Enhancing Online Learning Interactions: Investigating the Potential of GPT-3 for Personalized and Engaging Educational Experiences

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I. ABSTRACT:

Our research focuses on the development and implementation of the PATHWISE learning companion robot, an educational technology designed to provide personalized and socially interactive learning experiences for students. The robot utilizes artificial intelligence to generate prompts and cues that are both engaging and efficient in supporting student learning. We investigate the parameters used to ensure the appropriateness of the generated prompts, such as content maturity and complexity levels, and the role of instructors in selecting the reading assignments used to generate the prompts. The research highlights the potential of the PATHWISE learning companion robot to enhance the social aspect of learning in online education as well as the ability to replicate human-like comments similar to that of a human instructor.

II. BACKGROUND:

GPT-3 (third generation Generative Pre-trained Transformer) is a network machine learning model that has been trained on internet data to generate text. It was developed by OpenAI, in hopes of generating output text that is both sophisticated and relevant to the input that is provided. The model is built on a deep learning neural network, with over 175 billion machine learning parameters. The model is capable of performing a wide range of NLP tasks such as machine translation, summarization, question answering, and text completion. The goal of this technology is to provide human-like responses to text that is provided based on a small segment of input from the user. The benchmark utilized by our group to determine whether or not a comment was sufficient or not was a framework developed by a grad student on our research team. The goal for the type of comments produced by our tool were three types of comments, knowledge, social, as well as interest comments, all comments that serve a purpose between the student and instructor interaction.

III. FRAMEWORK:

The framework presented outlines three types of comments: Knowledge Comments (KC), Social Comments (SOC), and Interest Comments (IC). Each comment type aims to foster different aspects of a child's learning and social experience while engaging with the content.

Knowledge Comments (KC) are designed to enhance the child's understanding of the content. There are four subcategories of Knowledge Comments:
a. KC1 - Prediction: These comments encourage children to make predictions based on information from the text. Example: "I know seals are smaller and less able predators than sharks. I bet the great white shark would eat the seals!"
b. KC2 - Summarize: These comments provide concise summaries of important ideas and themes from the text. Example: "The great white shark is big and fast, making it a great hunter. When the shark is hunting, she uses her sense of hearing and her sense of smell to search for food in the ocean even when it can't see the prey!"
c. KC3 - Questioning: These comments ask questions that prompt the child to think critically about the text's content. Example: "Lagoons exist because something will separate

them from the oceans. Look at the picture, what do you think separates this lagoon from the Pacific Ocean?"
d. KC4 - Vocabulary Support: These comments clarify complex or confusing terms for young children. Example: "How sneaky! Mimicry is an adaption that living things use to trick predators."

Social Comments (SOC) aim to establish a connection between the child and the robot, making the learning experience more engaging and enjoyable. There are four subcategories of Social Comments:
a. SOC1 - Robot Self Disclosure: These comments reveal personal information about the robot, helping the child see it as a friend and a peer. Example: "I remember when I went for a hike in the forest with my friend Minnie once, I almost got lost! But I loved being around nature."
b. SOC2 - Recall Past Interactions: These comments reference shared experiences between the child and the robot to build a sense of shared history. Example: "I really liked when we read about the hiking adventure in the wild robot. I wonder if we'll see Sam get lost in the forest like the robot did."
c. SOC3 - Memory and Adaptation: These comments personalize the experience by catering to the child's topic preferences, which have been collected for each child. Example: "#space @userid I know you will love reading this book because it's all about space!"
d. SOC4 - Emotional Response: These comments include an emotional response from the robot, based on Plutchik's wheel of emotion. Example: "[sad] This makes me so sad. I can't believe the forest fires killed so many animals."

Interest Comments (IC) aim to spark the child's interest and motivation to engage with the content. There are two subcategories of Interest Comments:
a. IC1 - Value: These comments convey the value of the content by relating it to something important or valuable to the child or society. Example: "I'm so used to technology that sometimes don't even notice it. But I know the programming they talk about in this book helps fly planes, invent new medicines, and predict earthquakes. I love how much computer science can actually help people."
b. IC2 - Belongingness: These comments highlight the work, skills, and practices of scientists and how children can participate in similar activities. Example: "I like science because there is always so much more to discover. I can see you adding a lot to the science community too!"

IV. METHODS:

The method to collect data on the effectiveness of comment generation using this model was to test the GPT-3 model on different inputs. Different inputs were used, with varying texts from scientific journals, to observe the responses that the model would provide. These texts were also accompanied with text to prompt the model to generate a comment based on the text. The inputs and prompts were carefully selected to cover a broad range of topics and levels of complexity, and ensure there wasn't any room for potential discrepancies.

A sample prompt used in the study could be:

> "The problem is that gillnet fishing isn't very selective. It's not just the target species (the ones we're trying to catch) that get caught. Everything from sharks to turtles are caught too. We call this bycatch – and most of the time these animals are thrown back into the sea, dead or injured. Generate a comment describing how you can relate to this text "

These comments were then analyzed for their relevance and appropriateness based on the criteria provided by the framework for comments. To gauge how the model would react based on the different parameters, the prompt to ask the model was also updated with varying parameters. These parameters included limiting word size, adjustments to tone and mood, and alterations to content maturity. These parameters were added in the input text, and the output was compared with previous runs. This was done to record how each parameter would affect the result and potential areas of improvement to generate a better comment.

Additionally, the model's performance was analyzed multiple times on the same input to ensure consistency of the output and to observe. any patterns or trends in the generated comments. The model needed to routinely generate appropriate responses, so it was tested multiple times to find potential outliers in outputs.

Overall, the method used in this study aimed to comprehensively evaluate the effectiveness of GPT-3 in generating relevant and accurate comments. The evaluation process involved testing the model on a diverse range of inputs and prompts and analyzing the generated comments based on objective criteria and guidelines. The results of the evaluation were analyzed to identify any patterns or trends in the data and to determine the overall performance of the model.

V. CONCLUSIONS:

The study on automating text generation using GPT-3 demonstrates the potential of this cutting-edge AI model to revolutionize online learning by providing personalized, engaging, and socially interactive experiences for students. By evaluating GPT-3's ability to generate contextually appropriate and relevant comments across various texts and prompts, the research sheds light on the model's strengths and areas for improvement.

Our findings indicate that GPT-3 can consistently produce comments that fall within the framework of knowledge, social, and interest, contributing to a more dynamic and interactive learning environment. Moreover, the ability to fine-tune the model's parameters, such as content maturity, tone, and complexity levels, allows for a more customized learning experience tailored to individual students' needs. However, it is important to acknowledge the limitations of the study and the model itself. While GPT-3 is a powerful AI tool, it is not infallible and requires ongoing evaluation and refinement. Instructors still play a crucial role in selecting appropriate reading assignments and monitoring the AI-generated prompts to ensure their relevance and suitability.

In conclusion, the PATHWISE learning companion robot, powered by GPT-3, holds promise as an innovative educational technology that can enhance the social aspect of learning and mimic human-like interactions between students and instructors. Future research should explore the long-term effects of integrating GPT-3-powered robots in online education and strive to optimize the model's performance to provide a seamless and enriching learning experience.

VI. REFERENCES:

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