articles necessitates further specialization.

I leveraged the pre-fine-tuned model, which had undergone an initial round of training specific to machine learning content. This model had been adjusted to align with the unique structure, terminology, and style typical of machine learning literature, making it a more suitable starting point for my project. The fine-tuning process involved re-training the model on a curated subset of the arXiv dataset, focusing on papers closely related to machine learning. This dataset was selected using advanced techniques like sentence embeddings and K-means clustering, ensuring that the training material was highly relevant to the task at hand.

The advantage of using this pre-fine-tuned model lies in its prior exposure to relevant content, allowing for a more efficient adaptation to the specific nuances of machine learning articles. This is a key aspect of transfer learning – leveraging existing knowledge and adapting it to similar, yet distinct tasks. By doing so, I avoided the extensive computational resources and time typically required for training large models from scratch.

Link to HuggingFace Model: https://huggingface.co/bakhitovd/led-base-7168-ml

Link to HuggingFace Dataset: https://huggingface.co/datasets/bakhitovd/ML_arxiv

LINK EXTRACTION:

```python
def get_all_links(content):
    soup = BeautifulSoup(content, 'html.parser')
    links = set()
    for a in soup.find_all('a', href=True):
        href = a['href']
        # Filter to include only clean-looking links
        if href.startswith('http') and '?' not in href and not href.endswith('/'):
            links.add(href)
    return links
```

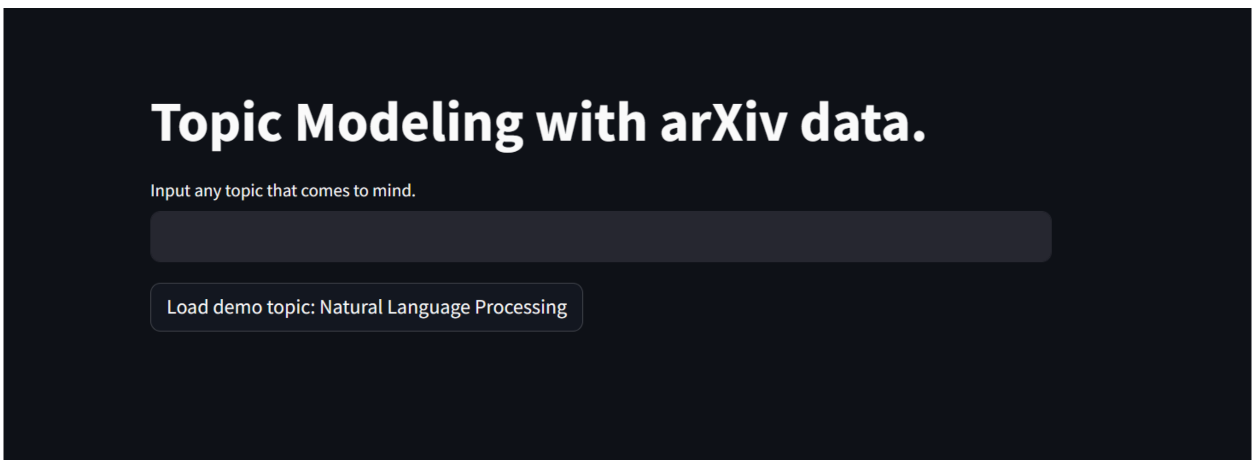
The `get_all_links` function in Python is designed to extract all unique, clean-looking hyperlinks from a given HTML content. Here's a step-by-step explanation:

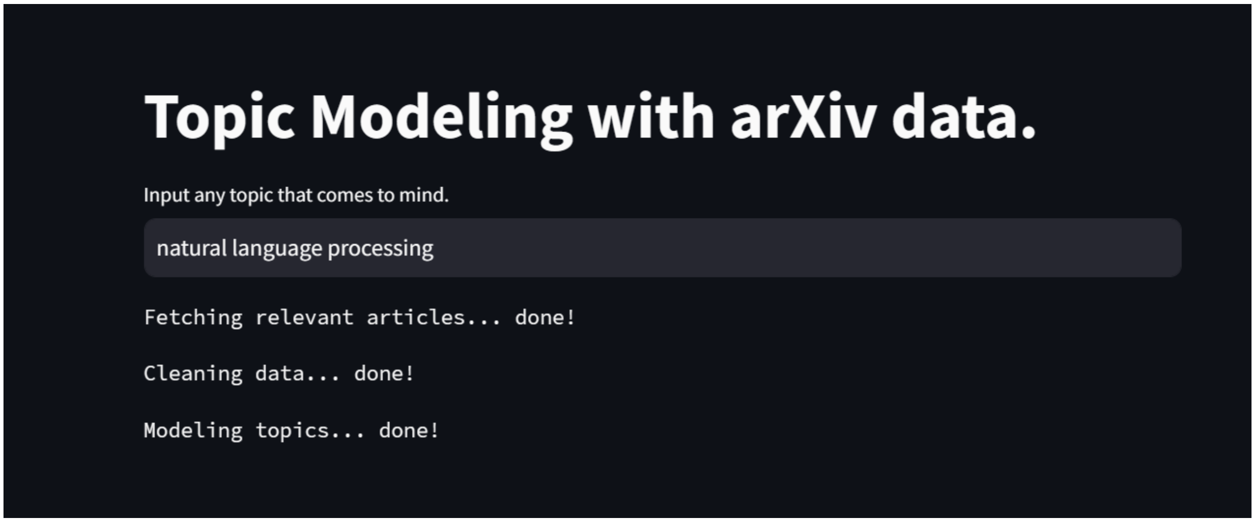
5. Parse HTML Content: It uses BeautifulSoup, a popular Python library for web scraping, to parse the provided HTML content. `soup = BeautifulSoup(content, 'html.parser')` initializes a BeautifulSoup object with the given content.
6. Initialize an Empty Set: `links = set()` initializes an empty set to store the unique links.
7. Find All Hyperlinks: The function iterates over all anchor (`<a>`) tags with an `href` attribute, which are hyperlinks in HTML. `for a in soup.find_all('a', href=True)` loops through each hyperlink found in the HTML content.

8. Extract and Filter Links: Within the loop, `href = a['href']` extracts the hyperlink reference. The function then applies a filter to include only 'clean-looking' links: those that start with 'http' (to ensure they are complete URLs), do not contain a '?' (often indicating a dynamic URL with parameters), and do not end with a '/' (often a sign of a directory, not a specific page).
9. Add Unique Links to the Set: If a hyperlink meets the criteria, it's added to the set using `links.add(href)`. Using a set ensures that each link is unique (duplicates are automatically removed).
10. Return the Set of Links: Finally, the function returns the set of unique, filtered links.

Results

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



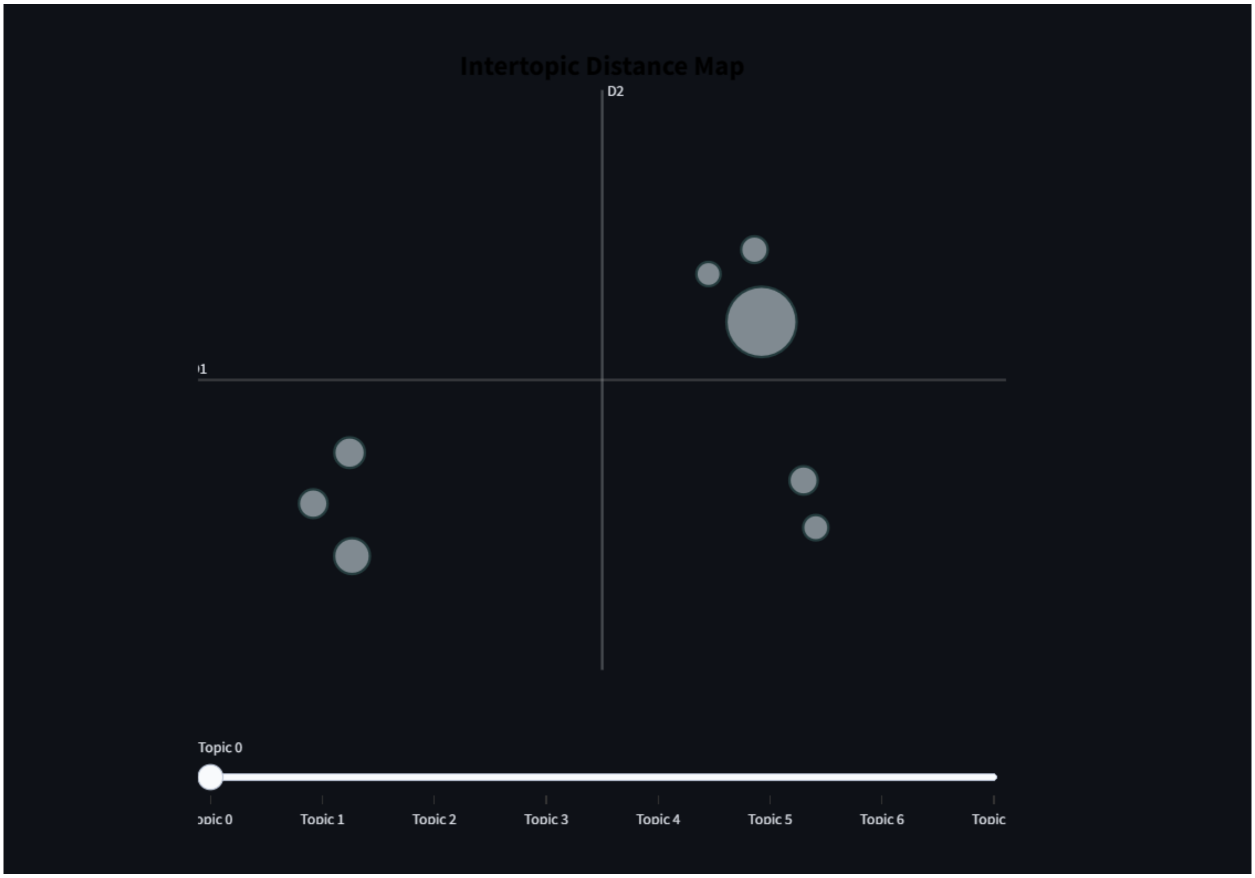


A sample prompt of Natural Language Processing is provided. This query is used to find relevant documents from arXive and the process is initiated. These are the visualizations provided as the output once the BERTopic is fit on the data.

	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.

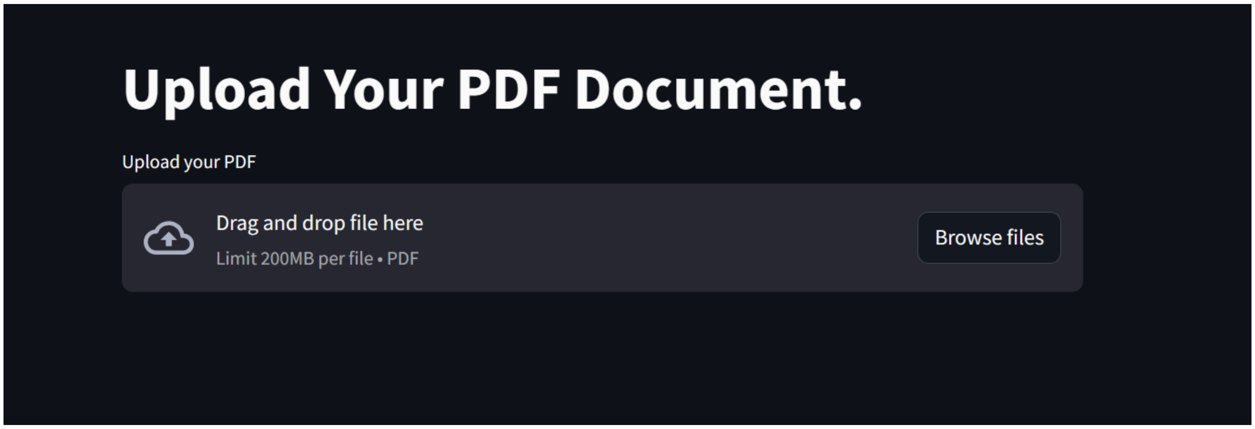
This is a visual representation of the same table above. The X-axis represents the c-TF-IDF score for each word that was unique to a particular topic. Each word in a topic describes the underlying theme of that topic and can be used for interpreting that topic. From a glance, the most frequent topics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

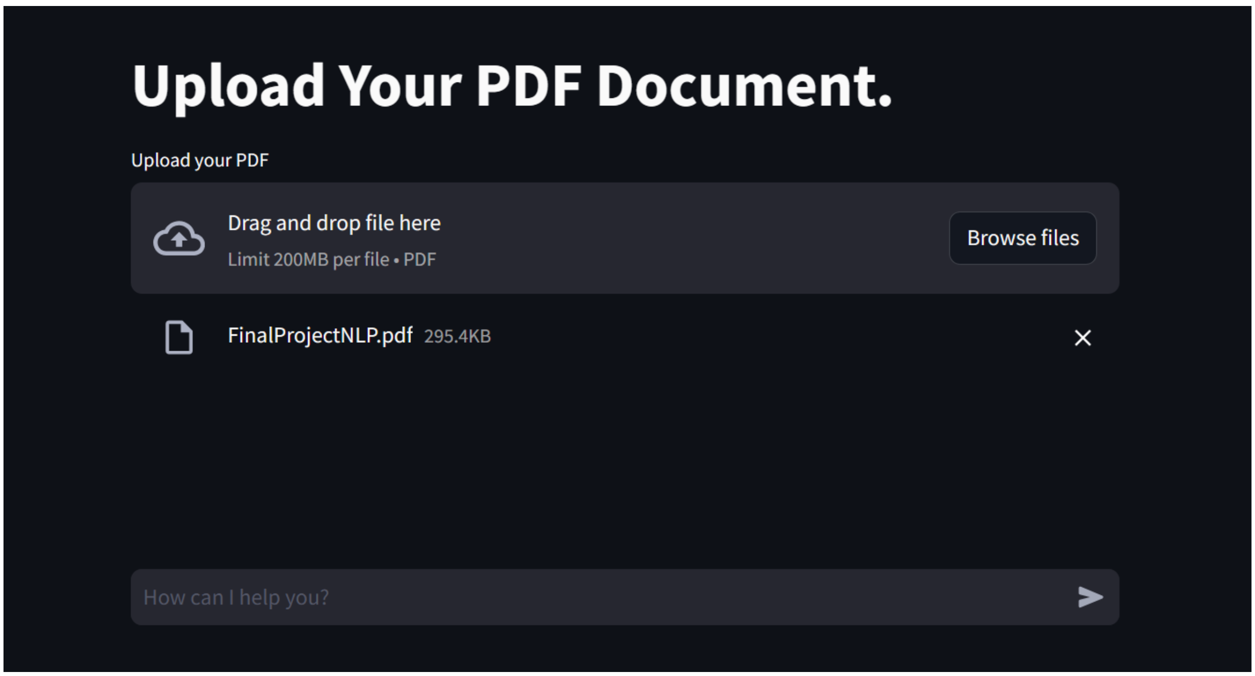


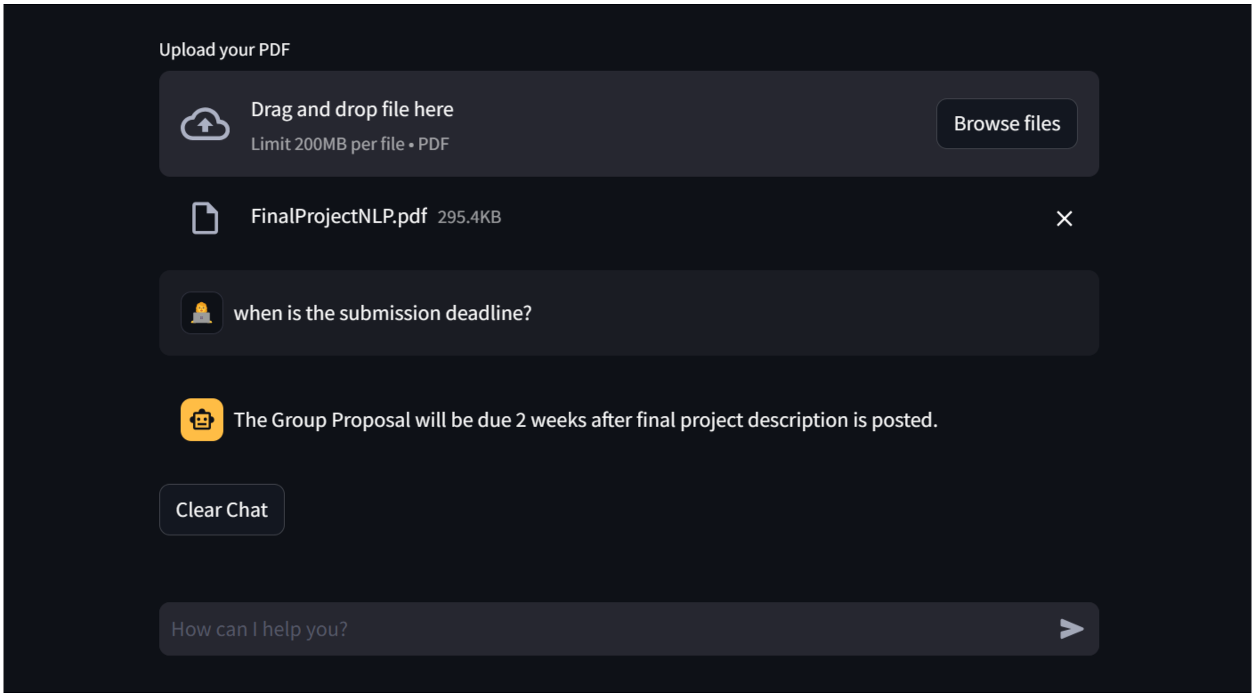
This plot gives us the inter-topic relationship between the identified key topics from the natural language related scientific papers. Embedded class-based TF-IDF representation of the topics in 2D using Umap is presented. Each circle indicates a topic, and its size is the frequency of the topic across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

Document – Q&A:

The page for the Topic Modeling looks like this –

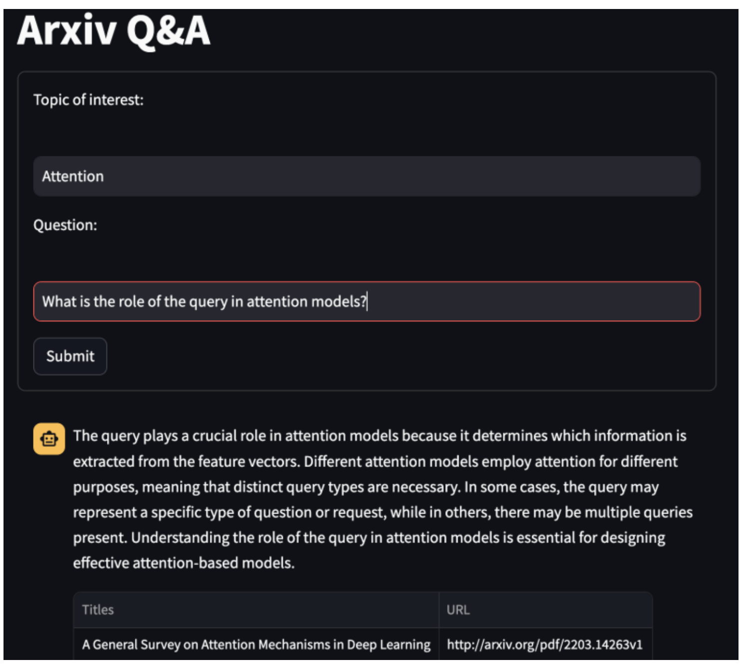

Upload Your PDF Document.
Upload your PDF
Drag and drop file here
Limit 200MB per file • PDF
Browse files


Upload Your PDF Document.
Upload your PDF
Drag and drop file here
Limit 200MB per file • PDF
Browse files
FinalProjectNLP.pdf 295.4KB
How can I help you?



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

Arxiv Q&A



<u>EXAMPLE: TYPE 1: MEDIUM ARTICLES ON MACHINE LEARNING AND RELATED TOPICS</u>

LINK :
https://medium.com/@bakhitovd/fine-tuning-a-longformer-model-for-summarization-of-machine-learning-articles-fa6a9b31182a

SUMMARY:

In this report, a machine learning strategy was built on a decision tree algorithm and a reinforcement learning algorithm. The models were limited to holding a maximum of 1000 shares either short or long. The strategies are stock symbol agnostic, and data has been provided in my github repository to be able to play around with additional symbols and parameters. The purpose of this report and further analysis is to decide upon which indicators to use to inform the decision of whether to enter a long or short position. Bollinger bands percentage, relative strength index, and an exponential moving average cross were chosen as the three technical indicators that all three strategies used. Secondly, the models have been limited to hold a maximum number of 1000 stocks either short (or long). Thirdly, the algorithms are stock symbols agnostic and data is provided on my github to allow the models to be played around with more symbols and parameter values. For the purpose, this report shows the results of four different strategies when used on the training data (data the models are seen and trained on). The first strategy was to build a model that increases portfolio value over time. Again, the model was constrained to holding only 1000 shares or until the model converges (whichever comes first). Second, the strategy was limited to only historical stock price data and any indicators secondarily created are based off historical stock prices (**adjusted close price). Third, the strategies were limited only to holding 1000 shares. Fourth, they were limited not only to short (buying 1000 shares) but also long (entering a long position). Fifth, the first machine learning algorithm was reinforcement learning (reinforcement learning).

LINKS PROVIDED:

https://github.com/Bakhitovd/led-base-7168-ml
https://huggingface.co/datasets/bakhitovd/ML_arxiv
https://huggingface.co/bakhitovd/led-base-7168-ml

LINK:

https://medium.com/@wesleywarbington_22315/ai-stock-trading-d71955621834

SUMMARY:

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LINKS PROVIDED:

https://github.com/wesleywarbington/tradingStrategies

EXAMPLE: TYPE 2: MEDIUM ARTICLES ON GENERAL TOPICS

LINK:

https://medium.com/from-the-red-line/was-the-circle-line-built-on-the-cheap-937e7a6df1a2

SUMMARY:

The circle line was built in the late 1990s to provide the circle line with 73 trains. Since then, the line has been underutilized, and significant investments have been made to keep costs down. But some of them may not have been optimal, especially considering their more polished equivalents along the dtl. This isn’t the first time that the downtown line has been written about, but it is a continuous series of errors and structural failures that got us to this point, so the finger can firmly be pointed at a single politician, civil servant, or group of engineers.

LINKS PROVIDED:

https://t.me/ftrlsg
https://en.wikipedia.org/wiki/No_U-turn_syndrome
https://en.wikipedia.org/wiki/Outer_Ring_Road_System
https://www.todayonline.com/singapore/faulty-circle-line-cables-be-replaced-january
https://eresources.nlb.gov.sg/history/events/5c6485bb-c357-48be-9d12-bf7c1d422d0e
https://eresources.nlb.gov.sg/newspapers/digitised/article/straitstimes20070915-2.2.7.4
https://eresources.nlb.gov.sg/newspapers/digitised/article/straitstimes20090818-1.2.10.1
https://eresources.nlb.gov.sg/newspapers/digitised/article/today20010407-1.2.16.2
https://en.wikipedia.org/wiki/Sim_Wong_Hoo
https://eresources.nlb.gov.sg/newspapers/digitised/article/today20120405-1.2.66.4

EXAMPLE: OTHER SITES ARTICLES ON MACHINE LEARNING AND RELATED TOPICS

LINK:

https://bair.berkeley.edu/blog/2023/11/14/ghostbuster/

SUMMARY:

ai-generated text detection systems often do poorly on data that differs from what they were trained on. In addition, if these models falsely classify real human writing as ai- generated, they can jeopardize students whose genuine work is called into question. We introduce ghostbuster, a state-of-the-art method for detecting ai-based text. Ghostbuster works by finding the probability of generating each token in a document under several weaker language models, then combining functions based on these probabilities as input to a final classifier. We evaluated across a range of ways that text could be generated, including different domains (using newly collected datasets of essays, news, and stories), language models (e.g., different varieties of english), or prompts (e,g., human-edited model generations). We found that a roberta baseline had catastrophic worst-case generalization performance, sometimes even worse than a perplexity-only baseline. We hope that ghostbuster can help with a variety of lower-risk applications, including filtering ai-__generated text out of language model training data and flagging online sources of information..

LINKS PROVIDED:

https://arxiv.org/abs/2304.02819
https://medium.com/nlplanet/two-minutes-nlp-perplexity-explained-with-simple-probabilities-6cdc46884584
https://github.com/vivek3141/ghostbuster
https://arxiv.org/abs/2305.15047
https://ghostbuster.app/experiment
http://bair.berkeley.edu
https://arxiv.org/abs/1906.03351
https://arxiv.org/abs/2210.09421
https://arxiv.org/abs/2301.11305
https://www.nytimes.com/interactive/2023/02/17/business/ai-text-detection.html
http://claude.ai

EXAMPLE: OTHER SITES ARTICLES ON GENERAL TOPICS

LINK:

https://www.spendlifetraveling.com/reasons-to-travel/

SUMMARY:

Why travel? Well, that’s what I want to share with you here because there are so many reasons to travel. For as long as my memory, my life has been an ordinary, passive, linear trajectory through life. Since childhood, I have yearned for crazy escapades, dreamed about fantastic experiences, and bemoaned the so- called 'ordinary’ route. Travel is stimulating, exciting, and engaging. You can’t help but feel liberated and inspired to make more of life. You see that you are fallible and life is cruel and that material wealth means very little in the grand scheme of things. You feel blessed and blown away by the generosity of strangers in a foreign land. You might experience true poverty in india. You might have all your worldly possessions stolen in colombia. And you might see the most mind-blowing natural beauty in nepal. But ultimately, though, you come through the other side and are all the better for it. Travel (and the adventures you have along the way) makes everything better..

LINKS PROVIDED:

https://www.whatsdannydoing.com/blog/best-backpacking-flashlight
https://www.spendlifetraveling.com/reasons-to-travel/#comment-140168
https://pinterest.com/sltraveling
https://www.spendlifetraveling.com
https://www.twitter.com/sltraveling
https://www.instagram.com/spendlifetraveling
https://www.facebook.com/spendlifetraveling

Conclusion

We 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, we 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

- https://github.com/MaartenGr/BERTopic
- https://towardsdatascience.com/interactive-topic-modeling-with-bertopic-1ea55e7d73d8
- https://towardsdatascience.com/topic-modeling-with-bert-779f7db187e6
- https://github.com/sejaldua/digesting-the-digest/tree/main
- https://towardsdatascience.com/dynamic-topic-modeling-with-bertopic-e5857e29f872
- https://github.com/amir-jafari/Data-Visualization/blob/master/Streamlit/combined_code/NLP/nlp_chatbot/utils_gen_ai.py
- https://www.kaggle.com/code/maartengr/topic-modeling-arxiv-abstract-with-bertopic/notebook
- https://python.langchain.com/docs/modules/data_connection/vectorstores/

- https://colab.research.google.com/drive/1Uq5d1vBc4CoXqPKzAWazGXU_SphnnQW0?usp=sharing#scrollTo=NAkSeS76O9tq
- https://api.python.langchain.com/en/latest/llms/langchain.llms.huggingface_pipeline.HuggingFacePipeline.html
- https://huggingface.co/models
- https://dineth9d.medium.com/chatbot-93a04bf31f50
- 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
- https://www.youtube.com/watch?v=9SBUStfCtmk
- https://www.youtube.com/watch?app=desktop&v=9ISVjh8mdlA