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Board 157: Conducting the Pilot Study of Integrating AI: An Experience Integrating Machine Learning into Upper Elementary Robotics Learning (Work in Progress)

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1. Introduction

Artificial intelligence (AI) and Machine Learning (ML) are rapidly changing our civilization and will be critical tools in many future careers. AI/ML can analyze large amounts of data sets in a short time; it will support a lot of fields to solve problems in a highly efficient way. It is increasingly important to introduce basic AI/ML concepts to students to build familiarity with the technologies they will interact with and make decisions about. Ideally, all students graduating from high school should have some understanding of AI, the ethical issues associated with AI, and the potential strengths and weaknesses of a society built on top of computer intelligence [3].

Although AI is increasingly used to power instructional tools for K-12 education, AI concepts are not traditionally part of the curriculum below the college level [4]. AI tools and activities have only recently become accessible to upper elementary students. Existing ML tools are easy for teachers and researchers to use, and eliminate R&D steps. However, these tools are not designed for K-12 education, and they may be too complex for upper elementary students to truly understand or explain. Other studies have combined AI/ML with educational robotics platforms [5][6]. These, however, either emphasized coding or used systems that are quite different from other early childhood robotics platforms. Current educational research into the teaching of ML and AI to primary school students has primarily focused on commercially available AI like Apple's Siri or Amazon's Alexa [7],[8],[9]. This places students in the role of end-users of technology, a vitally important thing for them to learn, but does not address students' possible roles as creators of AI and ML models. While learning to use and explore the capabilities of ML and AI platforms is important as a component of machine learning education, we believe that is also critical for understanding the functioning of AI and ML to train ML models. The depth of understanding that comes from training is vital to prepare students to be not just consumers but innovators and informed decision-makers.

While AI is new, coding and robotics have been in the classroom for a couple of decades and have been shown to promote critical thinking, problem-solving, interest and engagement with STEM, and learning in mathematics and physics [10]. The use of LEGO® Education robots has been shown to decrease dropout rates and increase self-efficacy among beginning programming students[11]. So our design builds off of this work and centers around an embodied robotics program via LEGO® Spike. Zimmermann-Niefield et al. showed that middle school students are "able to collect data, build ML models, test and evaluate ML models, and quickly iterate on this process." Additionally, they found that students rapidly built mental models to explain the behavior of the ML models [12]. Our aim was to develop an educational robotics-based, tangible AI interface and complementary instructional approach to introduce simple ML concepts to upper elementary students. With ML-powered controllers to animate students' robotic inventions, we believe it is possible to provide students without any previous engineering or programming experiences with ML learning opportunities.

In this paper, we introduce the integrating AI program, design, preliminary pilot findings, and the future plan for this three-year ongoing project.

2. Overview of Integrating AI

2.1 Robotics Platform

We designed a hardware platform for these pilot tests with the following criteria:
(1) Built-in multiple ML algorithms to support students in exploring the learning behavior of different algorithms.
(2) A system that was compatible with upper elementary classrooms. Specifically focusing on hardware that is safe, accessible, and easy for upper elementary students to use and learn from and with.
(3) To use parts that could be combined to build more complex systems with engineerable behavior.

To meet these pilot criteria, we decided to use LEGO® Education Spike™ Prime for our first pilot test. The reasons we chose LEGO® Education Spike™ Prime are (1) they allowed built-in multiple AI algorithms so that students can explore several different algorithms without any coding, (2) they provided an easy platform for our prototyping and an easy operating system for upper elementary students, and (3) they are compatible with other LEGO kits and provided a flexible and expandable building toolset for students.

We chose a simple ML algorithm, Euclidean Nearest Neighbor, hoping that it would be easy for our students to understand and implement it in two different modes intuitively. One mode was the one we used most, using 3 features out of the color sensor (red, green, and blue) to decide the angle of either one or two motors. The second mode used the same algorithm to choose between one of four action primitives using a pair of motors to move forward, backward, clockwise, or counterclockwise. We will introduce the details of the activities in the below section. The Euclidean Nearest Neighbor algorithm classifies new data points by giving them the same label as the most similar data point in the training set. While designing the system we found that our intuition of color similarity matched reasonably well with the results of the nearest neighbor algorithm.

2.2 Program Goals

We focused on designing a suitable learning environment including lessons where students would learn about machine learning through the process of engineering robotic systems. By the end of the program, our goal was for students to:

(1) develop positive attitudes towards and self-efficacy with machine learning tools
(2) gain an intuitive understanding of the processes involved in supervised machine learning
(3) learn how robots sense and react to the world

With inquiry learning in mind, we decided to design lessons that first taught students about machine learning through exploration and inquiry into pre-trained models and then asked them to build physical systems with these pre-trained models before finally combining training and building.

2.3 Pilot Test

We designed interventions for three five-day-long summer workshops in St. Louis, Missouri for our first-year pilot program. Two programs in June were educational day camps which already included 2 hours per day of LEGO® engineering activities, so we applied our program in these sessions. The first site included 27 participating students and the second site included 19 participating students. The third program in July was a workshop focused on using LEGO® robots as actors in a film and there were 12 students.

The intervention was based on our existing robotics programming using Spike™ Prime robotics kits. As these programs were run in a wide variety of out-of-school program facilities with limited instructional technologies, we developed our activities and visual instructions around easily accessible printable worksheets. The research team served as content experts and led instructors during the intervention, delivering much of the instructional material. Classroom management was supported by summer program instructors who were familiar with the Spike™ Prime robotics kits but untrained in Machine Learning. The summer program instructors did not receive prior training in the intervention curriculum.

We designed four activities to support students in exploring our system, learning AI and ML training processes, and preparing for a final project.

The first activity asked students to point the color sensor at different colors and record the behaviors of the system. A single motor, a color sensor, and a pre-trained model were used in this activity. This activity aimed to introduce students to LEGO Spike™ Prime, color sensors, and the behavior of a trained model. The handout we used can be found in Figure 1. A lot of students attributed moods and behavior to the motor in this activity. They said the motor “liked” or “preferred” certain colors over others and several students said, “Yellow makes it happy”. Six out of the forty students wrote down diagrams and angle estimates (i.e. 60°) to describe the motor's behavior.

Figure 1: A filled-out worksheet from the activity to discover the setup of the pre-trained ML

The second activity asked students to use the same materials and pre-trained model to build an assistive device for people with color blindness. The goal of this activity was to help students operationalize their knowledge from the first activity by putting it into practice. This is also a corrective process that students who had attributed randomness or emotion to the robots' behavior in the first activity tested that behavior out in this new context and were able to see that the behavior was consistent with the consistent operation of the sensor. This design is based on placemat (Figure 2) designs by Willner-Giwerc[13],[14]. Figure 3 shows a student's solution to the placemat who also filled out the worksheet in Figure 1.

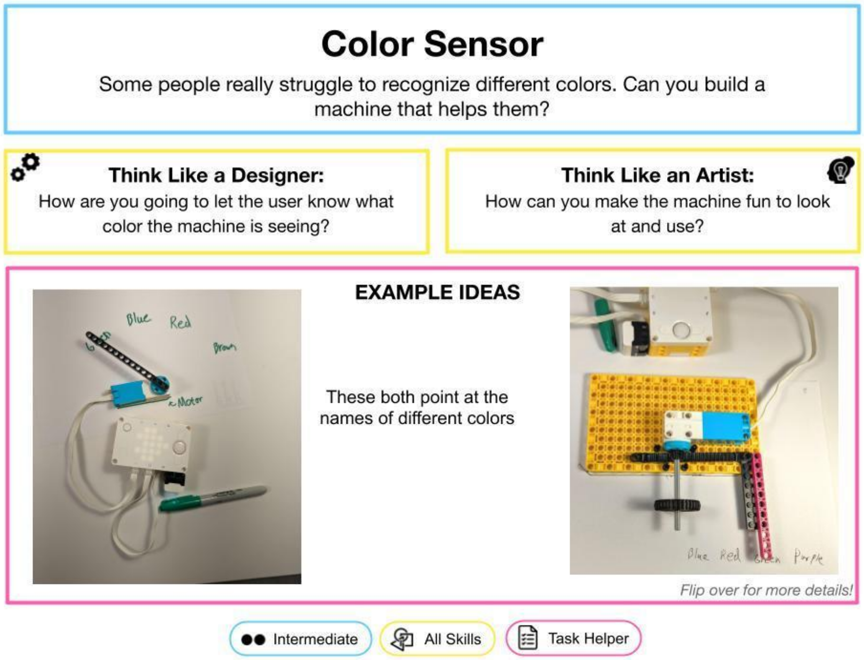

Figure 2: Color Sensor Placemat

Figure 3: A sheet of paper used as part of the solution to the colorblind helper activity.

The third activity asked students to design a robot that throws away the trash of a certain color while ignoring the trash of other colors. The goal of this activity was to help students learn the training process. However, most students interpreted this as asking them to build a sort of catapult. In this activity, we demonstrated how to train the system first, and handed out a graphical training guide with instructions for training the system. While doing this activity, many students needed further demonstrations of how to train the system but most spent the majority of their time on the mechanical engineering component of the activity (i.e., building the catapult).

The fourth activity asked students to build a “car” and train it to do one of four actions (move forward, backward, clockwise, or counterclockwise). This activity was designed to introduce the second program by nearest neighbor machine learning. Students built a car with a color sensor and motors demonstrated the training program and were then asked to train their cars to navigate a maze made of colored paper, staying on the paper and avoiding the floor underneath.

For the first two pilot programs, students built amusement park rides as a final project. We watched students apply the AI and machine learning knowledge they learned from previous activities while being creative and building something they are interested in. The remaining time was spent on a camp-provided curriculum based on further mechanical engineering LEGO® Education activities. The third pilot program used the remainder of the time to design, film, and edit short films.

3. Findings and Reflections

We recorded the video and audio of the pilot tests and analyzed students' behavior and conversation through these data. From the first two pilot tests, we found students wanted to be able to add more training data as a debugging method, so we added this feature for the third pilot.

The pre-trained model met our expectations since it let students focus on building and gave a clear introduction to how a trained system could behave. Students intuitively understood where further training was needed and even discovered things that we, as designers, had not thought of. For example, in the first activity a pair of students shared their discovery that “When you combine two colors...yellow and blue, it goes in the same direction as this (said while pointing at green). It goes in the same direction as yellow and blue combined so that's something that we noticed.” When a machine learning system is not behaving as desired, students were able to quickly understand the role of giving additional data points. For example, on the second day of the third pilot program, a catapult was moving erratically when the color sensor passed over the white paper while students moved the sensor from one colored square to another. We asked students how to fix its behavior, they responded "Now I am trying to train it with the white. Training it to do the same angle as for every other color".

Explaining the training process didn't meet our expectations. We expected students to understand the training process with one demonstration, but it was not intuitive enough. Although we provided a “fun” treasure map style instruction manual to attract students to follow it, students almost ignored it in favor of asking for help or switching from training to other methods of control (e.g., block-based coding). Although students almost universally grasped the training process eventually, we had to explain it to them repeatedly during the activities. We believe that the limited information displayed on Spike TM Prime is partially to blame. (Figure 4)

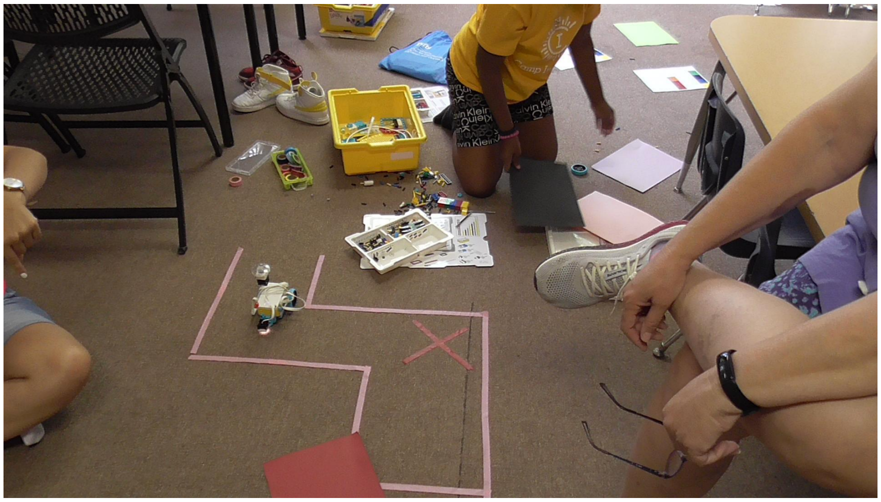

Figure 4: Students built an obstacle avoidance car

Figure 5: A carnival activity built by a student. Certain colors trigger basket-shooting attempts

Our design also allowed students to have agency in deciding what types of projects to work on and where to focus their efforts. Some students spent a lot of time working on the mechanical side of their projects and then simply added a motor and sensor at the end (as in figure 5) while others focused on the training while working with simpler machines. We noticed the building system was engaging and it was difficult to get students' attention to the training process when they focus on the building process.

We also found hardware limitations affected students' activities. For example, the color sensor was affected by lighting conditions and distance from its target. This was a mixed blessing and led to teaching some students about the need to take environmental factors into account when training and testing while convincing other students that the behavior of the system was random or otherwise difficult to explain. The unpredictability of the sensor added a further bit of excitement for students because it produced a behavior that would otherwise have been difficult to code.

Another finding is the third pilot test students used an improved UX, but they spent considerably less time working with the trainable machine learning. These students had previous experience with block programming so they can program the motors directly through the LEGO® education app. We found that students tended to use training as a method of last resort because they need to learn the pre-training model, they prefer to either manually set the motors to spin continuously or program the motors where their previous experience made it feasible.

Robotics introduces challenges (time spent building, hardware limitations) but we find that the student’s excitement about machine learning was worth that trade-off. The nearest neighbor algorithm is accessible, understandable, effective, and fun for students. We figured out upper elementary students have strong intuitions about robot behavior based on our pilot tests. Educators can make use of this in their educational experience. Appropriate machine learning visualization for this age group remains an open problem.

4. Future Work

Our next goal is to design tasks where trainable ML outperforms block coding and manual controls so that students will prefer to train their robots. These experiences will support improvements to our next year's research plan. We plan to develop new activities with the objective of attracting students to pay more attention to the machine learning training process than the building process. We also plan to improve our program by moving from four individual activities exploring different forms of ML sense-making to a progressive pedagogical system of activities to help students understand and apply the machine learning training process in a clear, accessible, and attractive way. Finally, we are using our pilot findings to inform our design of a new ML-powered hardware kit that costs less and provides more flexibility for data visualization and system state visibility than our pilot system. We hope that by lowering the cost of kit materials, we can ultimately provide more opportunities for lower-income students to study machine learning.

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