Empowering Education: A Paradigm Shift in Content Delivery Through Automated Personalization

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Abstract
E-learning platforms have evolved to become essential instruments for educational content delivery. However, a significant challenge lies in the development of high-quality educational content, a process often constrained by resource-intensive requirements and the expertise necessary for content creation. This study introduces an innovative system designed to revolutionize content creation and delivery in an educational setting by leveraging the capabilities of Natural Language Processing (NLP) and Large Language Models (LLMs), specifically Generative Pre-Trained Transformers (GPT). Our approach utilizes prompt engineering, a method of tailoring input text to guide the output of these models, thus generating content that is aligned with the specific needs of educators and learners.
Empirical evaluation of our system indicates promising results. User feedback reveals a high acceptance rate, with approximately 84% of participants expressing satisfaction. Moreover, 82% of users verified the accuracy of the generated content, and 83% indicated their willingness to integrate this content into their teaching practices.
This research also aims to explore further the potential of automated content creation in enhancing networked learning environments. Our focus will be on expanding the applicability of this technology and investigating its impact on the broader educational ecosystem.

Keywords
Education, Natural Language Processing, Content Generation

Introduction

As the demand for a high-quality education continues to surge, there is a growing interest in harnessing the potential of Intelligent Tutoring Systems (ITS). These educational tools represent an advancement in the realm of educational technology. An ITS is a technologically empowered system designed with the primary goal of providing students with a highly personalized and meticulously tailored learning experience, specifically catered to the dynamics of their classroom settings.

One of the key distinguishing features that render ITS a game-changer in education is its inherent capacity to engage in continuous monitoring of a student's progress and comprehension during the learning journey. This dynamic interaction between technology and pedagogy fosters a more supportive and effective learning environment.

Despite the undeniable benefits that ITS bring to the educational landscape, it is important to acknowledge a practical consideration. As educators navigate the intricate terrain of the learning process, there inevitably comes a point where they must generate bespoke content that aligns seamlessly with their classroom's unique objectives and student demographics. While this customization is essential for delivering a truly tailored educational experience, it also demands a considerable investment of time and effort. (Nkambou R. 2010)

Other challenges in educational content creation include: tailoring the content for a large number of students means taking into account a diverse range of learners; meeting regulatory compliance means involving subject experts and course coordinators to ensure the content meets the students need; keeping content relevant is difficult when content is curated for learners in one culture and then exported to learners in another varying culture.

The system proposed interfaces with the GPT model and has been designed to carry out various educational tasks such as generating lesson plans and generating questions for students to answer. Such a system has the potential to disrupt education as we know it by changing the way content is created.

As Networked Learning is the process of a collaborative learning experience whereby learners relate to educators and other learners, such a system has the potential to impact this new way of learning by using AI (Artificial Intelligence), one such way AI could have an impact is by focusing on AI-driven feedback systems which in turn facilitates peer-to-peer feedback and educator guidance. (Networked Learning Editorial Collective 2021) (Jia, F. Sun et al 2022)

Motivation

The motivation behind this research is driven by the compelling prospect of automating the content creation process within the context of an ITS. This would significantly reduce the amount of time and effort required by educators to generate content. The overarching goal of this project is to harness the power of automation to streamline and enhance the creation of educational materials, thereby addressing several critical challenges in contemporary education.

At its core, the concept of automated content production represents a paradigm shift in the way we envision and implement personalized learning environments. In traditional educational settings, the process of tailoring instruction to the individual needs and learning styles of each student can be a labour-intensive and time-consuming endeavour. However, with the advent of automated content creation, we have the potential to revolutionize this aspect of education.

One of the primary advantages of automated content production within ITS is its capacity to significantly enhance the scalability of customized learning environments. In essence, it empowers educators and ITS developers to efficiently generate a vast array of tailored educational materials without the constraints of time and resources that typically accompany manual content creation. This scalability is of paramount importance, especially in educational contexts where a wide range of students with diverse learning requirements need access to high-quality instruction.

Moreover, the integration of automated content creation into ITS has the potential to amplify the effectiveness of the learning experience. The ability to rapidly adapt and generate content that precisely aligns with each student's unique needs and proficiency levels is a game-changer. It ensures that learners receive instruction that is not only personalized but also optimally challenging, striking the delicate balance between providing support and fostering independent learning.

Objectives

This research aims to investigate what approaches and technologies are required to build a system that can generate educational content from a NLP prompt and how such a system can impact networked learning.

Thus the following objectives were identified:

- Investigating state-of-the-art NLP models and techniques relevant to building the proposed system, particularly the GPT series of models
- Identification of NLP models and techniques for a system that can output content for the classroom from a natural language prompt

Literature Review

Intelligent Tutoring Systems

ITS offer personalized, one-to-one education using AI and Machine Learning. They enhance learning by providing immediate guidance and feedback and analysing student behaviour to adapt to their needs and preferences.

An Intelligent Tutoring System (ITS) consists of key components that collaborate to deliver personalized learning experiences:

- Student Model: The student model represents a learner's performance, knowledge, and preferences. It evolves as the student progresses, enabling tailored feedback and assistance.
- Tutoring Strategy: The ITS employs a tutoring strategy that customizes education through AI. It focuses on modelling domain knowledge, diagnosing student understanding, and providing feedback and guidance based on individual needs.
- Content Library: ITS relies on a content library comprising multimedia resources such as text, images, and videos. These resources enable flexible and personalized learning experiences.
- User Interface (UI): The UI serves as the point of interaction between the student and the system. It aims to facilitate learning and engagement, offering progress tracking, clear instructions, and adaptive content to create an immersive learning environment.

In summary, ITS components work together to provide adaptive, personalized education by understanding and responding to each student's unique needs and progress.

Benefits And Challenges

Intelligent Tutoring Systems (ITS) aim to provide personalized learning experiences, adapting to individual student needs through machine learning analysis of interactions. They offer immediate feedback, which is particularly valuable for complex subjects. ITS also tailors its teaching methods to match students' learning styles, whether visual or auditory. These systems grant instant access to up-to-date educational resources, including

libraries, simulations, and games. Educators benefit from automated grading and the ability to identify struggling students for timely support.
Despite their advantages, ITS development and maintenance can be costly, and assessing their effectiveness is challenging. However, they extend educational access globally and cater to various learning demographics, including students with disabilities.
Automated Content Generation Within ITS
Automated content creation offers the advantage of rapidly generating substantial information, which is invaluable in industries like science and technology. Moreover, it can customize content for individual students by analysing their learning preferences, progress, and performance data.
An example of this is MathBot, a conversational chatbot. A system that provides students with feedback. The system uses a conversational graph to generate questions and direct the conversation such that when a flaw in the learner's logic is detected, earlier concepts will be reviewed. (Grossman et al 2019)
Nevertheless, our research has identified a void in the current landscape of educational systems, as none appear to be utilizing LLMs for the generation of educational content. This observation underscores the necessity and relevance of the proposed work.

Large Language Models

LLMs are deep neural networks trained on extensive text data to generate human-like natural language content. These models have gained prominence due to their impressive language comprehension and human-like content creation. We delve into their nature, functioning, diverse applications, and potential ethical concerns.
AI systems known as LLMs can comprehend natural language and produce writing that appears human-generated. These LLMs rely on deep neural networks, a type of machine learning model skilled at discerning intricate patterns in data. During training, massive volumes of text data, including novels, news stories, and web pages, are fed to LLMs. (Cheng, Huang, & Wei, 2023) They learn to predict the subsequent word in a sentence based on previous words, developing a profound understanding of word relationships and context. (Schwenk H. 2005)

The Educational Landscape

Throughout the past few decades, the educational system has seen changes in the way that education is approached, with persons seeking to digitise and automate the way things are done. Taking Sweden as an example, the educational policies of Sweden have acknowledged automation as far back as 1957 and major reforms from as early as 1969 aimed to digitise the curriculum. (Rensfeldt, A. B., & Rahm, L. 2023) (Rensfeldt, A. B., & Player-Koro, C. 2020)
When it comes to education being combined with AI, it is important to consider the imaginaries (the big ideas or visions that people have about the future of education with AI) and the problematisations (problematisations are the specific issues or challenges that these visions aim to address). Problematisations operate under the assumption that something needs to be fixed. (Rahm, L., & Rahm-Skågeby, J., 2023)
Educational problems and technological solutions, particularly through the lens of AI, relate in a way that AI aims to address key challenges in education. When analysing educational systems, certain problematisations surface, such as the lack of personalisation in educational content, the imaginary related to this would be the idea of implementation of AI systems to produce content personalised towards the student that is making use of the content, considering their unique needs and preferences. Other problems and their consequent solutions include the amount of administrative work required by educators and how in turn, these administrative tasks can be automated by AI or how there is a lack of standardisation in grading students' work and how AI could be used to grade and provide feedback.
The imaginaries, however, introduce their own set of concerns, such as where the processing of student data is concerned, what privacy and rights do the students have in such a situation and whether the algorithms used could be biased and thus do more harm than good. Another concern raised, is the explainability of AI education systems and how some of these systems are not necessarily transparent in their decision-making processes.
Due to the evolution of educational technology and automation, it is logical to raise the question of whether new technologies (such as LLMs) can be used to facilitate learning and make it more accessible to others who for one reason or another struggle to learn. LLMs already have a myriad of applications in education, for instance, LLMs can be (and are) used to create a digital teacher, whereby the student can be taught by a digital agent while the student can also ask questions of the agent.

Methodology

The system (explained in detail in Figure 1) that is being proposed in this research makes use of prompt engineering techniques which are combined with an LLM. Prompt engineering enables us to steer the model towards a desired output by honing the given prompt and being direct about what is needed. Thus, enabling the LLM to generate outputs which are accurate and contextually appropriate. The LLM being leveraged in this instance has been trained on a vast and diverse dataset, enabling the LLM to generate accurate and appropriate outputs.
The function of receiving the information from user input is vital. This is achieved by supplying the user with a Graphical User Interface (GUI). The GUI provides a grid of functions each accompanied by an interface which has been designed to be user-intuitive, enabling educators to easily navigate the system. The functions available in the system include functions such as generating questions, generating ideas and the summarisation of text.

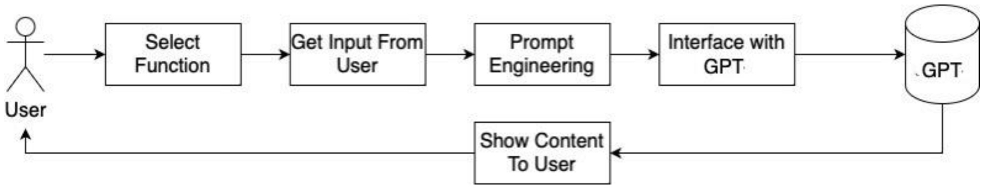

Figure 1: Interaction between the user, system and GPT (Source: Author)

Prompt Engineering

After a function has been selected, the system makes use of prompt engineering to get the desired output from the given input. The details of the prompt engineering process are not visible to the user and are done in the background by the application. This means that before the prompt is sent to GPT, the prompt is modified by adding text before or after the input.
The prompts were designed by taking the desired function into consideration along with the required input, which is prepended to the input. An example of this would be the summarisation feature where the keyword “Summary” followed by a colon is put after the text to be summarised, like the prompt structure used in zero-shot learning. The main challenge encountered regarding prompt engineering during this research was ambiguity, prompts were refined to be non-ambiguous through a process of iterative experimentation.

Training The Model

Training a machine learning model involves providing it with a dataset containing pairs of input and output. This enables the model to learn and subsequently make predictions on new input data. In the specific case of our model, it was trained using a synthetic dataset, which means that instead of utilizing real-world data, the dataset was artificially generated.
For many of the tasks that the model was designed to perform, this synthetic dataset encompassed a wide range of input and output pairs. The synthetic dataset was created through GPT itself, by using prompts and examples generated randomly which were taken as the input value for training and GPT’s output which was taken as the output value for training. This was chosen over real-world data due to the ease of collecting AI-generated responses rather than manually crafting both the input and output values for training the model.
The synthetic dataset was formed by generating a wide array of prompts encompassing the system functions and then relying on GPT to generate the output value of the input-output pair.

Evaluation

To assess the system and methodology of this study, various aspects were identified and analysed. A questionnaire was subsequently distributed via online channels such as social media to gauge real-world user experiences with these system aspects. The questionnaire garnered a sample size of 156 respondents consisting of educators primarily located in Malta.
The initial three questions were asked with the aim of assessing the system’s content generation capabilities. The question “This tool can be useful to create worksheets” got an 85% positive response rate, the question “The content generated is relevant” got a 79% positive response rate and “The content generated is correct” got an 82% positive response rate. The fourth question “I would use this tool in my classroom”, the positive response rate was 83% indicating that the system would see real-world adoption. From these results one can see that the content

generation capabilities of the system get a positive sentiment. These results also indicate that the system is good at producing the required content.
From these four questions, one can conclude that the system has a good potential to solve the problem initially mentioned as the responses from the educators have been overwhelmingly positive. The majority of the rest of the non-positive responses were at the Neutral option, with the negative options being selected rarely (less than 4%). This indicates that while there is room for improvement, there is no reason to believe that the system's way of producing content is flawed.
However, we also wanted to test whether the system could potentially be expanded for student use. Thus, educators were asked whether they thought that the evaluated system would allow students to take a hands-on approach to their learning. 73% were positive this would be the case, however, the other 27% were not convinced of this, responses varied from reasons such as the system completing the student's work for them to the respondent believing that students need a physical hands-on approach to learn. When surveyed on whether the system would help with better learning outcomes, the positive response rate was 78% with the rest of the respondents leaning toward a neutral sentiment. When asked the reason for their answer, most participants highlighted that such a system would be engaging for students due to its electronic nature.
These results bode well and serve to introduce new possibilities in the realm of content creation in education by showing that making use of LLMs in educational systems is a viable solution. Something which is only now being explored.

Ethics

While such a system has the potential to aid education, when making use of AI in any domain, especially one that deals with a vulnerable group, one must consider the ethical ramifications that such integrations present. Such concerns include:

- Data Privacy: Such a system would be privy to a significant amount of data such as student information and educational materials. It is important to ensure the privacy and security of this data.
- Bias: As LLMs are trained on large datasets, they may exhibit biases as a consequence of those biases being present in the dataset they were trained on.
- Lack of Human Expertise: While the system aims to assist educators in content creation, there is a risk of over-reliance on automated systems. It is important to recognize that human expertise and judgment are essential in the educational process. The system should be seen as a supplementary tool rather than a substitute for educators.
- Explainability: AI systems, including NLP models, can be complex and difficult to understand. It is important to ensure that the system's decision-making processes are transparent and explainable.

Addressing these ethical concerns is crucial to ensure the responsible and ethical implementation of the proposed system in education. Future system iterations could seek to address these issues by employing algorithms to redact sensitive data before it can be processed by the system and employing LLMs which are designed with explainability in mind and with measures against bias in place (such as Reinforced Learning with Human Feedback where a reward model trains the LLM to be less biased.

Conclusion

Large language models offer immense potential for language interaction, spanning creative writing, natural language processing, and beyond. However, their usage raises critical ethical concerns, such as data privacy and bias. Safeguards and ethical guidelines must be established, as bias within the LLM used could lead to unfair outcomes for some groups of students (Baker & Hawn, 2022; Zhang et al., 2023; Weidinger et al., 2021). Furthermore, concerns such as what data is collected when such systems are used is of vital importance to address. Despite these concerns, large language models hold vast potential in NLP, revolutionizing language interaction, improving communication, and advancing research across domains.
The findings of this work show that there is a gap when it comes to creating content for education using AI. The results in the evaluation show a positive attitude towards such systems and strongly suggest that the proposed system would be beneficial out in the field. The implications on these findings could potentially impact how education and networked learning are approached.
Future work on this system will focus on expanding the system such that it is also for student use such that the student could generate materials on their own without requiring input from an educator. Furthermore, more

investigations will be carried out with regards to the ethical issues that present themselves currently such that the correct precautions will be taken.

References

Baker, R. S., & Hawn, A. (2022). Algorithmic Bias in Education. *International Journal of Artificial Intelligence in Education, 32*(4), 1052-1092. https://doi.org/10.1007/s40593-021-00285-9

Cheng, D., Huang, S., & Wei, F. (2023). Adapting Large Language Models via Reading Comprehension. arXiv preprint, 2309.09530.

Graesser, A. C., Hu, X., & Sottilare, R. (2018). Intelligent tutoring systems. In *International handbook of the learning sciences* (pp. 246-255). Routledge.

Grossman, J., Lin, Z., Sheng, H., Wei, J.T., Williams, J.J., & Goel, S. (2019). *MathBot:* Transforming Online Resources for Learning Math into Conversational Interactions.

Jia, F., Sun, D., Ma, Q., & Looi, C.-K. (2022). Developing an AI-Based Learning System for L2 Learners' Authentic and Ubiquitous Learning in English Language. *Sustainability*, *14*(23), 15527. https://doi.org/10.3390/su142315527

Networked Learning Editorial Collective (NLEC). (2021). Networked Learning: Inviting Redefinition. *Postdigital Science and Education, 3*(2), 312-325. https://doi.org/10.1007/s42438-020-00167-8

Nkambou, R., Bourdeau, J., & Psyché, V. (2010). Building intelligent tutoring systems: An overview. *Advances in Intelligent Tutoring Systems*, 361-375.

Rahm, L., & Rahm-Skågeby, J. (2023). Imaginaries and problematisations: A heuristic lens in the age of artificial intelligence in education. *British Journal of Educational Technology, 54*(5), 1147-1159

Rensfeldt, A. B., & Player-Koro, C. (2020, December). "Back to the future": Socio-technical imaginaries in 50 years of school digitalization curriculum reforms. In *Seminar. net* (Vol. 16, No. 2, pp. 20-20).

Rensfeldt, A. B., & Rahm, L. (2023). Automating Teacher Work? A History of the Politics of Automation and Artificial Intelligence in Education. *Postdigital Science and Education*, *5*(1), 25-43.

Schwenk, H., & Gauvain, J. L. (2005, October). Training neural network language models on very large corpora. In *Proceedings of human language technology conference and conference on empirical methods in natural language processing* (pp. 201-208).

Wang, X., Gao, S., & Lajoie, T. (2019). The Impact of Intelligent Tutoring Systems on Student Learning: A Meta-Analysis. *Educational Psychology Review*.

Weidinger, L., Mellor, J., Rauh, M., Griffin, C., Uesato, J., Huang, P.-S., Cheng, M., Glaese, M., Balle, B., Kasirzadeh, A., Kenton, Z., Brown, S., Hawkins, W., Stepleton, T., Biles, C., Birhane, A., Haas, J., Rimell, L., Hendricks, L. A., Isaac, W., Legassick, S., Irving, G., & Gabriel, I. (2021). *Ethical and social risks of harm from Language Models*. arXiv preprint, 2112.04359.

Zhang, J., Ji, X., Zhao, Z., Hei, X., & Choo, K.-K. R. (2023). *Ethical Considerations and Policy Implications for Large Language Models*: Guiding Responsible Development and Deployment. arXiv preprint, 2308.02678.