

CASE STUDY

Utilizing LLMs and LangChain

in Education for Automated Knowledge Assessment

At a Glance

The integration of LLMs and LangChain in the educational sector represents a revolutionary approach to automating knowledge test generation and answer evaluation. This case study explores how our innovative application of AI tools has enhanced the efficiency of student learning, providing personalized resources and effective feedback, while significantly reducing the time and effort required from educators.

Industry

Education Technology (EdTech)

Technology

- OpenAl ChatGPT
- Lang Chain
- Azure Document Intelligence
- Google Translate API
- Fast API
- SqlAlchemy
- Angular
- · Docker, Kubernetes

Overview

This case study outlines the opportunities of practical introduction of Al tools like LLMs and LangChain in the educational process; it also focuses on the possibilities of increasing the efficiency of students' learning process, providing personalized learning resources and materials, as well as effective management of learning resources.

We are learning more and more at an ever faster rate, and there is a need for new approaches to help students learn and prepare for exams. We focus on improving the learning experience with the usage of Large Language Models and LangChain technology to develop knowledge tests based on educational documents, assess student responses, and offer guidance on improvements. The purpose is to increase effectiveness, provide more individualized feedback, and improve learning outcomes.

Manual procedures of developing and grading examinations are tiresome and demand considerable time and effort from educators. Al and natural language processing enable new approaches to learning with opportunities to improve these processes. When using LLMs like GPT-4, the OpenAl language model, and LangChain, which is the framework for creating applications with LLMs, they can be used to improve the speed and efficiency of test creation and evaluation as well as produce a better, more personalized learning experience and results.

Approach

Learning new knowledge involves studying large quantities of learning materials like textbooks, documents, spreadsheets, and images. We start by feeding educational documents into an LLM that consumes content to identify essential concepts/details. This can include documents of different formats (PPTX, DOCX, PNG, JPG, PDF, etc.) and in different languages. Azure Document Intelligence is used to process different document formats and content to validate and prepare them to be consumed by the LLM. Azure Document Intelligence is a cloud service that helps extract, analyze, and process data from different documents with the use of AI, which makes the process easier and more efficient. If documents are in different languages, Google Translate API translates documents to a common language. The capabilities of LangChain help us build a structured knowledge base from these documents. LangChain is a versatile toolkit designed to construct applications that combine large language models with other data sources and services to produce context-aware interactions. Next, the LLM generates multiple-choice questions, short-answer questions, and essay prompts based on the extracted information.

For instance, a set of educational text documents related to a given topic forms the input to the system. The LLM scans the entire text for concepts and facts and generates a pool of different questions based on those concepts. Students complete their answers to the generated tests, which are then reviewed by the LLM. In factual questions, the model looks for accuracy, while for essay-type questions, it looks at the quality of the reasoning and depth of the knowledge being demonstrated. The system receives answers from students, grades these answers in terms of correctness, completeness, and rationality, and produces the grades and comments.

Based on the evaluation, the system provides personalized feedback to students. This includes highlighting strengths, identifying areas where the student struggled, and suggesting additional resources or study topics to improve understanding. The process involves evaluating answers and identifying gaps in knowledge, which the LLM uses to generate feedback and recommendations, resulting in a personalized feedback report with study suggestions.

Implementation at a University

This technology was implemented at a mid-sized university in its biology department in an attempt to save the faculty time in preparing and grading tests as well as give students comprehensive and instant feedback. The university offered students a choice of texts and handouts that were scanned and entered into the LLM. All this information was then structured into a coherent knowledge base with the help of LangChain. The LLM prepared a set of test questions, which was then validated by faculty members.

The generated tests were administered to the students through an online platform whereby the answers were provided through the same platform to be marked by the LLM. After the test, every student was given a report that included the student's performance on the test, as well as strengths and weaknesses. Suggestions for further study material were also offered.

The implementation of this approach led to a 70% decrease in the amount of time that the faculty spent on test creation and grading. Test results were provided to students, including comprehensive comments, immediately after the test, compared to the few days that were required previously. The student success rate increased by 15%, attributed to fast feedback and effective study recommendations.

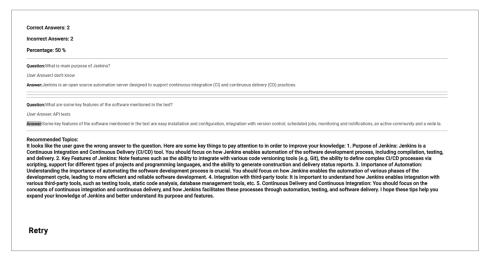


Figure 2: Example of test results with study recommendations

Advantages of this approach are significant. It is scalable and able to accommodate multiple documents as well as numerous student tests, which is beneficial to large classes and institutions. Guided learning supported by fast feedback and personalized learning recommendations promotes effective learning. Teaching staff can focus more on teaching and learning materials, while spending less effort on administrative tasks.

The process of continually monitoring the automatically generated questions as well as the correctness of the evaluations performed by the LLM is essential. If not properly managed, LLMs can be as prejudiced as the data used to train them, and this has to be monitored and adjusted. Future considerations involve integration with Learning Management Systems and improvements in accuracy and relevance by constantly updating and training the LLM with new data.

Conclusion

Integrating LLMs and LangChain in educational settings presents a promising approach to automating knowledge test generation and answer evaluation. This technology can contribute to the improvement of the learning experience and increased success for students by offering valuable and specific feedback and study recommendations. Despite challenges identified in this case study, the experience is definitely positive and should encourage adoption and further development of educational technology in the future.

