

Engaging Students from Rural Communities in AI Education with Game-Based Learning

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ABSTRACT

As the presence of artificial intelligence (AI) technologies increases throughout everyday life, so does the need to engage rural communities in AI learning experiences, as these communities often have limited access to such educational opportunities. This work presents three game-based learning activities rooted in core AI concepts: natural language processing, search, and reinforcement learning. These activities were implemented in a summer camp with middle grades students in a rural area of the USA. We share an overview of the activities, as well as key observations and takeaways from student responses in post-activity surveys.

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1 INTRODUCTION

Recent advancements in AI in combination with the rapid adoption of these technologies have highlighted the need for K-12 AI education. Rural students are often at a disadvantage because they have limited access to these technologies as well as educational experiences that introduce them to AI concepts [1, 3].

To help address this disparity, our work presents three game-based learning activities that aim to teach concepts from core areas of AI [4]: natural language processing (NLP), search, and reinforcement learning (RL). These learning activities were incorporated into

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Figure 1: NLP activity.

a five-day, AI-focused summer camp for middle grades students. The camp was held in a rural community of the United States, and a total of 10 students participated. Students interacted with each learning activity for approximately 30 minutes and completed a post-activity survey. We present a description of each activity and the key takeaways from students' survey responses.

2 NLP ACTIVITY

One day of the camp focused on exploring “Natural Interaction” with AI systems. During this day, students completed an NLP-based chatbot activity. Prior to this activity, students were introduced to several NLP applications, such as speech recognition and sentence generation, and interacted with real-world applications like Siri. Students then engaged with the NLP game-based learning activity, where they were tasked with building a non-player character (NPC)’s dialogue (Figure 1). The interactions with the NPC followed a Use-Modify-Create scaffolding progression [2]. The first phase (*use*) allowed students to view example question-answer (QA) pairs and then ask the NPC various questions. Next, students could *modify* some of the answers to provided questions to see the impact of their changes. In the final phase, students were able to *create* their own questions and answers and see how the NPC’s dialogues could change based on student-authored QA pairs.

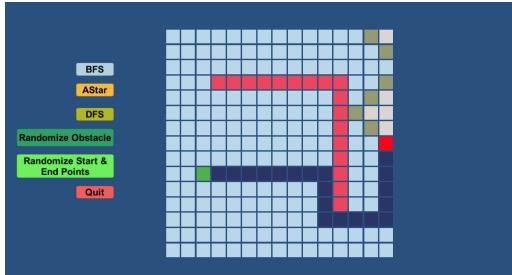


Figure 2: Search activity.

From the survey, students understood voice assistants' ability to process natural language. However, when asked for challenging scenarios for an AI system, students responded with examples of non-NLP tasks, such as taste food or have a physical presence. This indicates that students developed an understanding of the capabilities of AI, but not necessarily limitations of NLP. We could improve this understanding by incorporating nuances of natural language into the dialogue activity.

3 SEARCH ACTIVITY

We incorporated our search-based pathfinding activity into the summer camp day centered on “Perception” in AI systems. Students were first introduced to pathfinding using real-world examples (i.e., Google Maps). Then, we presented our game-based maze activity that incorporated three common pathfinding algorithms: Depth-First Search, Breadth-First Search, and A* Search. This activity was based on an existing open-source project¹, which we revised to meet our needs. Students were provided with a 2D grid where they could dynamically generate the start point, end point, and obstacles (Figure 2). Then, they could choose from the different algorithms to see how they explored the search space.

Based on the survey responses, real-world examples—particularly autonomous vehicles—resonated with students. Students generally answered that A* was most efficient, but were unable to provide detailed reasoning. Common responses, such as “not waste any more time,” indicated that while students understood the concept of efficiency, a clear comparison of algorithms was not evident. Future improvements will include adding self-driving cars into the activity to connect to real-world examples (e.g., creating a scenario where a car needs to get from one point to another). Additionally, incorporating rewards to distinguish the applicability of algorithms in different scenarios may help further improve students’ understanding of efficiency while promoting their engagement.

4 REINFORCEMENT LEARNING ACTIVITY

The reinforcement learning (RL) activity was incorporated into the “Machine Learning” day of the camp. An introductory presentation explaining RL and the concepts of agents, rewards, and exploitation and exploration was initially shown to students. They then interacted with the game-based reinforcement learning activity, built on

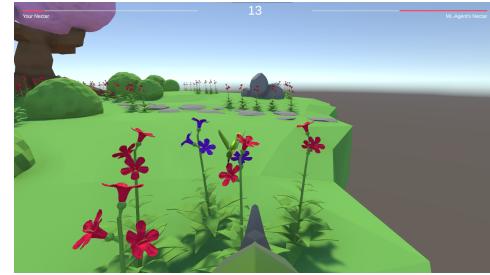


Figure 3: Reinforcement learning activity.

an existing public Unity project², where they acted as a hummingbird trying to collect nectar from flowers (Figure 3). In the game, students contend with an adversarial agent, another hummingbird, and must gather nectar from more flowers than the opponent. There were three levels of increasing difficulty in the game, with more difficult levels having an agent trained longer using RL.

Students were very engaged with the activity, often being vocal about wanting to beat the other hummingbird. Based on the survey, students were able to understand that the time spent training the adversarial hummingbird affected its performance. However, not many students associated negative rewards with performance. Additionally, several students were unable to define the agent in this setting and thought they were training the hummingbird through gameplay. Future improvements will include drawing a distinction between training the adversarial agent by itself and playing against an opponent. Furthermore, including more visualization of key concepts like rewards and exploration vs. exploitation could help.

5 CONCLUSION

Overall, students reported enjoying the activities and showed a high level of engagement in the activities. For future studies, we aim to incorporate AI ethics concepts into the materials and examine learning gain to assess the potential impact these materials can have for rural communities.

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¹<https://github.com/dbrizov/Unity-PathFindingAlgorithms>

²<https://learn.unity.com/course/ml-agents-hummingbirds>