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Generative AI and Learning: Using Retrieval-Augmented Generation (RAG) for C++ Tutoring

**Abstract:**

By utilizing advancements from the field of AI, we aim to develop a tutoring app that answers the questions of intro-level C++ programming students, while creating a framework to expand into other academic areas. A Retrieval-Augmented Generation (RAG) approach will provide targeted feedback, dynamically generating context-specific responses by interfacing with a locally hosted AI.

Our goal is to minimize the risk of oversaturated or hallucinated responses. By processing incoming questions from users and communicating with the AI model, a RAG method ensures that the answers generated by the backend are both concise and relevant to the search. The front end will allow students to easily input their questions and view immediate feedback, ultimately enhancing the interactive learning experience. The functionality will be custom-built, while the graphic design from a previous personal project will be used. Combined, these systems will create a user-friendly application that provides students with clear and direct responses to their specific queries.

Overall, the project aims to create a scalable and efficient tutoring tool. Not only would this tool improve students’ understanding of C++ programming concepts, but it could be integrated into other educational platforms. Unlike the VS Code extension Continue or other similar tools, our project is designed as a two-part web application for easy integration into current LMSs (Learning Management Systems). The desired outcome is an engaging, adaptive, and accessible learning environment that can be extended to additional subjects and environments in the future.

**Paper:**

The objective of our project is the design and implementation of an AI-based tutor app that effectively addresses introductory-level C++ programming questions for beginning computer science students. We chose C++ as the focus because it is a foundational programming language to the software engineering process. It is important for a beginner to understand the more complex syntax of C++ before they can effectively learn topics such as pointers, memory management, data structures, and algorithms. The building blocks of these data types are laid in an introductory course, but the learning curve for C++ is steeper than higher-level languages such as Python. These advanced concepts are more tedious and harder to grasp early on/in the beginning. An accurate and effective tutor app will enable a beginning student to absorb the new material more effectively.

The frontend?

The backend, implemented in Python, will serve as the engine of the application. It will process incoming questions from users and communicate with the Llama 3.2 model via the REST API, ensuring that the answers generated are both concise and relevant. This design minimizes the risk of oversaturated or generic responses, providing students with clear and direct explanations tailored to their queries.

By using a Retrieval-Augmented Generation (RAG) approach to providing targeted feedback, our goal is to develop a basic, but effective AI framework that facilitates learning. Instead of relying on a pre-stored database of answers, the system will dynamically generate context-specific responses by interfacing with a local Llama3 AI model through Ollama’s local REST API.

Ollama and Llama3

Retrieval-Augmented Generation is (at) the cornerstone/the heart of our project. It is a generative AI process that combines the power of Large Language Models with a curated supply of information. Retrieval-Augmented Generation supplies the AI with contextual information from a data store that is related to a user query. It then uses this context to inform and guide the generative process, giving the AI a stronger knowledge of the topic at hand. (Lu, Yiu, 2.3) (citing references format?)

This approach also solves many of the outstanding issues that exist with generative AI. One of generative AI’s largest and most well-known flaws is that of hallucination, where the AI generates fabricated/fabricates information with no factual basis. In a recent study, the authors found that out of 5000 ChatGPT responses, 19.5% contained hallucinations. (Li et al) Retrieval-Augmented Generation has been shown to improve code generation and summarization (in studies/thus improving… needs more to finish sentence) ***Citation Needed***. By implementing Retrieval-Augmented Generation, we intend for this app to draw from a stricter data pool, thus limiting the AI’s answers from straying into hallucination and solving the problem of hallucination with the use of our tutor.

LLM/SLM

(*beginning of introduction section)*

The value of our project is in its ability to provide an introductory computer science student with a course-specific learning tool. The app is not intended to replace textbooks or teachers, but to help support currently established methods of education. By focusing on specific material as the basis for our tutor app’s responses, we can add support to the development of problem-solving skills for these students, enabling a stronger knowledge of the material.

Online education already exists, though the online materials traditionally used to learn introductory computer science have their limitations. For example, Python Tutor helps students visualize runtime data structure changes during program execution. Visual Algo helps students visualize algorithms through animation. These are good tools and help provide insight into programming, data structures and, algorithms, but they are not always helpful with introductory topics. The issue is accessibility. Since uninitiated students will often lack an understanding of basic concepts, traditional online resources may not always be effective for them. These tools may not offer the flexibility to offer the best examples early on in a student’s coding education. Some newer students can struggle finding pertinent information without a clear overview of the problem.

By using Retrieval-Augmented Generation, the program will dynamically adjust to each unique question, providing students with a personalized response to each question and empowering them with answers that will help build a broader understanding. Because Retrieval-Augmented Generation has the ability/capability to draw on current class materials, it can also focus in on a class-specific information set. By sourcing information from traditional educational resources, such as a textbook, the tutor remains consistent informationally with classroom materials. This feature allows the app to deliver this information in a more engaging, personal way for each student. By using relevant coding examples, it can offer an efficient method in reaching inexperienced students with supportive information, allowing them to better digest the textbook information.

This app can also help build confidence by approaching the information in an unthreatening way. Eliminating the fear of being judged by a tutor or faculty member, students are free to explore answers to their questions in an effective and comfortable environment. By freely pursuing basic questions, students can build their understanding and confidence to ask more precise questions of an instructor. This serves to lower barriers for new students and facilitate quicker, more stress-free progress and eventual mastery of the basics of C++ programming. As students better understand the material, they are more likely to continue in the degree path. (Li…)

*(beginning of related works section)*

This is significant, because Computer Science is currently facing obstacles. There is a growing reliance on software in all aspects of modern society, requiring more programmers. This causes more students to consider software careers. This increased interest drives the record undergraduate enrollment in Computer Science that many schools are seeing. The problem is that these schools are facing both a lack of qualified faculty and varied curriculum challenges. The combined force of these factors is stressing Computer Science education. As Ma, Martins, and Lopes pointed out, “Providing individualized support to many students in introductory courses, especially regarding mastery of complex material, has been challenging.” A strategic use of AI could further the educational reach of the faculty that now exist, reducing the need for an instructor’s direct involvement in simpler questions. (Li…)

Without a working knowledge of computer concepts, many beginning computer science students need to be able to learn and review the intro. Ma, Martins, and Lopes, instructors at the University of California – Irvine conducted a study of AI tutors within the context of computer science education. They looked at a pool of 455 students at the University of California – Irvine. They deployed five RAG Man tutor apps to assist the students with their supplemental homework assignments. These tutor apps were designed to give guidance, not solutions. In this way, the students developed experience by participating in a more practical process, ultimately finding their own answers. (Li…)

Their research suggested that, “AI tutors can positively impact student success and provide important help, especially to students who would be struggling in challenging courses.” (Ma) They concluded that the increase in the number of students continuing through the degree path, when using the RAGMan tutors, was considered statistically significant. Furthermore, the student feedback was very positive, demonstrating a positive user experience. User satisfaction helps to ensure a broader use of these tools. (Li…)

Creating a virtual personal assistant for computer science students is very promising based on the results of such research. Our tutor app seeks to provide/provides a pressure free, efficient, and personalized tutor experience for introductory students that is able to draw specifically on trusted course materials. If we continue to prioritize the feedback and interactions of the students, we can further enhance these learning tools, making them more effective and user friendly.

Our tutor app has the advantage of accessibility. This would benefit students financially, as personal tutors can be very expensive. Most students cannot afford to pay a human tutor $50-$200 per hour for guidance. Also, for students enrolled in schools with high class populations, it can be hard to get access to tutoring help from other students or faculty. It could also provide students with active, accurate support outside a tutor’s or professor’s available hours. Though both affordability and accessibility, the app would be a great supplement to traditional teaching resources such as textbooks and class lectures. The app would make extended support possible as students begin to establish their basic skills.

As a learning tool, it would also be cost-efficient for educational institutions to implement. By using Ollama, a locally hosted AI, running the Llama 3.2 model, we were able to reduce the costs often associated with generative AI. Most large language models cost per token. These operating costs accumulate with each use. However, Ollama allows you to run a variety of models locally. After the initial cost of setup, this limits the continuing costs of operating to just maintenance and electricity.

This also reduces the environmental impact of AI. A recent article by ???... shows the difference in the impact of cloud AI versus that of a locally run iteration…

BEGIN YOUR REWRITING / ADDING HERE (to the end of the paper)

*(beginning of solutions/implementation section)*

The Retrieval-Augmented Generation pipeline begins with the indexing of the collection of data/documents that are being leveraged as the source of relevant material. In our case, we used the ZyBooks text, chapters one through six to supplement the generated answers. The whole process of Retrieval-Augmented Generation begins when we index the collection with ChromaDB, a vector database that will store the documents paired with their embeddings. The embeddings are small, semantic (mathmatic, array of float numbers, might need to make a reference to an article on this) representations for similarity searches.

We chose ChromaDB because it is able to seamlessly integrate with Python, through a library. Is known for its efficiency. ChromaDB became the preferred choice. The indexing phase is crucial to facilitate accurate matches to the user queries.

Moving onto the next step, the retrieval stage. When the student makes a query, the query is matched with the most relevant data in the vector database (It does this by getting the embedding of the user question and then finds the stored document whos embedding is mathmaticly closest). Next, the augmentation occurs. So, the retrieved information is combined with the user’s query to create an augmented input that will be sent to the Llama AI model. (It should be noted it is also combined with other context, such as the message history between the user and the bot, as well as the user’s code) The enhanced context will enable the Large Language Model to generate a more concise response.

Lastly, the generation occurs with an answer that integrates the Llama model’s generation capacity with the supplied relevant context. The answers seem more calibrated and centered around the students’ query.

The first step to minimizing hallucinations is the indexing stage. We chose the first six chapters of the ZyBooks online text, which is used in our CSC-108 Intro to Computer Science course here at Quinsigamond Community College. The indexing happens before the runtime of the Retrieval-Augmented Generation itself. Indexing builds a strong foundation for the retrieval of concise data. (Seems duplicate)

Next the data is processed into chunks using Langchain and then converted into numerical vector embeddings by importing Langchain\_Ollama (More accurate to say it is sent to Ollama or the llama model to have the embeddings generated). Using Ollama’s built in embedding function provides better performance and stability for the app. Then the embeddings are indexed in ChromaDB, the vector database. ChromaDB offers fast similarity search and semantic retrieval. (Too fancy, need to convey that it is able to find similar information in a document better than a relational DB like SQL)

The indexing pipeline sets up before runtime ~~and ensures the accurate retrieval of data~~. The retrieval process is the basis for concise responses. The retrieval uses the indexed information stored in ChromaDB and employs the embeddings to find the most relevant information for each user query.

Basically, when a student submits a query, the retrieval functionality processes the text into a vector embedding, using the same embedding function we used in the indexing stage. This ensures that the query embeddings and indexing embeddings reside in the same space and are similar in context.

The query embedding is then passed to ChromaDB, where the semantic search takes place. ChromaDB efficiently identifies and retrieves the most relevant chunks to the query. So, it’s this combination that creates the accuracy and precise context needed to help the student. This remedies the typical downfall of generative AI where it just generates an answer from metadata without concise context. Again, the retrieval process builds the foundation for the optimal educational experience for the student. It creates a beginning-user-friendly environment.

Furthermore (Used way too much), the retrieved content is then inserted into a structured prompt along with the original user query. The prompt would be a guideline or tone for the Large Language Model to follow. This augmented prompt is then sent to the Llama 3.2 model, and a response is generated based on the contextual data. The result is the student receives an accurate answer that is grounded in the course material (and other context). Thus, avoiding hallucinations. Also, system prompts allow it to be guided against responding with hallucinations if the model doesn’t know the answer or doesn’t have enough information. This is an important part of the process as well.

*(beginning of the section about the modularity of the backend)*

*I have not checked past this, I just got sent it and have no time today to look at it.*

Also, one of our goals (*needs to be added to abstract?)* was to create a tutor app that could facilitate other courses and subjects for future work. Our goal was to have an interchangeable backend that can be integrated easily with other subject matter, if that subject matter data is in .txt format. Basically, we can use the RAG tutor for any subject or course and still maintain consistent, efficient experience for the students.

The main components of our backend operate independently of the C++ material so that we can use it for other subjects quickly and efficiently. Our RAG pipeline uses LangChain for text processing, langchain\_ollama for generating semantic embeddings, and ChromaDB for vector-based storage. The combination of these tools creates a formidable RAG pipeline that is totally flexible in the subjects it can cover and be used as a tutor. Instead of embedding specific rules for C++ education, the backend will use any .txt material that a tutor or instructor provides the system. The texts are divided into chunks, each chunk is transformed into an embedding vector that represents its semantic content. These vectors are then stored in ChromaDB, providing efficient retrieval when a student submits a question.

Furthermore, any user can convert course textbooks, lecture notes, or supplementary materials into standardized .txt files. These files should be segmented by chapters or topics/ideas to facilitate contextual chunking. This subdivision is critical because it preserves the proper context and ensures that the retrieved content directly relates to the student’s/user’s query.

Next, using LangChain, the text files are taken in and split into semantically coherent chunks. Langchain\_ollama then generates embeddings from these chunks, which are stored along with metadata into ChromaDB. This process requires no adjustments to the backend code, which remains the same regardless of the subject matter.

The next phase includes when a user submits a question, the backend converts the question into an embedding using the same model, ensuring compatibility with the indexed content. A semantic similarity search is executed in ChromaDB, and the most relevant text chunks are retrieved. These retrieved chunks are then augmented with the original question to construct a concise prompt for the LLM. Lastly the LLM generates a response that is concise and relevant to the user’s question.

The backend gets its functionality through a REST API, which makes it simple to be integrated into learning systems such as Canvas or Blackboard. Whether the LS uses a web interface or some other interface, the API endpoints take care of queries and responses without any further changes required from the LS. The modularity ensures that teachers, professors, and tutors can employ the backend easily regardless of the learning system.

**Furthermore, this modularity offers significant advantages in terms of scalability. Upgrades to the embedding model or improvements in the vector database can be implemented centrally, benefiting all courses that use the system. This ability to serve multiple subjects with the same core engine reduces redundancy and enhances the overall reliability of the tutoring system. (check this paragraph)**

Finally, the flexibility of our backend allows it to be used with other course materials if they are in a structured .txt format. Simple integration is made possible by the REST API and the other interchangeable components. Additions to the tutor app could include more advanced feedback systems for the students, which seems to be a focus of some of the RAG tutor research that I cited earlier in this paper. The more we can measure the performance of the application, then the more we can improve upon its functionality. One of the main ways to do that is to efficiently get detailed feedback from the students.

The cost of premium AI services of outpaces the speed benefits. We found Llama to be an excellent when weighing speed, flexibility, and cost.

**MY OUTLINE**

Approach

Why choices (RAG, LLM, OLlama, Llama)

The advantage of our app is that it is set up to be able to use any model avalible for Ollama. THis means that you can use a bunch of different models, and with the Results-Agumented Generation, increase their accuracy. This allows for you to reach near comercial qualtiy, but at a very reduced cost.

Another study by Wang and Ramon **(Quantitative Evaluation of Using Large Language Models and Retrieval-Augmented Generation in Computer Science Education)** quantified the performance of different AI models and how effective they were by a cost-effective analysis for instructors. "Implementing RAG enhances the ability of LLMs to answer context-specific questions accurately. This improvement is particularly noticeable in models with integrated course materials and pre-answered question databases and allows open-source models to close some of the gap with GPT-4."

Moreover, they found that advanced model Large Language Models did outperform open-source models in Q&A tasks. However, the performance gap wasn’t significant enough to justify the cost-benefit of using locally hosted open-source models. The needs of the instructor/students should be considered in this regard.

Though we took a unique path, a significant inspiration was Ragman

UC-I Study (Ma…)