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UNLEASHING PERSONALIZED EDUCATION USING LARGE LANGUAGE MODELS IN ONLINE COLLABORATIVE SETTINGS

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Abstract

The Artificial Intelligence community has long pursued personalized education. Over the past decades, efforts have ranged from automated advisors to Intelligent Tutoring Systems, all aimed at tailoring learning experiences to students' individual needs and interests. Unfortunately, many of these endeavors remained largely theoretical or proposed solutions challenging to implement in real-world scenarios. However, we are now in the era of Large Language Models (LLMs) like ChatGPT, Mistral, or Claude, which exhibit promising capabilities with significant potential to impact personalized education. For instance, ChatGPT 4 can assist students in using the Socratic method in their learning process. Despite the immense possibilities these technologies offer, limited significant results are showcasing the impact of LLMs in educational settings. Therefore, this paper aims to present tools and strategies based on LLMs to address personalized education within online collaborative learning settings. To do so, we propose RAGs (Retrieval-Augmented Generation) agents that could be added to online collaborative learning platforms: a) the Oracle agent, capable of answering questions related to topics and materials uploaded to the platform.; b) the Summary agent, which can summarize and present content based on students' profiles.; c) the Socratic agent, , guiding students in learning topics through close interaction.; d) the Forum agent, analyzing students' forum posts to identify challenging topics and suggest ways to overcome difficulties or foster peer collaboration.; e) the Assessment agent, presenting personalized challenges based on students' needs. f) the Proactive agent, analyzing student activity and suggesting learning paths as needed. Importantly, each RAG agent can leverage historical student data to personalize the learning experience effectively. To assess the effectiveness of this personalized approach, we plan to evaluate the use of RAGs in online collaborative learning platforms compared to previous online learning courses conducted in previous years.

Keywords: *Personalized education, large language model, generative AI, collaborative learning.*

1. Introduction

Personalized education has been extensively researched by the Artificial Intelligence (AI) community during the last decades (Kamalov, Santandreu-Calonge, & Gurrib, 2023). It is worth mentioning several proposals of tutoring and personalized systems that were capable of guiding students to achieve true learning using several paradigms. Unfortunately, the real-world applications of those systems were limited to case studies. This was mainly due to the difficulties faced by intelligent systems to represent knowledge and reasoning. Even, modern Machine Learning algorithms were limited to inferring and making predictions for specific tasks, and natural language understanding interfaces were only useful recently (Luan & Tsai, 2021).

Nowadays, we are in the era of Large Language Models (LLMs) such as ChatGPT, Claude, Llama, Mistral, and Gemini, among others. In particular, when ChatGPT arrived, it showed several possibilities and opportunities for real-world applications in almost every industry. In education, those LLMs have shown promising capabilities that could impact how the learning process has been traditionally addressed with technology. These LLMs have capabilities that directly can be applied to learning. For instance, it is possible to create exercises, answer questions about any topic, learning using role-playing and according to several styles. It is worth noting the capabilities of ChatGPT4 to apply the Socratic method for learning. However, this kind of technology is still under development and has several drawbacks being the most relevant hallucination, i.e., LLMs outputs answers that seem plausible and well-written but are actually false or misleading (Yao et al., 2023). Hopefully, to cope with hallucinations a technique called RAG (Retrieval-Augmented Generation) through carefully designed mechanisms allows one to obtain precise answers. A RAG system aims to interact with LLMs by sending proper context (PDFs, HTML, CSV) to obtain up-to-date, and natural language answers. Given that RAG is based on information retrieval methods, as well as clever indexing and storing, it is possible to provide richer search experiences combined with the power of LLMs. Currently, LLMs can handle multiple modalities, allowing for the search and analysis of papers, images, audio, and video. This capability enhances the learning experience, often through engaging conversations facilitated by RAGs. The integration and adoption of RAGs have driven the advancement of chatbots in real-world applications (Gao et al., 2024).

While various educational experiences using LLMs have been documented across different levels (elementary, high school, and university), there is minimal work incorporating RAGs in this context (Kamalov et al., 2023). We aim to address this gap by demonstrating how these emerging technologies can be applied in real-world scenarios, specifically within collaborative online learning courses. Our plan involves implementing multiple RAG agents to facilitate personalized education and enhance learning experiences. To do so, the agents are designed with specific functionalities: a) the Oracle agent, capable of answering questions related to the uploaded topics and materials on the platform.; b) the Summary agent, which summarizes and presents content tailored to individual student profiles; c) the Socratic agent, guiding students in learning topics through interactive engagement.; d) the Forum agent, analyzing students' forum posts to identify challenging topics and suggest ways to overcome difficulties or encourage peer collaboration.; e) the Assessment agent, presenting personalized challenges to students based on their needs.; f) the Proactive agent, analyzing student activity and suggesting learning paths as necessary. It is worth noting that every RAG agent can share historical student data that allows them to profile and personalize the learning experience.

2. Related works

A comprehensive analysis of AI in education by Kamalov et al. (2023) highlights four crucial applications: (1) Personalized Learning, (2) Intelligent Tutoring Systems, (3) Assessment Automation, and (4) Teacher–Student Collaboration. Our focus in this paper primarily centers on applications (1) and (2).s. Personalized Learning: This approach allows students to learn at their own pace, enhancing their engagement and improving overall learning outcomes (Luan & Tsai, 2021). AI algorithms and adaptive learning systems can analyze student data, identify patterns, and recommend personalized content and resources to optimize the learning experience. Additionally, AI can drive virtual tutors that offer one-on-one education tailored to each student's unique learning and emotional needs (Jonnalagadda et al., 2023). Intelligent Tutoring Systems (ITS): these systems can offer instant feedback, answer questions, and guide students through complex concepts, supplementing or even replacing traditional tutoring services. AI's capabilities can enhance learning experiences by incorporating gamification elements such as rewards, challenges, and competition. By tailoring these components to individual students, engaging and personalized learning environments can be created, boosting motivation and active participation (Mousavinasab et al., 2021). ITSs use advanced algorithms and machine learning techniques to understand students' learning needs and tailor their teaching methods accordingly. Natural language processing (NLP) allows AI to comprehend and interpret students' written or spoken input, enabling ITSs to engage in meaningful dialogues, answer questions, and deliver instruction across various subjects. It is important to mention that there are currently no reported results regarding the application of RAGs to personalized learning and ITS. We aim to address this gap by presenting a proposal within a collaborative online learning setting.

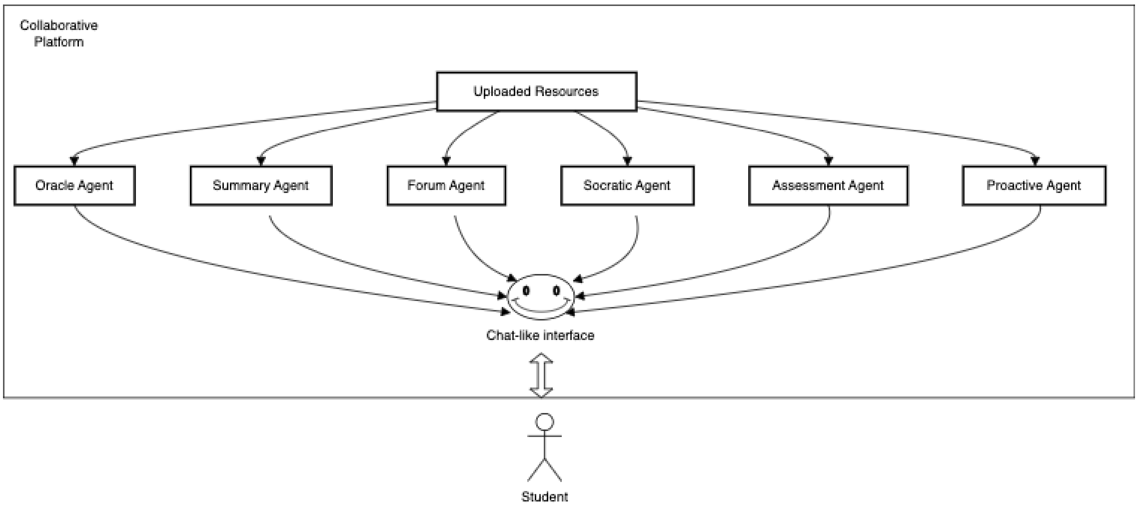
3. Background

Retrieval-Augmented Generation (RAG) is an architecture that augments the capabilities of LLMs like ChatGPT or Mistral, by combining the power of information retrieval techniques with generative AI (Gao et al., 2024). One of the key advantages of implementing RAG is the ability to control generative AI output, making it focus on specific content from documents, images, audio, and video. This means RAGs can ensure that the AI-driven responses generated by LLMs are based on accurate and relevant information from their content repositories, which is valuable in educational settings. To create a basic RAG system, five stages are necessary: i) Document loading: Within a collaborative learning platform, this involves uploading various resources like PDFs, HTML files, audio, video transcriptions, and more. ii) Data splitting: The uploaded data undergoes splitting, encoding using embeddings, and indexing to make it interpretable by Large Language Models (LLMs) such as ChatGPT, LLama 2, or Mistral. iii) Storage: The encoded and indexed information is stored in vector databases like Chroma for more efficient retrieval during the generation phase. iv) Retrieval: During generation, relevant contextual information is selected from the vector database and sent to the LLM. v) Output: The LLM then generates corresponding questions and answers based on the contextual information obtained in stage iv, i.e., from the contextual data. We intend to create RAG agents, which are software entities designed to reason and act based on environmental changes (Yao et al., 2023). Specifically, our focus lies on the ReACT agent model, a framework that merges the reasoning abilities of large language models (LLMs) with the capacity to take actionable steps. This leads to an advanced system capable of understanding and processing information, evaluating situations, taking suitable actions, communicating responses, and monitoring ongoing developments. This model holds particular relevance in the education sector, where agents are engineered to respond dynamically rather than following pre-set scripts.

4. Educational RAG agents

Our proposal involves educational agents that collaborate with students and help them achieve their learning objectives. To demonstrate this, we have designed the architecture illustrated in Figure 1 within a learning collaborative platform serving as a testbed.

Figure 1. Collaborative RAG agents.



In summary, a social collaborative online platform is ideal for our proposal due to its ease of integrating agents in this digital environment. Students are accustomed to this learning format through platforms like Moodle and others. Typically, these platforms offer various tools that promote student collaboration on tasks and exercises, along with access to documents, quizzes, and live or recorded sessions. However, these tools and resources generally lack personalized learning features. Our proposal addresses this gap by introducing specialized RAG agents that leverage Artificial Intelligence capabilities to customize students' learning experiences in a real-world context. Using a straightforward chatbot-like interface, multiple agents will engage with each other to offer advice, suggestions, and assistance to students. Based on resources available within a collaborative platform (such as PDFs, HTML files, video transcriptions, forum messages, etc.), the Oracle and Summary agents curate information sources that can provide specific answers and summaries. For self-directed learning, the Socratic agent poses guiding questions that help students explore a given topic without directly giving away the answers. Additionally, the Assessment agent presents challenges that encourage students to master a topic through hands-on experimentation. In terms of peer collaboration, the Forum and Proactive agents highlight collaboration opportunities and proactively suggest potential learning paths based on students' preferences and usage patterns. Each agent's role is elaborated as follows.

4.1. Oracle agent

This agent can answer questions regarding any topic uploaded to the collaborative learning platform. It is crucial that this agent can provide concise, relevant, and reliable information regarding the material and resources that have been uploaded to the collaborative platform. The main challenge is to avoid hallucinations which are common in LLMs but we can prevent this through careful design of the advanced RAG that allows us to stick to the context given.

4.2. Summary agent

LLMs can provide summarizations from general documents, as well as explanations using learning styles so as to improve students' topics understanding. The Summary agent aims to personalize the learning experience via summarization of resources previously uploaded to the collaborative platform. The challenge here is to provide concise and personalized summaries that can easily adapt to the student's learning preferences.

4.3. Socratic agent

The Socratic agent aims to guide the student to master a topic through questions without explicitly providing him/her with the answers. The idea is the student can manage to pose questions that denote understanding of a topic and can discover, guided by the agent, his/her learning path. To avoid loss of focus and LLM hallucinations we are limiting the Socratic method to resources available only through the collaborative platform. While there has been such functionality since ChatGPT4, the challenge is to tailor it to specific resources.

4.4. Forum agent

Collaborative learning implies establishing connections among peers to jointly cope with challenges posed by teachers and mentors. In this context, students are encouraged to pose questions about exercises, and topics that were hard to understand and therefore to solve. The Forum agent automatically recognizes questions and messages that could be solved through collaboration and promotes linking peers who have previously solved and are keen to share their solutions.

4.5. Assessment agent

To evaluate the effectiveness of the online learning experience, the Assessment agent encourages students to constantly check whether they understood a topic or resource. To do so, it poses challenges and exercises to students, according to the personalized skills and abilities gained and the learning outcomes pursued.

4.6. Proactive agent

The Proactive agent encourages the use of collaborative and Artificial Intelligence resources that can improve the students' learning experience. According to the student's activity, the agent can suggest personalized paths that can boost his/her learning. This functionality goes beyond simpler notifications and implies profiling students and matching resources regarding their learning styles.

5. Implementation and preliminary results

Unlike previous reported works on intelligent tutoring systems, we envision creating a framework with RAG agents that can be applied to real-world scenarios. Thus, we describe implementations, preliminary results, and ongoing work addressed to this end, in particular, we focus on the collaborative platform, the implemented RAG agents, and the evaluation procedure.

5.1. The Collaborative platform

Currently, there are several initiatives to extend popular Learning management systems (LMS) with AI capabilities, however, this is still ongoing work. For instance, the popular Moodle LMS contains Artificial Intelligence plug-ins but with limited functionalities. In this sense, we plan to construct a new collaborative platform that has social and Artificial Intelligence capabilities at its core. This platform will have the basic features of any content management system, it will allow access to documents, quizzes, forums, videos, etc. but those resources will be available through natural language interfaces, enhanced by the use of RAG agents.

5.2. Implemented RAG agents

Utilizing the LlamaIndex framework (accessible at https://docs.llamaindex.ai/en/stable/) and the Mistral LLM, we have integrated RAG techniques into the Oracle and Summary agents (the other agents are still under development). This integration allows us to effectively respond to queries related to specific resources and topics, thereby minimizing hallucinations and providing contextually appropriate answers. To achieve this, we have leveraged advanced RAG techniques during both the pre-retrieval and post-retrieval phases (Gao et al., 2024). During the pre-retrieval phase, our focus has been on optimizing the indexing structure and refining the original query. We have employed techniques to improve data granularity, optimize index structures, and implement mixed retrieval methods. Furthermore, to enhance optimization, we have explored query transformation and expansion techniques. In the post-retrieval phase, our primary methods include reranking chunks and compressing context to refine results. It is important to acknowledge the challenges encountered when developing agents using open-source resources.

5.3. Evaluation methodology

For the past four years, the Department of Computer Science at UCSP has offered fully online diploma courses to groups of 30 individuals, focusing on Machine Learning for industry. The courses provided access to learning materials and exercises through Moodle, with real-time online classes. Despite implementing various teaching strategies, the success rate has remained low, with only 50% of students completing the Machine Learning project by the end of the diploma program. This serves as our baseline. Moving forward, we plan to introduce a revised version of the diploma course utilizing the proposed collaborative platform and incorporating RAG agents to personalize student learning experiences. Upon completion of this updated version of the diploma program, we will assess new success rates and objective achievement metrics, which we can then compare to those of previous versions.

6. Conclusion

Online courses have become widespread globally and are now a well-established learning resource, a trend that became particularly evident during pandemics. In this work, we propose methods to make online learning more enriching through peer collaboration and, primarily, through personalization. To achieve this, we explore the use of Artificial Intelligence. While the concept of intelligent frameworks is not new, the current context is highly favorable. Online learning is now more widely accepted, and LLMs like ChatGPT have shown unprecedented potential in real-world applications. This suggests that LLMs can significantly enhance personalization in education. To do that, within a collaborative learning platform, we propose the creation of RAGs (Retrieval-Augmented Generation) educational agents, designed to mitigate the hallucinations of LLMs. These agents can answer specific questions, guide learners along potential learning paths, mediate discussions, and collectively help to achieve desired knowledge outcomes in a personalized manner. Although our results are still preliminary, they indicate that autonomous tutor systems may soon be a reality. To evaluate the impact of these technologies we will compare results using traditional online settings against intelligent personalization.

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