POSTPHENOMENOLOGICAL STUDIES OF MACHINE LEARNING EDUCATION IN ELEMENTARY SCHOOL

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Abstract

Machine Learning has become prevalent in everyday life activities, affecting the lives of many people. In education the much-needed shift from rule-driven thinking to ML-based data-driven thinking is on the agenda. Traditional methods of examining the effectiveness of elementary school computational thinking courses, based on assessments of habitual programming skills, are insufficient for assessing data-driven thinking. This paper proposes a new, so-called postphenomenological assessing approach based on analyzing students' relationship with machine Learning, and through it, with the world around them.

Keywords: Elementary school, Computational thinking, Machine learning, Postphenomenology, Constructionism.

1 INTRODUCTION

Computational thinking (CT) skills are increasingly critical for individuals and therefore are learned in schools. It typically happens in programming classes and is known as 'Learning to code' (Howels, 2018). In recent years educators have gone beyond, aiming for students also to learn formal subject matters such as math, science or language arts using programming (Grover & Pea, 2018). This is referred to as 'Coding to learn', which enables students to take charge of their learning in various school subjects.

Learning is central to both artificial intelligence and human intelligence, and the former focuses on understanding how machines learn, and the latter is concerned with how humans learn (Spector & Ma, 2019). With the growing dominance of CT, these two efforts have become more closely connected (Dohn et al., 2022). Machine learning (ML) systems do not learn effortlessly. First, they need data, and lots of it, so today's world is commonly viewed as increasingly run by data. Secondly, ML systems work in a new way, they can evolve. Nevertheless, today's computing education continues to be dominated by teaching rule-based programming, while the much-needed shift from rule-driven thinking to ML-based data-driven thinking is on the agenda.

The critical problem of integrating ML in education is the significant difference between the basic principles of ML-based and traditional, rule-based programming. While in traditional coding, the computer was perceived as a means of executing user-created software, in the ML-based case, the computer becomes a learning device, and creating a software product involves a data-driven learning process. It means that the very principle of the learning environment in which the software is created changes. Another difference is that traditional coding is deterministic so that the results can and should be determined in advance by the coder-learner. In ML, the results cannot be predetermined, so the success factors are different.

Traditional methods for studying the effectiveness of constructing new technologies in education are usually based on the assessment of habitual programming skills. A widely used framework for assessing students' CT is the "Computation Thinking Assessment Framework" (CTAF) which comprises three dimensions: Computational Concepts, Practices, and Perspectives. The CTAF framework has been adapted for K-12 ML activities with a focus on Computational Concepts and Practices (Shamir & Levin, 2021). The latter, Computational Perspectives, is considered challenging to assess due to its philosophical nature (Brennan & Resnick, 2012). In this paper, we focus on this challenging third dimension – the Computational Perspective.

Computational Perspectives are the perspectives students engage in designing software about the world around them and about themselves. It consists of how students express themselves, connect with others, and question when engaged with technology. In this study, we enhance this with a 4th element: postphenomenological relations - relations of students with digital technology and, through it, with the world around them. See in Figure 1 the gray box.

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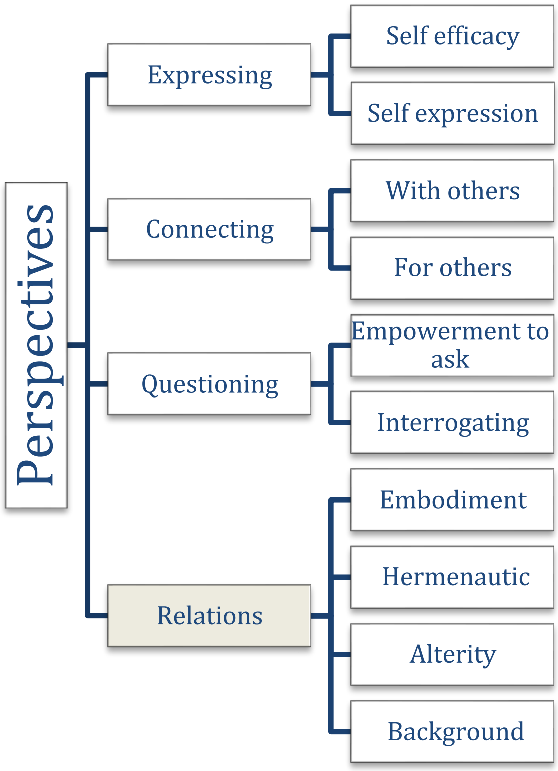

Figure 1. The enhanced Computational Perspectives framework.

Our study focuses on the various ways in which ML technologies mediate between human beings and the world, a vital and often neglected aspect of educational practice. We use postphenomenology, a branch of philosophy of technology that highlights the importance of technological mediation of experience, thereby enabling researchers to explore technological mediation and views about technology (Ihde, 1990; Verbeek, 2005).

One of the powerful tools offered by postphenomenology is the systematic analysis of the structure of the relationship that a person has with technologies, so the I-Technology-World formula is created. This formula represents a basic view according to which our experiences are mediated by the presence of technology (Wellner, 2015). Postphenomenology integrates phenomenology and pragmatism, both emerged in the late 19th century, to emphasize practice rather than representation (Ihde, 2009).

The relations between humans and their technologies cannot be reduced to a single essence. Rather, there are diverse relations that are represented by the I-technology-world formula as permutations that are produced with the addition of an arrow, parentheses, and dashes. The arrow represents an action or a direction of action (in phenomenological terminology – intentionality); the parentheses indicate that two ingredients function as one unit, or if it is a single unit – a withdrawal to the background, pushing the ingredient out of the scope of attention; and the dash signifies a simple connection of working together.

Ihde identified four relations: Embodiment, Hermeneutic, Alterity and Background.

In Embodiment relation, we experience a given technology as part of our body scheme which means that the combination of me and the technology is perceived as a single unit that experiences the world. It is represented in the following permutation: (I – technology) → world.

In Hermeneutic relation, technology provides meaning to the world. Technology is that through which we read the world and interpret it. It is represented using the following permutation: I → (technology – world).

In Alterity relation, the world withdraws to the background. Here the parenthesis function slightly differently, and they denote a withdrawal of the world, thereby positioning it outside the focus of the relations. The focus is on the reference to the technological artifact as a quasi-other. Its formula is therefore, this one: I → technology (– world).

In Background relation, the technology operates in the background unnoticed. It is represented using the following permutation: I → (technology –) world.

Cyborg relation is a new group of relations proposed by Verbeek (2008). One of its extensions is offered by Wellner (2018), which looks at the relations of specific emerging technology of ML. The four traditional permutations have been based on human intentionality and so the arrow has gone from the "I" towards the "technology" and the "world." With emerging technologies, it is time to reverse the arrow and reflect technological intentionality. It is represented using the following permutation: I ← (technology -- world).

2 METHODOLOGY

This section describes the curriculum that was administered for the purpose of this study, along with the population and the data collection.

Two different courses were conducted for two different groups of students. In both courses, the participating students consisted of 5th- and 6th-grade students at the ages of 11-12. In the Rule-driven course, 222 students participated from 12 different schools, and in the Data-driven course, there were 209 students from 13 schools. The courses were elective, and students have provided parental and personal consent to participate in the research study. Approvals were obtained according to the regulations of the Chief scientist's office of the Ministry of Education of Israel. The course took place during regular school hours and was administered by the schoolteachers.

2.1 Curriculum

Both courses had a similar structure, consisting of four learning modules and following the use-modify-create learning progression model for CT (Lee, 2011). Throughout the courses, students actively engaged with problem-solving tasks in 3 curricular topics: Science, Math, and Computer Science. The courses duration was 60 hours comprising 22 weeks of 2 hour-a-week learning; three full-day events, each 4 hours long; and four lectures held by experts, each 1 hour long. Each learning module comprised of 5-7 tasks that students worked on collaboratively using a variety of pre created scaffolds. In addition, students were required to reflect on how CT skills were used during their work. The solutions to the tasks were submitted using a learning management system which researchers had full access. The teachers had no prior knowledge of CT and had the role of guiding students in organizing their self-advancement through the tasks.

Figure 2 displays the modules for the 'Rule-driven construction' course, which focused on simulation construction, and Figure 3 displays the modules for the 'Data-driven construction' course which focused on ML.

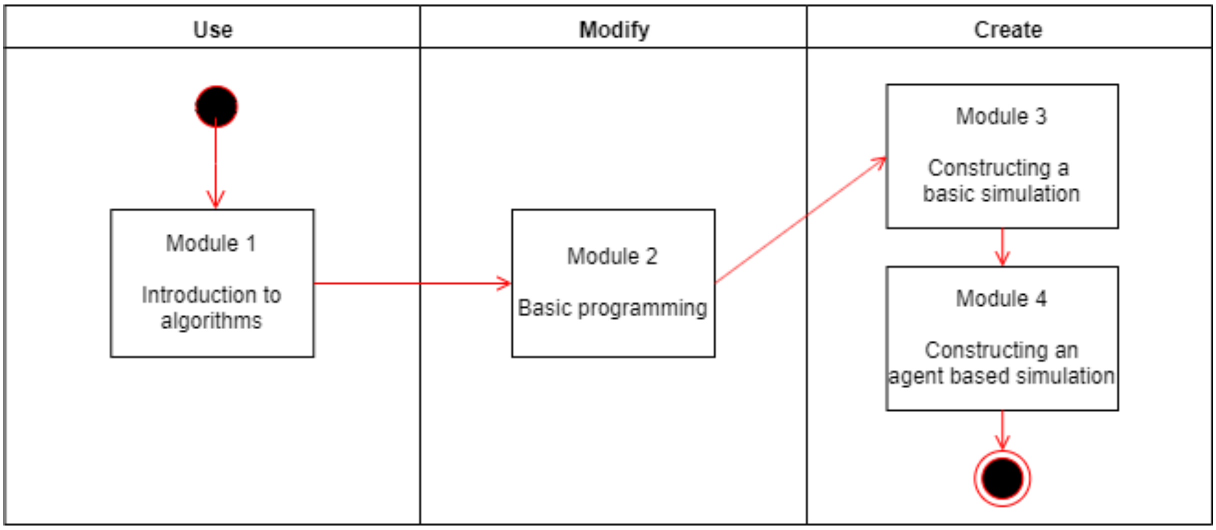

Figure 2. The learning modules of the Rule-driven construction course.

The four learning modules shown in Figure 2 are as follows:

Module 1 - Introduction to Algorithms. In this module, participants discuss how algorithms work setting the foundations for understanding rule-based programming. Students are given tasks of identifying algorithms in everyday life and how to describe them using flow charts.

Module 2 – Basic programming. This module advances students from users to modifiers, which is the 2nd level in the learning progression model (Lee, 2011). The participants perform a set of coding puzzle activities in which they need to code a script for a character to move from one point on the screen to another. In coding puzzles, the programming environment (PE) has a small set of optional commands to choose from. In addition, the PE informs the students whether they were correct and suggests how to solve the puzzle in case they are wrong.

Module 3 – Constructing a basic simulation. This module advances students from modifiers to creators by engaging them in the construction of a computer game on a science topic and then a simulation of the particle model. Specifically, they create a simulation showing particle velocity of motion as a function of temperature. In addition, they discuss the field of Computational Science, known as the third pillar of science. Theory and experiment are the two pillars of science that for centuries have underpinned our understanding of the world around us. We make measurements and observations, which we then link to theories that describe, explain, and predict natural phenomena. The constant interplay of theory and experiment, which allows theories to be confirmed, refined, and sometimes even overturned, lies at the heart of the traditional scientific method. For more than half a century, computational science has expanded scientists' toolkit to go far beyond what we could hope to observe. Computation is not just an extra tool. It is a new way of doing science, irrevocably changing how scientists learn, experiment, and theorize.

Module 4 - Constructing an agent-based simulation. In this module, students construct a simulation using an agent-based toolkit the researchers have created for the study. The main goal is for the students to have a deep understanding of how a simulation of phenomena is created based on its most basic particles (also known as agents) and the agents' individual programming.

The course is highly engaging the students in working with rules (a.k.a. traditional algorithms).

The 'Data-driven construction' course curriculum had similar features as the Rule-driven course's duration and structure. The difference was with the content relating to ML construction as shown in Figure 3.

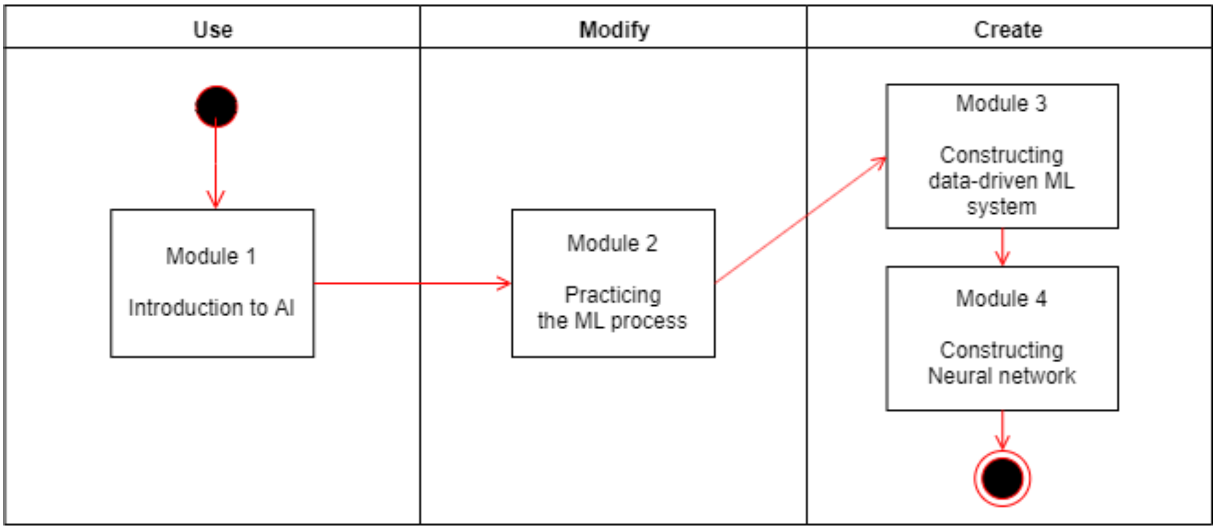

Figure 3. The learning modules of the Data-driven construction course.

The modules shown in Figure 3 are as follows:

Module 1 - Introduction to AI. In this module, participants discuss how AI works and how it is different from rule-based programming. They are given a few standard algorithm creation tasks to show the uniformity of their results in rule-driven computing. As contrast, they are shown examples of mistakes made by AI systems during the classification of input data. While doing so, they learn about data-driven computing. They are also encouraged to engage in a conversation with an AI chatbot and are encouraged to see if the chatbot passes the Turing test.

Module 2 - Practicing the ML process. This module advances students from users to modifiers, which is the 2nd level in the learning progression model (Lee, 2011). The participants perform a set of training activities on an ML system to classify images into two categories. The categories change between the activities with increased complexity. These activities require the student to train, test, and validate the classifier model. The ML platform used consists of a ready-made ML algorithm and a given ML training interface.

Module 3 – Constructing a data-driven ML system. This module advances students from modifiers of ML to creators. They perform most of the tasks of the ML process: they choose the categories to be classified, create the training and validation data sets, train the ML model and program a tool that accesses the ML model and shows how it does classification.

Module 4 - Constructing a neural network. In this module, students do not interact with a ready-made artificial neural network (ANN) as in the previous module, rather they construct it themselves using a Single-Neuron toolkit the researchers have created for the study The main goal is for the students to overcome the "Black box problem" of not knowing how an ML algorithm functions making the algorithms reasoning and its basis of predictions inaccessible.

The course is highly engaging the students in working with data and artificial neural networks (ANN).

2.2 Research Questions

This paper describes the findings of a study conducted with elementary school students learning two courses: "Rule-driven construction" and "Data-driven construction". The two main research questions were:

1 What are students' computational perspectives in the realm of ML construction, and how can they be assessed?

2 What are the differences between data-driven learning and rule-based constructionist learning regarding students' computational perspectives?

2.3 Data Collection and analysis

A qualitative method approach was used to evaluate the data collected using semi-structured interviews, which is a typical research method in postphenomenology (Adams and Turville, 2018). Aagaard and Matthiesen (2016) argue that research that employs interviews without capturing everyday intertwinement with material artifacts may give an incomplete picture. To address this lack of attention to materiality, qualitative researchers must develop both an ear for meaning and an eye for materiality by gathering lived experiences through utilizing exploratory open-ended questions and employing an interpretive inquiry lens.

The 1st phase of our analysis was to break down the interviews into various data elements and reassemble them. According to Adams and Thompson (2016), specific types of data elements that are of special interest to the researchers are called anecdotes. An anecdote is “recounting an incident of life” that involves a human interacting with the technology of interest. This experiential narrative is to be concise, describe a single event and be based on concrete, real or perceived experiences. Reassembling the data was done by selecting the anecdotes. The 2nd stage of our analysis was reflecting on these anecdotic materials, coding them and grouping them thematically. By doing so, we can reveal the technology’s implicit and explicit scripts, as well as a spectrum of human-technology-world relations.

The semi-structured interviews were held with a selection of interested students. They were later transcribed and analyzed. Some of the questions the interviewers asked are here force:

1 What does your artifact do?

2 How can it be extended?

3 Can you think of various purposes it can be used for

4 What was difficult in creating it?

5 Do you have a particular moment that stands out when you were creating your project? And what was it? What was special about it?

6 What does it mean for you to be able to create technology?

7 What would you do if the technology went missing?

8 What other technology would you like to create?

9 Would you recommend the course to other students and why?

10 What question do you have about technology?

To demonstrate how the questions extract the relation types between the student and the world via technology we'll dive into 2 questions. Question #1-"What does your artifact do?" can invoke an alterity relation where students focus on technology positioning the world outside the focus of the relation. The same question can also point to embodiment relations where the student and technology function as a single unit that experiences the world. In addition, question #1 can point to a hermeneutic relation where students demonstrate how their artifact can explain them the world. Let us look at another question for extracting relations – question #7-"What would you do if the technology went missing?" This can allow to bring the “invisible” qualities and mediating role of the technology to light. In postphenomenology, this is described as revealing and concealing structures, which focuses on the user’s attention or lack of it towards the technology artifact and the background of one’s lifeworld (Kiran and Verbeek, 2010).

3 RESULTS

We analyzed students' computational perspectives using a postphenomenological method in two different courses. We collected anecdotes of interaction with technology, analyzed them independently, and tagged thus creating similar thematic concepts to guide the flow of the analysis process. These thematic groupings respond to Research Question #1 (What are students' computational perspectives in the realm of ML construction?). The variance between these thematic groupings relates to Research Question #2 (What are the differences between data-driven learning and rule-based constructionist learning, regarding students' computational perspectives?). In this section, we describe in detail several thematic groupings and the concepts derived from them.

3.1 I create technology to solve real-world problems

Technology created by people assists them in everyday life. During the courses, the students were required to complete a project consisting of a science related digital artifact that they invented and created. The data-driven course required the artifact to be a ML system while for the rule-driven course the desired artifact was a software simulation.

One of the ML artifacts created by a group of students was the "Sweet-salty food recognizer". Given an image loaded by the user, the ML artifact classifies the input to one of six categories (Figure 4).

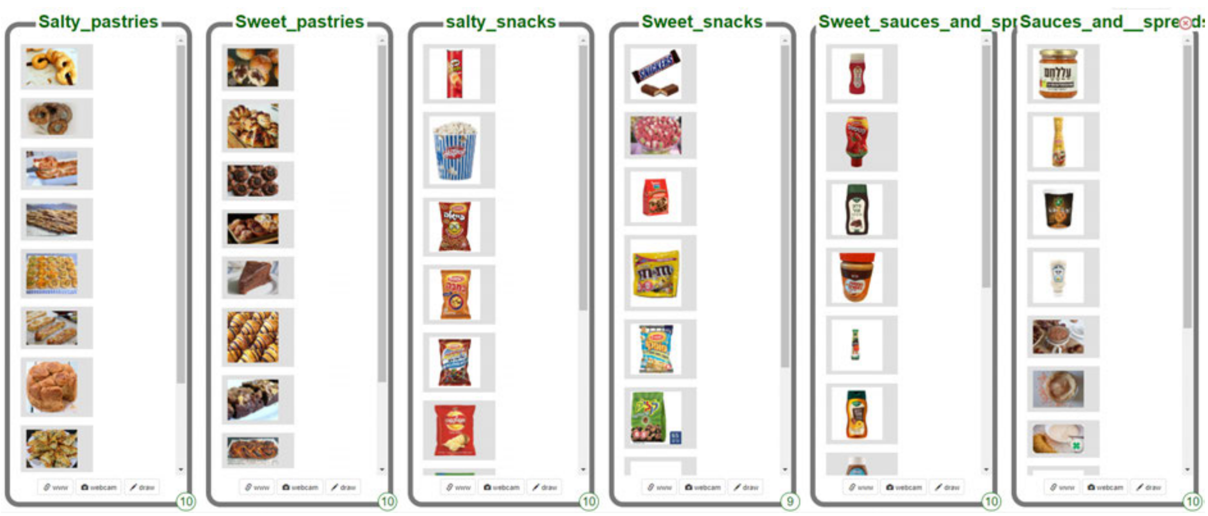

Figure 4. Training data set of the ML artifact.

Figure 4 displays the six categories the students chose for their project: sweet/salty snacks, sweet/salty spreads and sauces, and sweet/salty pastries. The figure also shows some image-based data they used to train their ML model. In the interview, they explained that their system aims to help people keep their health. Thus, people with high blood pressure can easily avoid salty food, and diabetics, and people seeking to lose weight can easily avoid sweet food.

One of the projects in the rule-driven course was a simulation of the sinkhole phenomenon (Figure 5).

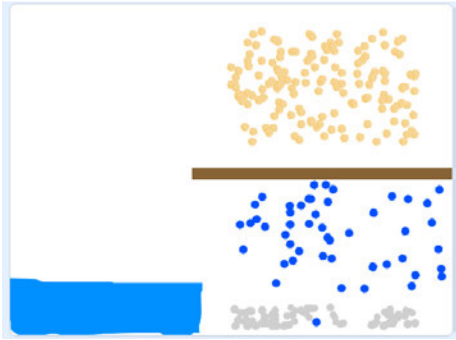

Figure 5. Sinkhole simulation.

Figure 5 shows the three types of agents (small circles) created by the students in their simulation: in Grey the salty layer, In blue the sweet water, and in yellow the soil. On the left is the dead sea next to which sinkholes form. The brown line symbolizes the top layer of soil which eventually collapses into the sinkhole. The students explained that their goal for constructing the artifact was for it to be used as a learning kit that translates a real-world phenomenon into a "text" that explains it.

In addition to these two examples, in both courses, the students created a variety of artifacts for the purpose of solving problems. The students articulated that in the interviews as well. For instance, one student said: "We could have chosen a variety of other ML systems to create, such as identifying when a door is open or closed to save air conditioning energy." This emphasizes that students feel they are empowered to create with technology a variety of solutions for real-world problems.

In both courses, the students were able not only to create a variety of solutions to problems but also to think of a variety of other artifacts. Additionally, they demonstrated the knowledge to construct their inventions. One student said: "I thought of a startup – a system that prevents using the car horn and disturbing everybody around me when the car in front of me doesn't drive when the green light turns on. The system needs a camera to take a picture of the license number, then ML to identify the licenses' digits, and through a database of registrations to send a message which will make an annoying sound to the sleepy driver. Of course, the driver needs to download my app and register to the service. I think this will make a better world with less noise." The app and the world are conceived by the student as one unit, and hence we identify here hermeneutic relations.

Another student said in an interview: "I'd like to create a simulation of endangered species to know when they will be extinct and to know how much time we have to save them. It will have lions and giraffes. There are still many of both in nature so there will be many agent instances in the simulation. When a lion agent goes near a Giraffe agent the latter will disappear. There will be a timer to know how much time takes for all Giraffes to disappear from the screen." Here again the app and the world are conceived by the student as one unit. The students stated that their technology can provide meaning to the world. Technology is that through which we read the world and interpret it thus having a hermeneutic relation.

3.2 Meaningful Student Accomplishment

Through anecdotes, we concluded that the artifacts students created are perceived by them as meaningful accomplishments.

When asked in the interview " What does it mean for you to be able to create technology?" a student answered: "I think every little thing we accomplish is meant to promote us somehow so that in the end we can do big things that will affect a lot of people in the world. I feel like I can do anything technologically advanced. Something many children do not feel". Hearing that another student that participated in the same group interview said: "Yes, if I was able to create an ML system, I could do anything."

When asked "Do you have a particular moment that stands out when you were creating your project?" a student replied: "The most joyful moment I had in the project was seeing it work and function properly, we still had to fix some things but the first time that the ML system gave its own classification was awesome because we worked so hard".

One way to understand the meaning of student accomplishments is in terms of human-technology-world relations. The students were seeing their world through a classroom world overlayed with an ML task. Their artifact has become a reflection of their identity and self-worth. In the language of postphenomenology, the student has developed an alterity relation with the technology. Thus, the student’s understanding of their self-worth and relative standing compared to other children (“world”) is perceived through interpreting their ability to create an artifact.

3.3 Technology as a threat to humans

Unlike themes #1 and #2, which were evident in both courses, the theme of "technology as a threat" was evident in the data-driven course only. A popular question the students posed in their self-generated question was about the threats of ML-based technology on humans. It was evident in different formats such as: "Can a ML system destroy all of humanity?", "Can ML take over all the jobs?", "Will ML dominate more areas one day and dictate the ways of the world?", and "Can ML insult people?". Our analysis of the human-technology-world relations perceives this as a cyborg relation because it unpacks the intentionality that technology has towards the users.

3.4 Technology creation as a social connector

We identified several anecdotes as socially related. Here forth are 2 of them.

Researcher: "Is there anything that involves social relations that you can relate to regarding your artifact"?

Student: "Well, it's not related to the school. So, I attended the Passover holiday family gathering with all the extended family on my mom's side. There, I showed my ML project to the whole family. The kids in the family asked how I did that, and I just explained it. I think now they understand ML a bit better than before. I got lots of praise, so it was an awesome experience to talk about my project and explain it to people and it even worked, it really classified user images."

Analyzing this anecdote, the student used her newly attained constructionist power in a social event even though this added workload and anxiety to her day. The student found a meaningful way to engage other children and adults from her family after school hours. It empowered the student to initiate conversations, create, and share with others. She said the family have praised her for her construction of the ML artifact. We see how creating the technology fostered the student's social connections. In Postphenomenology, terms this demonstrates on the one hand, embodiment because the student took her technology to her family gathering as if it was part of her. On the other hand, we see signs of cyborg relations because the technology caused the student to change her ways.

Next, we'll review another anecdote with a different social connection.

Researcher: "Pattern recognition is an important capability for a person that creates data-driven technology. Can you think of an event where you used pattern recognition other than for finding features in your data?"

Student: "Say in terms of teamwork, so let's say I've already worked with some of the students on a prior project so I knew how each one can contribute most, not to be mean, and who should not work on certain tasks. Some people are good with programming and others are better at working with data. At some point, I saw that we were too many working on the technology. If two kids, say, can now add 13 pictures to the data set and they do it super-fast, while two other kids took five pictures while they did 13, so I think it to have just those who did 13. We told the teacher, and she moved them to work on a non-ML project task. Those who contribute more should stay, and those who do less should do tasks that they find interesting."

Analyzing this anecdote reveals reducing social connections developed in a specific technological context. When the student wanted to move forward with her artifact and felt that several students delayed her team, she initiated removing them from the team, thus reducing the social connection. In Postphenomenology terms, the technology was in the background of the human action, therefore corresponding to a background relation.

4 CONCLUSIONS

In this study, we looked at technologies as playing an active mediating role between humans and their world. Specifically, we analyzed students' computational perspectives in two different technology constructionist courses. In one course, participants created ML based artifacts using a data-driven approach. In the other, students created computational agent-based simulations using a rule-driven approach.

We explored how 5th and 6th grade students used technology creation environments to facilitate students' learning, interact with others and form perceptions or insights. Through interviews, we were able to collect field examples of how students utilized and reflected upon their work. From which, some emergent themes and implications arose: (a) I create technology to solve real-world problems (b) Meaningful Student Accomplishment (c) Technology as a threat to humans (d) Technology creation as a social connector. Using a postphenomenology approach, these themes were further analyzed to find the human-technology-world relations.

While we were able to identify in both courses various human-technology-world relations, the data-driven course had a more versatile set. This difference could indicate that the data-driven course contributes to a richer experience for the student with technology and the world compared to the rule-driven course.

ML learning in elementary school is in its infancy. A reliable assessment tool for students' computational perspectives in ML-based data-driven thinking is absent from the current literature. Therefore, introducing postphenomenological methods will be valuable for researchers and practitioners alike.

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