University *of Ljubljana*
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Project 1: Conversational Agent with Retrieval-Augmented Generation

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Abstract

In this paper, we present a conversational agent that leverages Retrieval-Augmented Generation (RAG) and web scraping techniques to provide accurate, up-to-date responses focused on academic research. Our system combines multiple academic paper sources, with dynamic web scraping capabilities to create a comprehensive knowledge base. The agent uses vector similarity search and can handle both general queries and website-specific information retrieval. We demonstrate how this approach addresses common limitations of traditional language models, such as outdated information and hallucinations, while providing targeted academic research assistance.

Keywords

Natural Language Processing, Retrieval-Augmented Generation, Web Scraping, Large Language Models

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Introduction

It is widely known that the usefulness of the many Large Language Models are often offset by the colloquial hallucinations regularly found in the answers to specific questions. Looking to better put the focus on the information retrieval in answers of the AI agents, many of the models in use today make use of the Retrieval-Augmented Generation (RAG) technology.

The motivation for writing this paper and the research on the possibilities of integrating RAG technology and web scraping in models, comes from the academic experiences and use of Large Language Models and similar AI technologies in such an environment.

Our research and view is of that, that many such existing agents are too broad in area of search and simply lack the proper guiding, algorithms and fine-tuning that is needed for them to be used as a help in research in any of the academic spaces.

Many of the AI agents in use today do utilize web scraping and use the relevant information scraped from the web to fuel and better inform the answers that are being processed by them. The function of the RAG technology is a far better researched topic and is in active use today in many effective and vastly popular agents; however, our aim is to analize a way for an agent to be far more relevant for research and study of academic papers, able to effectively extract knowledge and broaden the extent of the groundwork for further study.

Our goal is to find a way for a simple agent to be more focused and, with that, far more precise in its findings for a specific topic, being able to speed up research and development to bring more relevant research papers to far more people.

We will view how a simple use of pretrained models, combined with the use of external data, acquired through web scraping, can help us understand the possibilities of this view of the NLP landscape. This agent will aim to be far more focused, finding direct links to actual submitted papers without being outdated in its information

Related work

The development of conversational agents with Retrieval-Augmented Generation (RAG) has been a growing area of research, with the aim of improving response accuracy by integrating external knowledge sources. This section reviews existing studies that have contributed to this field.

From Gao et al. [1] we have substantial examples of why RAG is important and how it helps AI be more accurate and reliable. The authors propose a novel RAG model that combines a large language model with a retrieval mechanism, allowing the model to generate responses based on both pre-trained knowledge and external sources. This approach significantly

improves the accuracy of the responses, making the model more reliable and informative.

For this project, we will, however, focus on a type of RAG that incorporates web-scraped data to address the problem of outdated information. The knowledge embedded in large language models tends to become outdated over time [2], making it crucial to retrieve and integrate external sources dynamically.

Pokhrel et al. [3] explore the integration of AI and web scraping in RAG. Their approach combines web scraping, vectorization, and semantic search, allowing users to input a specific website and then ask questions exclusively based on its content. While this method effectively retrieves domain-specific information, it requires the user to specify a website beforehand. In our work, we wish to build upon this approach by enabling both targeted and general prompts. If a user requests information from a specific website, our chat-bot will focus on that source. However, if no specific website is provided, the system will still perform web scraping in the background, integrating newly retrieved knowledge with the model's pre-trained information. This ensures that responses remain accurate and up to date while maintaining flexibility for both broad and focused queries.

The concept of leveraging web-scraped data through RAG was explored by Kanataria et al. [4], where authors proposed a novel framework that integrates RAG techniques with large language models (LLMs) like Llama 3, Mistral, and Gemini, enhancing the process of data retrieval and summarization from online sources. This framework combines web scraping, embedding models, and FAISS for efficient indexing, ensuring the delivery of real-time, personalized information. Our goal is to combine this approach with the one suggested by Pokhrel et al. [3], allowing the chatbot to dynamically retrieve and integrate information from any user-provided website, as well as from general web scraping.

Methods

In the sample work of our proof-of-concept model setup, the focus was mainly on the various resources and ways of implementing them. We've managed to group together and take use of many knowledge bases of academic research and compile the into the sample RAG pipeline that manages to access these papers in a keyword fashion and give answers enriched with these resources.

Papers, resources and fetching

In implementing many of these papers, that our python script fetches, they are then converted into vectors, and chosen based on similarity, using the FAISS library. There are many ways of obtaining academic papers that have been found and in turn implement in the test of the capabilities of the pipeline.

Many of the papers are possible to be obtained and have public API interfaces that gives much leeway in what and in what way we search.

Popular and massive academic libraries such as Arxiv and Semantic Scholar already have available python libraries allowing us the seamlessly implement them and their resources into our project. While other sites such as GoogleScholar and CORE have publicly open API interfaces still making it possible to quickly fetch the data.

While these resources are in fact readily available to us, some of the websites containing them were only available to be accessed through web scraping. Integrating the Playwright library and some simple web scraping methods, makes it possible to also implement these papers into the vectorization of this data.

Models, embeddings and similarity

While the baseline implementation only included simple and one model testing, it is important to highlight the different methods that are important in this situation and context.

The embedding model is also an aspect not that much highlighted in our testing case, but something to be researched upon further, given the importance of our RAG data

Our implementation also scores different specific hyperparameters that may be important to find the difference between.

For example the amount of the papers being fetched from remote resources are currently limited, to highlight rapid development of the model pipeline. While the amount currently is very much useful to be low, it is an important resource for our model that should be analyzed further and it's importance to the final result.

Similarly to the amount of papers being fetched, the k parameter in the FAISS vectorization is something that could massively impact the result and effectiveness of the data being implement to our answers . The k parameter is the amount of papers that are being fetched from the vectorized data and used to answer the question. This is something that could be further analyzed and tested, as it is a very important part of the pipeline.

Methods

Use the Methods section to describe what you did an how you did it – in what way did you prepare the data, what algorithms did you use, how did you test various solutions ... Provide all the required details for a reproduction of your work.

Below are LaTeXexamples of some common elements that you will probably need when writing your report (e.g. figures, equations, lists, code examples ...).

Equations

You can write equations inline, e.g. $\cos\pi = -1$, $E = m \cdot c^2$ and α, or you can include them as separate objects. The Bayes's rule is stated mathematically as:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}, \tag{1}$$

where A and B are some events. You can also reference it – the equation 1 describes the Bayes's rule.

Lists

We can insert numbered and bullet lists:

1. First item in the list.
2. Second item in the list.
3. Third item in the list.

- First item in the list.
- Second item in the list.
- Third item in the list.

We can use the description environment to define or describe key terms and phrases.

Word What is a word?.

Concept What is a concept?

Idea What is an idea?

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Figures

You can insert figures that span over the whole page, or over just a single column. The first one, Figure 1, is an example of a figure that spans only across one of the two columns in the report.

On the other hand, Figure 2 is an example of a figure that spans across the whole page (across both columns) of the report.

Tables

Use the table environment to insert tables.

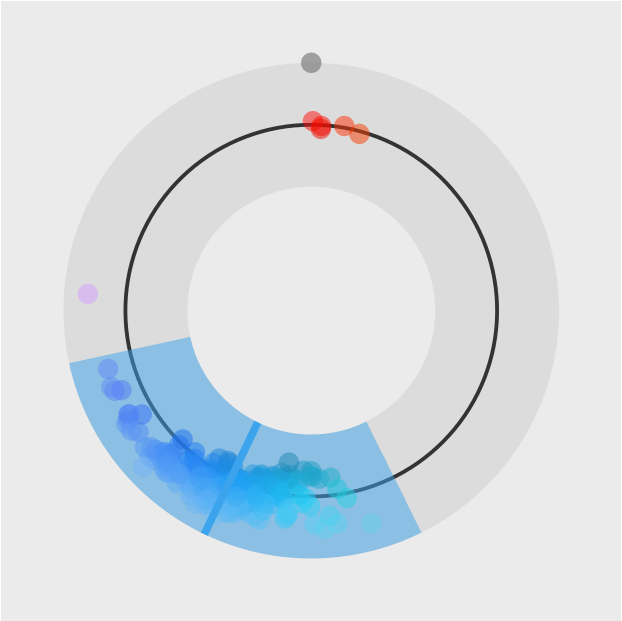

Figure 1. A random visualization. This is an example of a figure that spans only across one of the two columns.

Table 1. Table of grades.

Name		
First name	Last Name	Grade
John	Doe	7.5
Jane	Doe	10
Mike	Smith	8

Code examples

You can also insert short code examples. You can specify them manually, or insert a whole file with code. Please avoid inserting long code snippets, advisors will have access to your repositories and can take a look at your code there. If necessary, you can use this technique to insert code (or pseudo code) of short algorithms that are crucial for the understanding of the manuscript.

Listing 1. Insert code directly from a file.

```
import os
import time
import random

fruits = ["apple", "banana", "cherry"]
for x in fruits:
  print(x)
```

Listing 2. Write the code you want to insert.

```
import(dplyr)
import(ggplot)

ggplot(diamonds,
           aes(x=carat, y=price, color=cut)) +
  geom_point() +
```

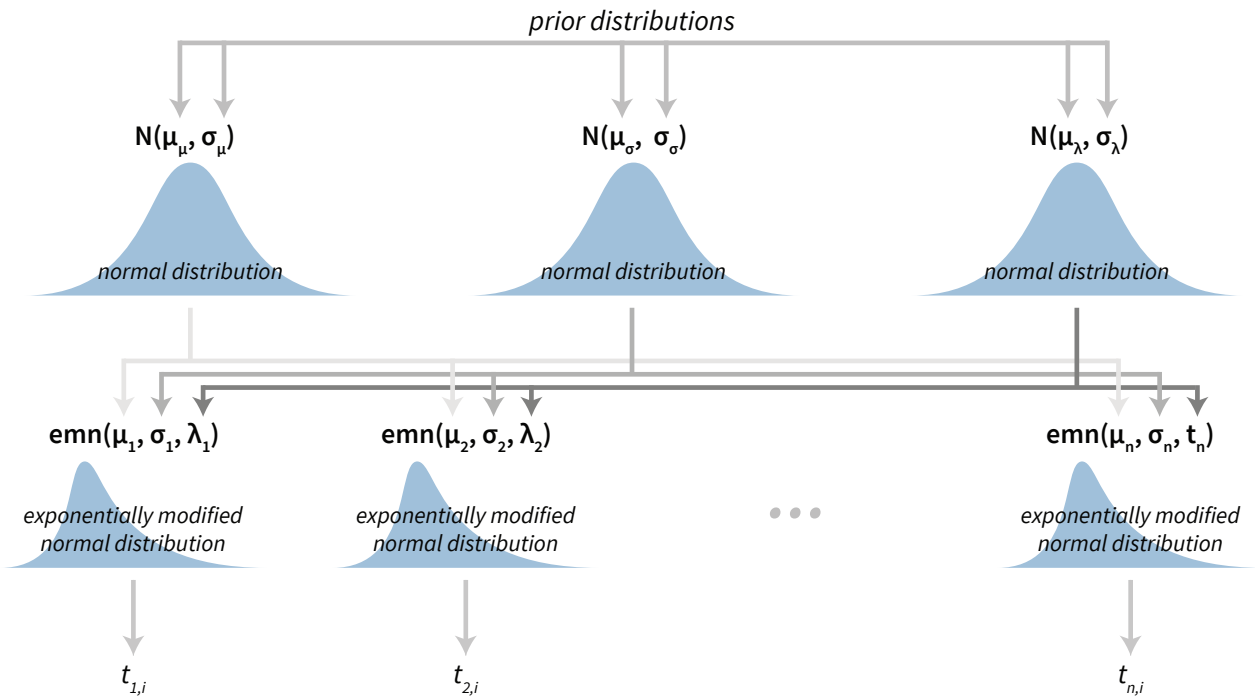

Figure 2. Visualization of a Bayesian hierarchical model. This is an example of a figure that spans the whole width of the report.

```
geom_smooth()
```

Results

Use the results section to present the final results of your work. Present the results in a objective and scientific fashion. Use visualisations to convey your results in a clear and efficient manner. When comparing results between various techniques use appropriate statistical methodology.

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Discussion

Use the Discussion section to objectively evaluate your work, do not just put praise on everything you did, be critical and exposes flaws and weaknesses of your solution. You can also explain what you would do differently if you would be able to start again and what upgrades could be done on the project in the future.

Acknowledgments

Here you can thank other persons (advisors, colleagues ...) that contributed to the successful completion of your project.

References

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