UR-116

Enhancing Engineering Education Through LLM-Driven Adaptive Quiz Generation

KENNESAW STATE UNIVERSITY

Abstract / Introduction

Aim

This study aims to develop an Artificial Intelligence (AI) quiz generation system for engineering students to enhance personalized learning. In the rapidly evolving field of educational education, the emergence of AI and, more specifically, Large Language Models (LLMs) such as GPT-4, Llama, Claude, and Gemini, has marked a significant advancement.

Literature Review

Our literature review method employs a systematic approach, analyzing peer-reviewed articles, conference papers, and authoritative reports to uncover the trends and challenges in AI-driven quiz generation. The notable gap identified in our literature review is the lack of LLM-based quiz generation methods specifically for engineering education, which incorporate interactive and adaptive learning features to enhance student engagement and comprehension.

Methodology

This study examines the application of OpenAI LLM with a Retrieval-Augmented Generation (RAG) system in creating personalized quiz questions for engineering education, focusing on a novel methodology to enhance learning experiences through dynamic, adaptive quizzes and tutorials, particularly targeting the development of math reasoning skills in visual contexts. The proposed methodology leverages the MathVista dataset, comprising 6,141 examples, to enhance the capabilities of the OpenAI LLM. The RAG system populated with this dataset serves as a reference context for generating more relevant and accurate quiz questions. Prompt engineering techniques guide the OpenAI LLM in creating detailed multiple-choice questions (MCQs) focused on visual-mathematical reasoning challenges.

Evaluation

The quizzes are designed to adapt to varying levels of student performance, incorporating feedback loops to customize future quizzes based on student responses. The evaluation of our AI pipeline's effectiveness employed metrics such as accuracy, relevance, and adaptability. The results indicated a significant performance in the generation of accurate questions with the least hallucinations.

Introduction

- This study explores the development of an AI-based quiz generation system utilizing Large Language Models like GPT-4, specifically designed for engineering education, to foster personalized and adaptive learning experiences.
- Leveraging the MathVista dataset within a Retrieval-Augmented Generation framework, our methodology aims to produce dynamic, accurate quiz questions that enhance math reasoning skills and adapt to student performance.

Challenges Addressed

- The primary challenge addressed is the insufficient customization in quiz generation for engineering students, which often fails to meet diverse learning needs and adjust to individual student progress.
- Overcoming the challenge of generating precise and contextually relevant quiz questions that minimize the risk of LLM generating incorrect or misleading information (hallucinations), ensuring higher educational value and reliability.

Methodology

- **Dataset Preparation and Preprocessing:** Utilize and preprocess the MathVista dataset, focusing on visual and mathematical components to establish a training foundation.
- **Retrieval-Augmented Generation and Prompt Engineering:** Employ RAG systems and prompt engineering to generate contextually relevant multiple-choice questions (MCQs) based on the MathVista dataset.
- **Adaptive Learning Loop:** Deliver quizzes, analyze student performance, and adapt content through a feedback loop to address learning needs and adjust difficulty.
- **Evaluation of Effectiveness and Adaptivity:** Measure the impact of quizzes on visual math reasoning and their adaptability to student performance levels.

Dataset

- The MathVista dataset enhances the AI quiz generation system by providing a comprehensive benchmark that includes 6,141 examples from 31 diverse datasets, focusing on visual-mathematical reasoning across various contexts such as IQ tests, functional plots, and academic figures.
- By integrating specialized subsets like IQTest, FunctionQA, and PaperQA along with 9 MathQA and 19 VQA datasets, MathVista addresses significant gaps in visual domain coverage and supports the evaluation oflogical, algebraic, and scientific reasoning skills crucial for engineering education.

Retrieval augmented generation (RAG)

- RAG prevents overfitting and catastrophic forgetting by referencing broad data sets.
- RAG enhances explainability and reduces costs of continuous fine-tuning.

Vectara:

Vectara is an API-first platform that simplifies the development of enterprise-ready Generative AI applications using a Retrieval-Augmented Generation (RAG) framework.

- Vectara handles the complexities of data ingestion, querying, and underlying system processes, enabling developers to focus on building user-centric features.
- It offers optimized defaults for chunking, preprocessing, and retrieval, significantly speeding up project initiation and reducing the need for extensive experimentation.
- Vectara allows customization in data preprocessing, retrieval strategies, and LLM integration, adapting to both small-scale projects and large enterprise deployments.

Results

- **Quiz Accuracy and Relevance:** Initial testing revealed that 85% of the quiz questions accurately reflected the visual mathematical reasoning challenges, with a low hallucination rate of less than 5%.
- **System Efficiency and Responsiveness:** The system demonstrated high efficiency with an average response time under 10 seconds per quiz question generation, ensuring a smooth user experience.

Discussion

- The high accuracy and low hallucination rate in quiz generation validate the effectiveness of the Retrieval-Augmented Generation system, emphasizing its capability to leverage the MathVista dataset for producing contextually relevant educational content.
- The adaptive learning loop's success in improving student performance highlights the potential of dynamic, responsive quiz systems to personalize educational experiences and enhance learning outcomes in engineering education.

Conclusion

The study demonstrates the potential of using Retrieval-Augmented Generation (RAG) systems combined with the MathVista dataset to create an effective LLM-based quiz generation system for engineering education. By incorporating adaptive learning mechanisms, the system not only improves accuracy and relevance in quiz questions but also adapts to individual learning needs, significantly enhancing student engagement and comprehension.

Future Research

Future research will explore integrating additional datasets, enhancing RAG algorithms for better personalization, and expanding the system to other disciplines to broaden its applicability and educational impact. We will also investigate further enhancements in student performance and adaptivity by refining quiz content and feedback mechanisms to optimize learning outcomes.

Devananda Sreekanth dsreekan@students.kennesaw.edu
Dr. Nasrin Dehbozorgi dnasrin@kennesaw.edu

C-DAY FALL 2023