Leveraging Interactive Generative AI for Enhancing Intuitive Learning

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This paper explores the use of interactive Generative AI (GenAI) in intuitive learning, highlighting two key advancements successfully implemented in the Stellar Nova platform. First, GenAI-generated scientific graphs enhance visual and intuitive learning experiences, enabling students to grasp complex concepts more effectively while making the learning process more interactive and personalized. Second, an AI-human collaborative framework leverages LLM-based agents with advanced conversation understanding and task execution capabilities. These agents work autonomously, coordinate seamlessly, and generate customized course content based on developer input. Empirical studies show that the AI-generated courses have been well-received by students, and the framework has demonstrated strong scalability in real-world deployment.

1. INTRODUCTION

Learning is a core pillar of social impact. However, a recent College Board report [1] revealed that 60–70% of students scored a three or below on AP exams in STEM subjects such as Physics, Macroeconomics, and Calculus. After school, many students struggle to find adequate resources to clarify concepts they did not fully grasp in class, highlighting a significant need for more intuitive learning tools. The rise of Interactive Generative AI (GenAI) presents a timely solution. This technology enables real-time interaction by dynamically generating content in response to user inputs. Since its emergence, many students have turned to tools like ChatGPT [2] to get support outside of school. As another example, Khan Academy introduced Khanmigo [3], an AI-powered tutor that guides students through step-by-step interactions to enhance logical reasoning skills.

Despite these advancements, intuitive learning through interactive GenAI remains in its early stages [4]. Its full potential has yet to be explored and integrated into mainstream education. Large Language Models (LLMs) have proven highly effective across diverse tasks, positioning them as foundational models for building autonomous agents [5-6]. The potential of collaborative problem-solving using a chat-based framework where an LLM agent and a user proxy agent simulated a conversation to solve complex math problems was demonstrated in [7]. As tasks grow more intricate, these systems provide a transformative method for leveraging LLMs to solve challenges across various domains [8-15].
This paper explores how interactive Generative AI (GenAI) can enhance intuitive learning through two key approaches:

- Generating Scientific Graphs – Leveraging GenAI to create visual and intuitive learning experiences, helping learners grasp complex concepts more effectively while making the learning process more interactive and personalized.
- AI-Human Collaborative Course Generation – Utilizing multiple LLM-based agents working in collaboration with human educators to generate structured courses.

To the best of our knowledge, this is the first global initiative to integrate interactive GenAI with human-AI collaboration for developing commercially viable courses with practical applications.

2. GRAPH GENERATION USING GENAI

As shown in Fig. 1, a machine-learning problem for typical question-answer problems is demonstrated, where T refers to the question that needs to be solved, A the final answer, S the logical steps needed to reach the solution, D the diagrams or scientific graphs that pair with S, N the total number of logical steps, thus $S = \{S_1, S_2, ...S_N\}$ and $D = \{D_1, D_2, ...D_N\}$. Mathematically, the problem to be resolved can be formulated as:

$$\max P(A, S, D \mid T). \quad (1)$$

Figure 1. A Neural Network to Resolve Question-Answer Pair Training

To the best of our knowledge, the current state-of-the-art in GPT models, including the latest GPT o1, does not demonstrate sufficient capability to directly generate D from T. Therefore, an intermediate representation is necessary to bridge this gap. A causal graph emerges as a viable option because it delineates internal reasoning logic, thereby preventing GPT from generating nonexistent relationships between quantities through hallucination. The primary contribution of the causal graph lies in establishing the correct sequence for the command list, aligning with vertices along a desired path. Let G represent the internal graph associated with a question T, we can generate the network architecture for graph generation as demonstrated in Fig. 2, where the Causal Graph Transform module converts T into G. This transformed G is then concatenated with T and input into a fine-tuned GPT model to train and generate A and C, where C is a list of commands that can be utilized to derive D and S . The outputs A and C undergo processing in a text processing and rendering module. Here, A is separated from C, and the commands are used to derive S and D . This step ensures that the process is presented in a format that is more intuitive for humans, complemented by diagrams to enhance user understanding.

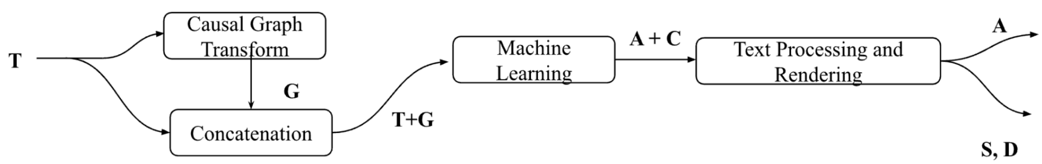

Figure 2. The GenAI Network Architecture for Graph Generation

Clearly, the Fig. 2 is to resolve the problem that can be formulated as:

$$\max P(A,\ S,\ D|\ T), \tag{2}$$

The NLP understanding of   and generation of   can be achieved by using a GPT model (e.g., GPT 3.5) and it was observed that the accuracy is very high, which means:

$$P(G\mid T)\ \approx\ 1 \tag{3}$$

Then Eq. (2) can be rewritten as:

$$\begin{aligned} P(A,\ S, D,\ \mid T,\ G)\ &=\ \frac{P(A,S,D,T,G)}{P(T,G)} = \frac{P(A,S,D,T,G)}{P(T)P(G|T)} \\ &\approx \frac{P(A,S,D,,T,G)}{P(T)} = P(A,\ S,\ D,\ G\mid T)\ \approx\ P(A,\ S,\ D\mid T), \end{aligned} \tag{4}$$

as $(A,\ S,\ D)$ are almost independent from G. The equation shows that solving Eq. (2) provides the solution to Eq. (1). Therefore, the solution presented in Fig. 2 can be applied to address the problem illustrated in Fig. 1.

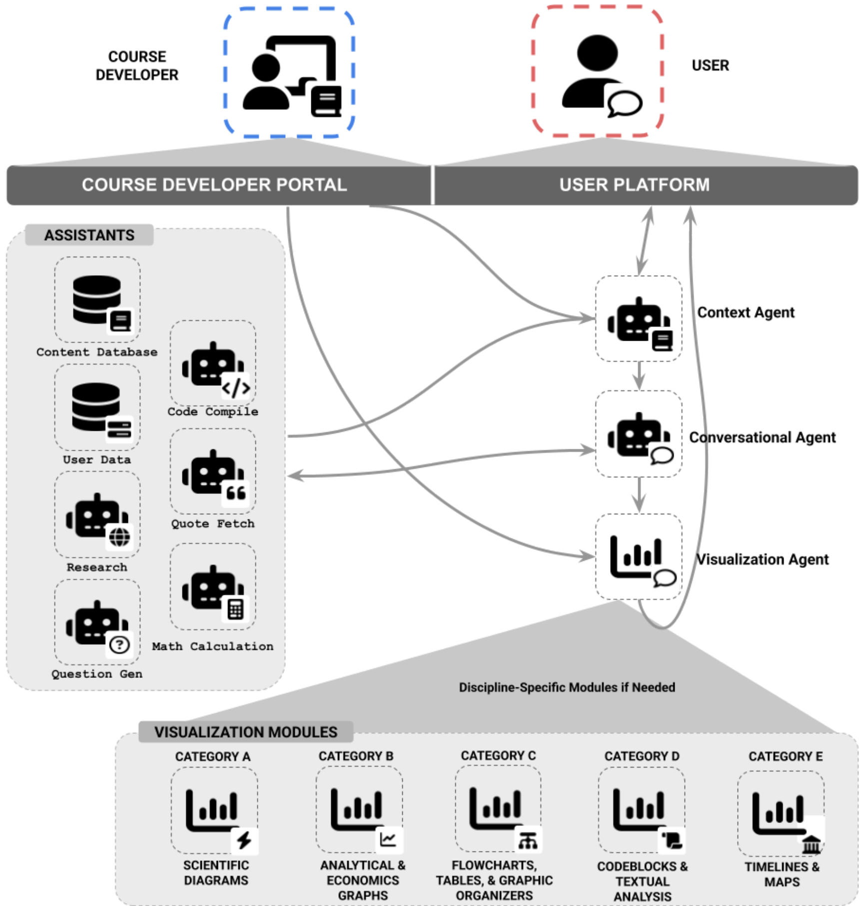

Figure 3. The Human and AI-agents Collaboration Framework

3. HUMAN AND AI-AGENTS COLLABORATION FRAMEWORK

In this work, we explore an automation framework for course developers to develop multiple courses simultaneously and for learners with a unified interface. As shown in Fig. 3, the framework consists of two human roles and four specialized agents, and each agent is equipped with dual capabilities: conversation understanding and task execution. The human roles include the end user (or learner) and the course developer. The end user interacts with the system to study and engage with available courses, while the course developer creates and uploads courses to the platform for learners to access. The functionalities of the four specialized agents are detailed in the following workflows, which outline the processes for both the learner and the course developer.

The learner experience in our framework is designed to be seamless and user-friendly. When a learner submits a natural language query, the Context Agent analyzes the input to determine its intent and relevance to the course content. It then identifies the appropriate course context and forwards this information to the Conversational Agent, which serves as the system's "brain". The Conversational Agent interprets the query, generates, or retrieves a suitable response, and, when needed, activates the Visualization Agent to create visual outputs. These visual aids enhance comprehension, making the learning process more engaging and effective.

As shown in Fig. 3, the Visualization Agent is divided into five modules, corresponding to various categories that collectively cover all currently designed courses, with individual courses often utilizing multiple categories. Importantly, the system is extensible, allowing for new categories to be added in the future. This ensures the Visualization Agent remains flexible and adaptable to handle emerging disciplines that may require novel types of visual outputs. The System Assistant is a specialized LLM agent equipped with tools to handle a wide range of tasks assigned by Conversational Agent, such as question generation, user data tracking, supplies information management, code compiling, real-time information retrieval and so on. These tools are seamlessly integrated into the workflow of the Conversational Agent, ensuring a cohesive and interactive learning experience. By leveraging these specialized agents, our framework streamlines input processing, generates meaningful responses, and presents information in an engaging format, enhancing both learning efficiency and effectiveness.

For course developers, the framework offers a dedicated interface, the Course Developer Portal, designed as a clean and intuitive dashboard. Through this portal, developers can customize the data used by the Visualization Agent and Assistants they wish to incorporate into their courses. For visualizations from the Visualization Module, such as diagrams, developers have the option to create custom visual elements not available in the existing library, using an interface tailored to the specific category of the visualization. In terms of content, the portal provides tools for adding the course syllabus, units, and lessons, along with a selection of pre-made practice questions. This content would later be able to be referenced by Context Agent and Content Database Assistant. These resources enable developers to input a wide range of course-related data, including lessons, practice questions, answers, charts, agent behavior customizations, and diagrams. All content is stored in a unified knowledge base, which supports both the course development process and the generation of answers for end users. This seamless integration ensures that the effort invested in course creation directly enhances the learning experience, effectively connecting the process of course development with the delivery of engaging and interactive educational content.

Once a course's knowledge is stored in the system, the LLM takes on the responsibility of generating answers to any user queries. This capability allows the system to handle a wide variety of courses within a unified framework, eliminating the need for architectural changes. The same principle applies to visualization efforts—once the type of chart or graph is defined, data from different courses is processed uniformly. This ensures that the same structure can be reused across all courses and disciplines, streamlining both knowledge delivery and visualization, regardless of the subject matter.

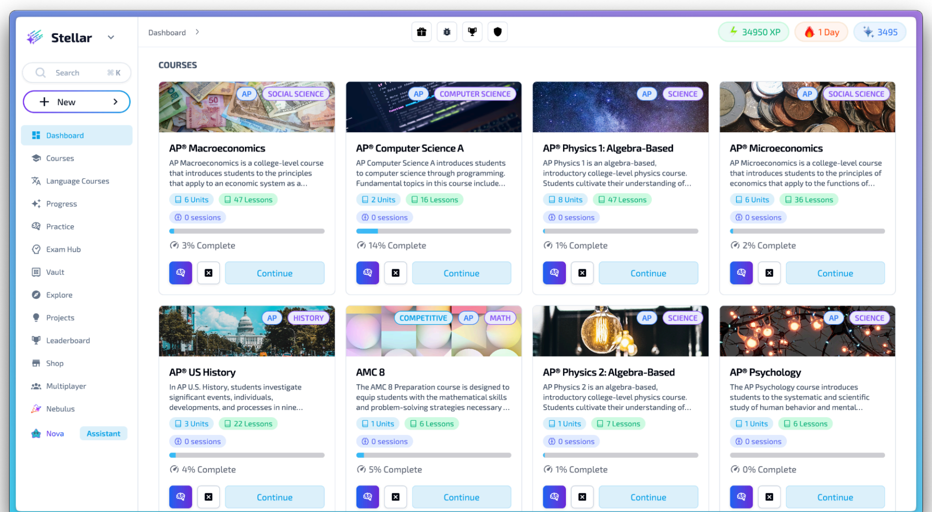

Figure 4. Courses Page of Stellar

4. CONCLUSION

The proposed interactive GenAI techniques [16] have been implemented in an intuitive learning platform called Stellar Nova [17], launched in November 2024. As of this paper's submission, over 500 students have used the platform, with 20% engaging for more than an hour almost daily. User feedback has been overwhelmingly positive. One student shared, *"Nova helps me visualize concepts in Economics and Physics in ways that other AI tools, like ChatGPT, can't. I appreciate the detailed, step-by-step explanations for solving problems."* Another student noted, *"I struggle with History, but Nova makes learning easier by generating timelines, tables, and Venn diagrams. I also love that it creates practice questions and provides multiple ways to answer them."* So far, over fifteen courses have been developed using GenAI technology and deployed on the platform, as shown in Figure 4, the course page of the product.

5. ACKNOWLEDGEMENTS

We would like to extend our special thanks to Neel V. Parpia, Chief Technology Officer at Stellar, for his outstanding work on developing the user interface, LLM streaming capabilities, and custom markdown format of Stellar Nova. We also thank Amaar M. Chughtai, and Warren Y. Li, who were invaluable as developers throughout the project through UI and Prompt Engineering. We also would like to extend our thanks to Aaryan D. Parikh, Aditya V. Siddabathuni, and Alex H. Chen, who played a vital part in the non-development-related aspects of Stellar. We also thank all of our other volunteers at Stellar.

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