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Learning Machine Learning With Very Young Children: Who Is Teaching Whom?

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Abstract: *While artificial intelligence and machine learning-based technology is becoming a commonplace feature of people's everyday lives, so far few theoretical or empirical studies have focused on investigating it in K-12 education. Drawing on the sociocultural theory of learning and participation, this case study explored how six very young children taught and explored Google's Teachable Machine in non-school settings. Through fine-grained analysis of video recordings and interviews with the children, the article illustrates the content and the process of teaching where 3-9 year old children were producing machine learning datasets and models as well as observing, exploring, and explaining their own interaction with machine learning systems. The results illustrate the quick-paced and embodied nature of the child- computer interaction that also supported children to reason about the relationship between their own bodily expressions and the output of an interactive ML-based tool. The article concludes with discussions on the emergent process of teaching and learning as well as on ways of promoting children's participation and sense of agency in the age of machine learning.*

Keywords: Machine Learning, Computational Thinking, K–12, Participatory Learning, Early Childhood, Participatory Research, Artificial Intelligence.

1. INTRODUCTION.

The early 2000s has seen major upheavals in the technological landscape. The introduction of ubiquitous computing, cloud services, mobile technology, and the Internet of things have made the 1960s vision for "computer utility" into reality. Prices of sensors have plummeted as their size has shrunk, transforming sensor data into a commodity of abundance. For more than fifty years, Moore's Law has upheld an exponential growth of computing power, with a continuous downward trend of hardware price. The breakthrough of machine learning in the early 2000s was based on the above—ubiquitous computing, data deluge, and a surge in computing power—as well as on the development of statistical and optimization techniques and new measures for success [1,2].

As the availability of new technology has enabled people to make "smart" artifacts – ones embedded with sensors and communication circuitry that allows access to cloud computing services—everyday items are starting to be aware (figuratively) of their environment and of other devices, items, and users in their vicinity. Whether it is called ambient intelligence, pervasive computing, or ubiquitous computing, combining machine learning with everyday items has been identified as one of the economic megatrends of the next few decades [3].

Technology that adapts to its users and contexts of use by learning from large amounts of data opens up new horizons of opportunities and concerns.

New technology related to the data-driven shift in computing has been adopted into use in all segments of life today, including work, leisure, social relations, and learning, and at the moment the limits and pace of those changes are yet to be established. Increased monitoring and tracking of people's lives enables assistive technology and amplified cognition—such as the ability to never get lost, to understand signs in foreign languages, and to find music and movies to match one's mood [4]. Tracking of people's lives is based on traces people leave while using apps to aid them: location data, tweets, status updates, personal photos, music choices, shopping history, upvotes and "likes", browsing history, and so on. But while ubiquitous tracking equips software with an uncanny ability to predict what people need and want at any given moment, it also risks using people's personal data for advertisement, behavior engineering, manipulation, and government surveillance [5].

Much has been written about the impact of new, data-driven machine learning on the labor market [6], on education [7], on professions [8], on societies [9], and even on people's love lives [10]. While the old digital divide was about access to technology [11], new digital divides are forming along competencies and skills. Marginalization, social exclusion, income differences, new social classes, and other dividing lines of societal inequality will increasingly be drawn by people's ability to harness cognitive technology to do jobs for them [4].

But while machine learning and ubiquitous computing have become commonplace features of people's everyday lives, education systems are still a long way from realizing them in the classroom. Exploration of machine learning applications in education is challenging due to the fact that the mechanisms and opportunities of machine learning are unfamiliar to most people outside computer science. What is more, the ongoing discussions about artificial intelligence (AI) in the media have driven negative perceptions and fears that call for a ban or regulation of some forms of ICT, especially in the hands of children and youths [12]. There are, indeed, some real and legitimate concerns about the effects of machine learning and its applications [13,14] as well as about child online safety in general. Yet, many efforts that focus on protection of children's development and security are done at the expense of children's participation in the digital age [15]. The education system should teach children how their world works and how to use technology to explore the world: today, both are increasingly driven by applications of machine learning. As an entire generation of children are growing up with AI, the more dire the need for education that prepares children for a world abundant in such technology [16].

As a response to the ML and data driven upheavals of society, many researchers call for increased "data literacies". While definitions of data literacies differ in terms of the skills and knowledge they emphasize, the often include skills such as ability to identify how and where personal data are generated and processed [17], ability to control personal data trails and practices [18,19] as well as skills to constructively engage in society through and about data [20]. While critics have begun to draw attention to the ways in which continuous personal data generation is influencing people's lives, researchers are only just beginning to direct attention to the fact that nowadays children are also the objects of a multitude of data collection about them [21]. At this point, many countries have included computational thinking in their K–12 curricula, but efforts and curricula towards greater data literacies and understanding related principles of the underlying algorithmic processes are sorely missing from education [17,22].

Given the ubiquity and potential of ML—beneficial and malign alike—there is a clear need to investigate how to facilitate children to reason and develop a greater understanding of the ML- rich technological world around themselves. Understanding how machine learning models the world represents one form of data literacy, which empowers children to explore, understand and question ML systems and data-driven practices that they encounter in their everyday lives such as those used in facial recognition, voice detection, and image parsing [23]. Machine learning is also considered as a vital part of computational thinking [4] and there are arguments to include ML education as part of the computational thinking and participation agenda in K- 12 level [24]. However, educational initiatives that involve children in exploring and co- designing ML systems have been rare due to the inherent difficulties in bringing such abstract and highly complex phenomena into young children's creative grasp.

This sociocultural informed study aims to explore young children's early encounters and insights into machine learning based technology. This article presents empirical work and analysis that illustrate how six children, aged 3-9 years-old, taught and explored machine learning based technology in non-school settings. While the nature of the present case study is highly exploratory, the main contributions of this paper are pedagogical insights and an empirical exploration of how young children can begin to explore and develop their understanding of ML based technologies in a playful and embodied manner.

2. PEDAGOGICAL FRAMEWORK.

2.1 PARTICIPATORY LEARNING.

Our approach to exploring young children's insights and encounters with machine learning builds on the sociocultural and culture-historical theories of learning and participation. This theoretical standpoint generally views learning as systemic processes that connect the subjects (the actor or actors participating in the activity), the object of their activity, and the tools that actors use as mediational means for acting on the object [25,26]. Accordingly, children's learning and action reside not only in individual abilities; it is also distributed across the tools and affordances that are within the reach of children in the "zone of proximal development"[25,27]. This means that when collaborating with more experienced others through tool-mediated actions, a child may be able to solve problems or complete tasks that he or she does not yet have the developmental capacity to do independently [25].

Elaborating upon Vygotsky's premise, Rogoff [28] argues that children learn through apprentice-style relationships when participating in the everyday activities of their families and communities. Rogoff's [28] notion of guided participation stresses the active role of children in observing and participating in organized societal activity. Such interaction between children and their caregivers involves use of various kinds of cultural tools and semiotic signs adapted to the specific activity at hand, including tacit forms of communication [28,29]. In guided participation, the parents informally teach their children, who gradually gain understanding of the various tools, artefacts, and discourses that are integral to their everyday family and community life [28]. As children's understanding of and skills in using the tools of culture grow, they can take more and more responsibility from the hands of their caregivers and do things independently [28,30].

Instead of strict adult control or acquisition-oriented instructions, participatory learning also emphasizes children's active contribution in shared meaning-making and endeavors [31]. This highlights the creation of environments that provide children with opportunities to explore real world phenomena in an interest driven and inquiry-oriented manner [32,33]. The children should be able to connect their interests, previous knowledge, and experiences to the learning situation, and have the opportunity to increasingly explain, interpret, and share their own observations with their peers and teachers [33,34]. The more skilled partner may provide encouragement, means, and metacognitive support adjusted to children's interest and skills, within their dynamic zone of proximal development [29]. In essence, the key issue in participatory learning is to create positive experiences that promote children's sense of agency, or the feeling of being the author of one's actions in the world [35].

2.2 LEARNING BY TEACHING A COMPUTER.

While research on providing children with agentive experiences with machine learning is in its infancy, at the same time educational research has also shown that the practice of teaching a computer is in itself a good way to learn [e.g. 36–38]. In his pioneering work, Seymour Papert [36] explored his educational vision on Logo-programming based Turtle Geometry, a software environment for constructing geometric shapes. The guiding pedagogical principle behind Turtle Geometry was that when teaching a computer, children embark on an exploration about how they themselves think [36,38]. In that exploration process, the Logo turtles became external representations of thinking that the child controlled using words [36,38].

Ackermann [38] pointed out that Papert's arguments about mediated action also resonate with sociocultural theories of learning, originating in the work of Vygotsky [25]. To Papert, projecting out—or externalizing—our inner thoughts was as important as internalization of our actions [38]. He argued that when the children themselves are responsible for teaching and giving directions to a computer, they need to align their internal mental model with the external representation. They also need to reflect their own know-how and to express it precisely enough so that the computer can carry it out [38]. Ackermann [38] claims that when switching back and forth between doing it yourself (engaging one's body) and teaching to "another" (instructing some responsive tool), the process may sustain the interaction and at the same time, enhance the development of a deeper understanding of what action leads to a specific response. Externalizing ideas also makes them tangible and shareable which, in turn, helps people to communicate and develop ideas together with others [38]. In socio-cultural terms, this highlights the tool-dependent nature of human reasoning [27] in which children may construct understanding in an embodied way with what Papert called "objects-to-think-with" [36].

While Papert's faith in children's self-directed learning is admirable, critics have pointed out that he overlooked the potential influence of the social and cultural environment [39]. Ames [39] argues that the ideological underpinnings of Logo were also mediated by White Western influences and values, such as individualism. As Logo depends on written English, it also contains expectations about language literacy [39]. There again, a growing body of research has also documented the ways in which children's ideas and intellectual curiosity can be a powerful and generative fairway for exploring key concepts in computer science in a meaningful fashion [e.g. 40–42]. From this perspective, the general goal of instruction involves providing children with powerful tools for thinking and making, including computers, and the opportunities to externalize and develop thoughts in a supportive social situation [40-42]. However, there is a very limited body of theoretical or empirical research on young children's encounters and meaning-making around ML.

FROM PROGRAMMING TO TEACHABLE MACHINES.

In parallel with the shift from rule-driven programming to data-driven programming, the 2010s has witnessed the emergence of child-friendly tools for exploring machine learning. With the democratization of AI technologies, children can now communicate with machines not only via code but also via natural language and computer vision technologies [16,43,44]. This makes it easier to help to familiarize children with AI technologies as no writing or programming experience is required [16,43].

In order for children to explore the big ideas of AI, Touretzky, Gardner-McCune, Martin & Seehorn [43] argue that children should have the opportunities to interact and tinker with machine learning based technologies. Children could examine representations created by intelligent agents, for example, by having a computer learn to recognize their facial expression or simple gestures [43]. Instead of just sending a series of commands to the agent, the idea of a feedback loop provides the youngsters the opportunity to reflect on how the agent might represent the world, perceive the information it receives and how it modifies its behavior accordingly [16]. For example, Google's Teachable Machine, the tool used for the present case study, is very easy to use for even very young children as they can train a machine learning model by using familiar cultural signs, such as their own facial or bodily expressions. After training, the Teachable Machine responds to the child's bodily actions and translates them to a child-friendly symbolic medium (e.g., sound of a bird, picture of a bunny). In this regard, following Papert's vision, these external artefacts and input-output pairs that the children taught the computer represent the children's own thinking and bodily action in the real world.

What is more, the child does not necessarily need to know the rules or basic logic of programming in advance. Rather than deductive reasoning and rule-based programming that drove Papert's Logo programming language experiments, by using well-designed machine learning-based tools, a child can engage in the process of data-driven programming: providing the machine with a training data set and then using the trained model to control the machine. In that inductive process, the child's exploration is driven by background knowledge, such as the input design [45], as well as by the use of an external artefact, the computer, which gives powerful means and clues for reasoning the relationship between the input and output. While teaching a computer is based on a behaviorist model of instruction (stimulus-response), here the children themselves are positioned as active subjects (teachers), and not the objects of teaching typical in more traditional models of instruction in education.

However, as of today, only few initiatives to introduce ML education appear in the literature, with some early contributions from Wolfram [46] and Kahn et al. [47], and with earlier initiatives, of a very different kind, dating back at least to the 1970s [e.g. 48]. On the other hand, some very recent work described projects and workshops where school kids explore and design ML systems in educational settings. For example, Zimmermann-Niefield, Turner, Murphy, Kane & Shapiro [23] investigated how youth with no programming experience can incorporate ML classifiers into athletic practice by building models of their own physical activity. According to their findings, the youth were able to collect data, build models, test and evaluate models, and quickly iterate on this process that emphasized making, exploration, and play. In their study on machine learning for school students, Mariescu-Istodor and Jormanainen [24] developed an ML tool and hands-on learning activities for children and youth to explore how object recognition works. With the support of computer scientist, the school students were training ML system with their own drawings of animals and thus, were able to explore the basic mechanism and concept of ML in creative ways. Their study opened the black box for older students, exposing how the system classifies images, but kept the inner mechanisms hidden from younger students. Another recent study of Druga and her colleagues [16] explored how children from four different countries imagine smart devices and toys of the future and how they perceive current AI technologies. The authors describe that the way children collaborated and communicated while expressing their AI perception and expectations were influenced both by their socio-cultural background and previous experiences with coding and interacting with AI technologies.

So far, previous research has charted pedagogical grounds and presented hopeful findings for promoting computational thinking and ML in education. While the democratization of AI technology has opened new opportunities for children to become active subjects and creators of ML systems, critics have also begun to draw attention to concerns related to the (mis)use of personal data when children and youth interact with ML-based technology [17,49]. Making human bodies, psychological states, and natural language machine-readable means that also embodied experiences have become "traceable" and may provide valuable data for platform owners [49]. Thus, it is important to recognize the tensions and trade-offs that researchers, teachers, and educators may face when developing and studying pedagogical models and tools for integrating ML topics into education.

3. RESEARCH DESIGN.

In order to ensure an equitable and inclusive AI education for children, there is an evident need for participatory research that also takes the young children's voices, views, ideas, and experiences into account [44]. The design of this study followed the current trends of including children as meaning-makers and members of research and development work around technology and technology-mediated practices for children [e.g. 50,51]. The pedagogical rationale behind participatory research approaches is to empower children to understand and make a difference in the technological world around them [51].

To facilitate children's agentic experiences in technology driven society, this study aimed to explore children's early encounters with and insights of machine learning based technology. As an exploratory study, it looked at how and in what ways very young children teach and explore machine learning based technology. Similar to sociocultural studies of mind, this study did not posit standard developmental capacities on certain ages, but rather focused on the ways in which children's thinking and sense of agency are related to the affordances and social situations of the moment [27]. The reason is that the way one understands and conceptualizes young children's encounters with digital technologies depends more on the tools and sociocultural context than on children's age [52]. This study analyzed, in minute detail, the ways in which six children, aged 3-9 years old, constructed with the support of a familiar tutor their interaction with a machine learning system and, in turn, how the responses of their machines shaped children's actions and interactions during the exploration. The research questions were:

1. What do the children teach the computer?
2. What kinds of interaction processes emerge when the children teach the computer?
3. How do children perceive and explain this unfolding process of teaching and learning?

3.1 PARTICIPANTS.

The participants of the study were six children from Finland, aged 3-9 years-old. In this participatory study, children were asked to describe themselves in their own words and to make pseudonyms for themselves.

Out youngest participant was Toma, a three-year-old boy. He said that he likes swimming, animals, and playing. One of Toma's hobbies is skating. When he grows up, Toma wants to climb on the roof. Kaisa is a six-year-old girl who likes football, basketball, volleyball, and ice hockey. When she grows up, Kaisa wants to drive her bicycle without training wheels. Kaisa's big brother, Kimi, is an eight-year-old boy. He likes football and riding his bicycle and driving an all-terrain vehicle. In the future, he wants to mow lawns.

Helmi, an eight-year-old girl, likes dogs. She plays football. In the future, Helmi wants to have her own dog and work as a veterinarian. Helmi's little brother Tuukka, a five-year-old boy, likes swimming. In the future, Tuukka sees himself as ice hockey player. Lastly, Helmi's best friend Hertta, a nine-year-old girl, likes football and goldfish. Hertta sings in a choir. In the future, Hertta sees herself working either as a doctor or as a veterinarian.

3.2 RESEARCH ETHICS.

Working with very young children requires special attention to research ethics. The present study was guided by the ethical principles of research in the humanities and the social and behavioral sciences, provided by the Finnish Advisory Board on Research Integrity (2009). The recruitment of participants was based on child and parental interest and willingness to be involved. The guardians of all the participating children gave informed consent to conduct the research. The researchers explained the study's aims to the participating parents and the parents were further guided to explain these aims to their children. The parents were also informed that their own, as well as their children's, participation was voluntary and that both of them had the right to withdraw from the intervention at any point. Moreover, these joint discussions, agreements, and guidelines provided the basis for participant-led data collection in which the data produced and shared for research purposes rest on participants own decision-making.

3.3 DATA COLLECTION.

The data collection was done by the parents or a familiar adult, and took place at the children's homes. Children's interaction with a Teachable Machine was video-recorded using a GoPro camera or a smartphone. Prior to the experiment, participating adults were given a very short introduction to Google's Teachable Machine (GTM). Firstly, the adults facilitated children to select three different "emotions"—or more specifically, facial expression of those emotions— that the children would like to teach to a computer by using their own facial and bodily expression. Example emotions were joy, sadness, or tiredness. Emotions were selected as the first object of teaching because such hyper generalized semiotic signs always connect to children's personal life experiences [cf. 53] and can be communicated using facial expressions familiar to children (e.g., a smile). What is more, emotional expressiveness is one of the key elements in the development of children's emotional regulation and competence [54]. While learning and socialization of emotions is ubiquitous in children's everyday contact with parents, teachers, caregivers, siblings, and peers [55], researchers and educators in early childhood education have also supported children to recognize and name emotions, for example, through laminated illustrations or puppets with detachable faces that depict different emotional expressions. This study used facial expressions as a way for children's interaction with a machine, and training it to recognize expressions.

Secondly, the children could freely explore the input-output relationships with GTM. Here, the adults were guided to support children in making their own observations and interpretations of the GTM's outputs to different inputs. Thirdly, after the exploration the children were interviewed by their parent/familiar adult. The children were asked to explain, in their own words, what happened and why when they taught the computer. Adults could participate and support the children's narration and ask for clarification, if needed. Moreover, the children were asked to adopt the computer's perspective through five questions (What does the computer see? What does the computer do? How does the computer do things? What did the computer learn? What else could you teach to a computer?). These joint discussions were held near the computer so that it served as a point of reference that the children could lean on when narrating their experiences and insights. Interviews were video recorded so that the children's gestures and facial expressions could also be captured when they were reflecting on their own bodily actions and interactions.

Fourthly, some of the children were also co-teaching a computer with their sibling or friend. That experiment explored how the dynamics change in collaborative learning, as well as how children explain and rearticulate their previous experiences when teaching another child. Table 1 summarizes the data used in analysis.

Table 1: Teaching session of the experiment and the video data collected

Settings	Participants	Collected data from the use of the ML tool (min., including interview)
Teaching a computer with the support of parent or familiar adult	Toma (3y) and mother	16:33
	Tuukka (5y) and mother	21:50
	Kaisa (6 y) and a familiar adult	08:06
	Kimi (8y) and a familiar adult	9:30
	Helmi (8y) and her mother	36:49

Peer teaching a computer	Kimi (8y), Kaisa (6y) and a familiar adult	12:16
	Helmi (8y) and Tuukka (5y) and their mother	18:12
	Helmi (8y) and Hertta (9y)	21:38

3.4 DATA ANALYSIS.

Data were analyzed using qualitative content analysis. At the beginning, all the video data, including interviews, were watched several times in order to form an overall impression of the children's interaction with the learning tool. Based on that, the data were divided into three main phases: 1) Teaching (creating training data and training the machine learning model), 2) Exploration of the model with test data, and 3) Explanation. These main phases included children naming the emotions and other content to be taught to a computer, producing the data and creating the classification model, exploring the output, and reflecting on or explaining the process of teaching and learning.

First, the researchers identified the emotions and other content of teaching that the children taught the computer. Based on this identification significant teaching sessions for further analysis were selected using the Atlas.ti program. In this second phase of analysis, a theory- driven coding template was constructed based on Vygotsky's basic mediated-action triangle [26], elaborated with Rogoff's [28] notion of guided participation as starting points. In these fine-grained timelines of interactions [see 55] the subjects (children, parents), the object of the teaching activity (teaching of a particular emotion) and the tool being used (Teachable Machine) were plotted in parallel and in chronological order. This enabled studying the emergence and duration of ongoing interactions as well as tracking down how children's verbal and nonverbal actions build on previous ones and how they are related to the computer's outputs. The three resulting categories and subcategories are presented in Table 2.

Table 2. Coding and definitions.

Main code	Sub code	Definition
Active exploration (subject → tool)	Verbal initiation toward a computer	Child's verbal initiation toward a computer, e.g., repeating what the computer says aloud, responding to what a computer says aloud
	Nonverbal initiation toward a computer	Child's nonverbal initiations such as smiling or raising hands
Feedback from a computer (tool→ subject)	Response from a computer	Animation, sound, speech
Guided exploration (subject ←→ subject)	Giving the interactional initiative to peer or adult	Child-initiated verbal or nonverbal instructions, e.g., pointing, providing encouragement, hints, guiding questions, praise, answering children's questions, laughing with parent or another child
	Response to interactional initiative from peer or adult	Child's verbal or nonverbal response to the initiative received from a parent or peer
	Receives interactional initiative from peer or adult	Parent or peer-initiated verbal or nonverbal instructions, e.g., pointing, providing encouragement, hints, guiding questions, praise, answering children's

	Sharing	Child's verbal or nonverbal initiative towards parent or sibling/peer (e.g., sharing a memory, idea, showing one's discoveries or explanation)

The construction of timelines supported the analysis of children's interviews as it enabled tracking down the tool-mediated actions and social interaction behind children's own reasoning and explanations. Accordingly, children's explanations were interpreted as part of the interactional context from which they were produced.

To increase the reliability of the study, the results of the analysis were negotiated by two researchers. However, the limitation of the present study is that the empirical research was situated in real-life settings where numerous contextual factors, variables, and processes are always present and in interaction with each other [57]. Given the small number of participants, it is also unclear how an activity like the one presented here could work, for example, with a full classroom of elementary school children. As an exploratory case study, this study did not aim at generalisability, however, detailed descriptions of the research context and design features of the intervention, data, and methods support the transferability of the findings [58].

4. RESULTS.

4.1 CONTENT AND PROCESS OF TEACHING.

When the children were asked to name emotions to be taught to a computer, all of them wanted to teach expressions of happiness and anger. As for the third emotion, children chose sleepy, sad, scared, or cheering (as an expression of great happiness). After teaching these emotions, the children also wanted to teach some other gestures and hand signs, such as thumbs up, thumbs down, heart, cheek pull, and showing rabbit ears. The following three vignettes illuminate the teaching process in more detail, elaborated with the children's experiences and explanations of this unfolding process of teaching and learning.

4.1.1. CASE OF A 3-YEAR-OLD.

The first example of fine grained process analysis comes from the youngest participant, 3-year- old Toma. Toma chose to teach the computer feelings of "happiness" [smile], "anger" [angry facial expression] and "cheering" [raising hands up]. When creating the ML training data set, Toma's mother supported Toma to name these feelings as well as to record them. At the beginning of the exploration, his mother also asked guiding questions such as "what happens if you raise your hands up"? After the model was trained, Toma explored the input he gave the computer in relation to the GTM's outputs, which triggered short .gif animations (cat, dog, bunny) and spoken English words (hello, awesome, yes). While the English words were unfamiliar to a very young Finnish boy, Toma was especially interested in exploring the animations of animals familiar to him. These animals bridged his previous experiences: for example, during the session Toma told his mother that he found bunny droppings at the kindergarten yard. Moreover, Toma quickly realized the general idea of the animal animation as a representation of his own actions, as he had no problems in showing his mother how the cat, dog, or bunny appeared on the computer screen. This first teaching session lasted 07:59 minutes.

A little later, Toma wanted to try the learning tool again. However, this time the output was done with Finnish words: the computer said aloud, in Finnish, the three feelings that Toma had chosen to teach it. While the speech synthesizer's Finnish pronunciation was a little confusing for Toma, he again quickly recognized a connection between his own actions and computer's reactions. Figure 1 illustrates this emergent process of teaching and exploration in his second teaching session.

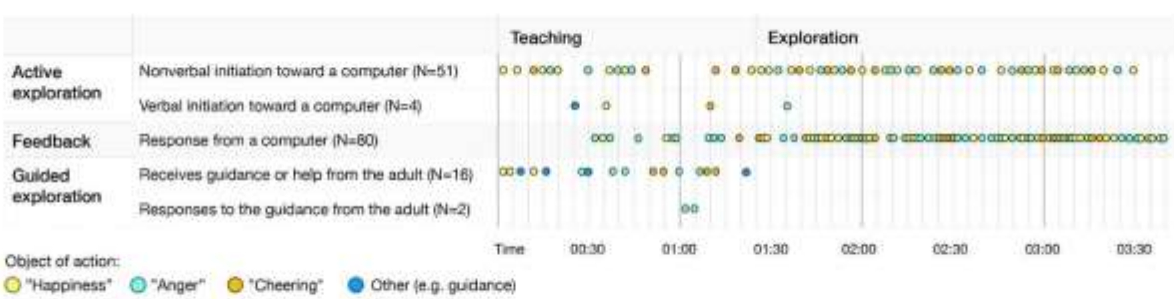

Figure 1. Emerged process of interaction with teachable machine.

Figure 1 shows how Toma's mother was supporting Toma to teach the computer, but withdrew to the background as the exploration progressed. The exploration phase consisted of very lively interactions between Toma and the computer, as Toma made 51 nonverbal initiatives towards the computer, which in return was naming Toma's own bodily expressions aloud. When the model successfully interpreted Toma's actions, Toma typically switched to some other emotion. This created a chain of quick interactional chances for exploring how the machine responds to his own multi-modal input. The resulting interactions showed how Toma built and tested an ML-based emotion classifier through his own representational gestures and thus, explored abstract conceptual ideas and procedures in a highly embodied manner. From the early childhood education point of view, the child was also engaged in an important developmental activity of identifying, naming and externalizing emotions [cf. 53].

4.2.2. CASE OF 6- AND 8-YEAR-OLD.

Our second example illustrates how 6-year-old Kaisa and her big brother, 8-year-old Kimi explored the Teachable Machine in collaboration. At first, Kimi had about two minutes of introduction and adult support on how to create a training data set and train a classifier. Kimi taught the same emotions as Toma, apparently because Toma had told Kimi about his teaching experience. Like Toma in the previous case, Kimi engaged in self-directed exploration of input- output interactions by giving quick, nonverbal interactional initiatives towards the computer.

After a little while, Kimi's little sister, 6-year-old Kaisa, came to explore GTM, and again, the process of interaction was quick-paced. The children were asked if they would like to teach a computer together to recognize their faces and who is on the camera—which meant that the computer was saying aloud the names of the children when they were showing their faces to the camera. As for the third class, the children named cheering. The analysis of the co-teaching process revealed that the interaction was again a rapid-paced interplay between the two children as well as the computer that was speaking the children's names aloud. When introducing themselves to the Teachable Machine, the children made different kinds of facial and bodily expressions and had much fun teaching them to the computer.

Interestingly, during this exploration phase, Kaisa began to show dance moves to the Teachable Machine and asked her brother do the same. Following Kaisa's initiative, the "cheering" was named and re-written as "dancing" and the focus of teaching turned to dancing (stretching the limits of what the Teachable Machine can do). When a computer was first saying their names aloud, the children interpreted that as a kind of a call for dance—as they often began to dance after hearing their own name. The interaction with a computer was again highly quick-paced and these interactional turns were so quick that it sometimes sounded like the computer was saying two-word sentences such as "Kimi dances". While both children were keen on showing their dance moves, the children were also shifting their dancing turns as well as dancing together in front of the computer. This showed how an easy-to-use ML tool gave children ample room for imagination and collaboration for exploring and familiarizing themselves with AI technologies. Figure 2 illustrates the emergence and nature of this child-initiated exploration of Teachable Machine.

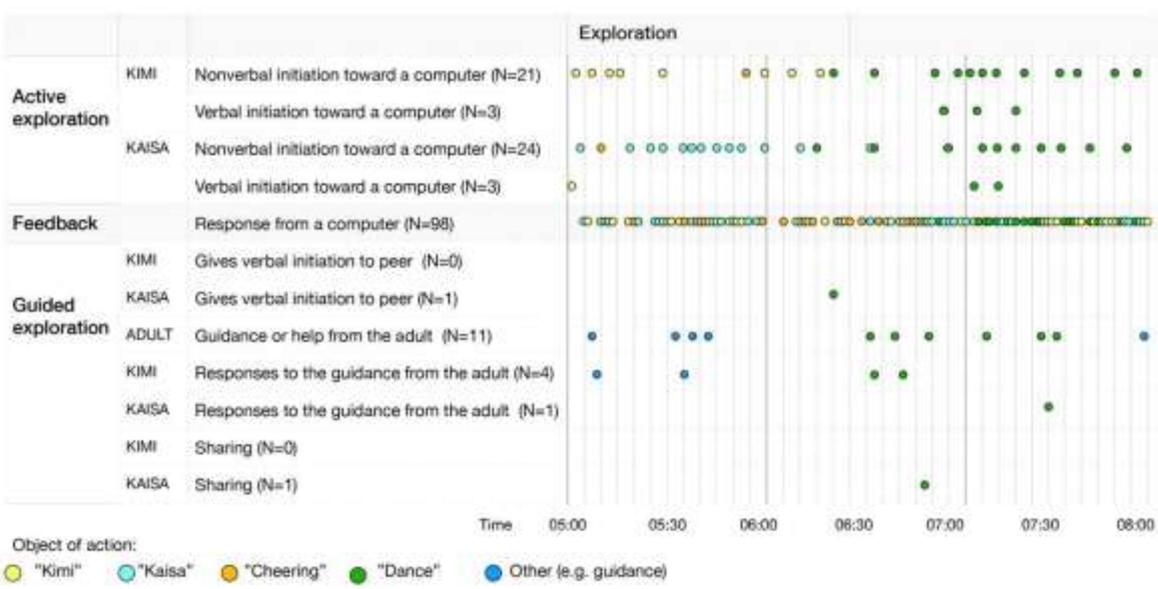

Figure 2. Co-teaching a Teachable Machine.

4.1.3 CASE OF 8- AND 5-YEAR-OLD.

Our third vignette from 8-year-old Helmi further illustrates the process of teaching a computer. At the beginning of the exploration, Helmi's mother gave a five-minute introduction to the tool by showing a video (in English) and at the same time, explained the idea and function of the tool to her daughter (in Finnish). As Helmi had been studying a little bit of English at school as her first foreign language, her mother suggested that Helmi would teach emotions to a computer in English. Helmi named the emotions “happy”, ”angry”, and “sleepy”, and the mother supported Helmi to spell and write these words for the Teachable Machine.

The analysis showed that Helmi quickly realized the general idea of the Teachable Machine. Moreover, she was also able to deliberate on and explain why the classifier she had trained sometimes failed to recognize her new input. The moments of failure were interesting in terms of positioning, which drives the process of exploration and explanation. First, Helmi verbalized the failures of the Teachable Machine to correctly identify her expressions through her own emotions by saying that she is not angry. A little later she switched her locus of explanation to the computer’s perspective and then explained to her mother how her own behavior and the model she taught affected these failures in the interaction.

Figure 3. Learning the limits of the classifier that Helmi trained.

As Helmi was interested in teaching, she further taught the use of Google’s Teachable Machine to her little brother. At this phase, their mother withdrew to the background and Helmi took the role of peer teacher. Here, Helmi supported her brother to name the emotions to be taught, guided him to create the training data set and encouraged him to explore the output. This created a chain of interaction changes, where Helmi typically gave a verbal instruction to Tuukka, who then responded by taking bodily initiatives toward the computer, which then reacted to Tuukka’s initiative through a speech synthesized response and animated .gif (figure 4). Moreover, the computer’s success was often evaluated by Helmi. This shows how over the course of the activity, Helmi could master the basic use of the ML tool to guide her brother to create a “program”.

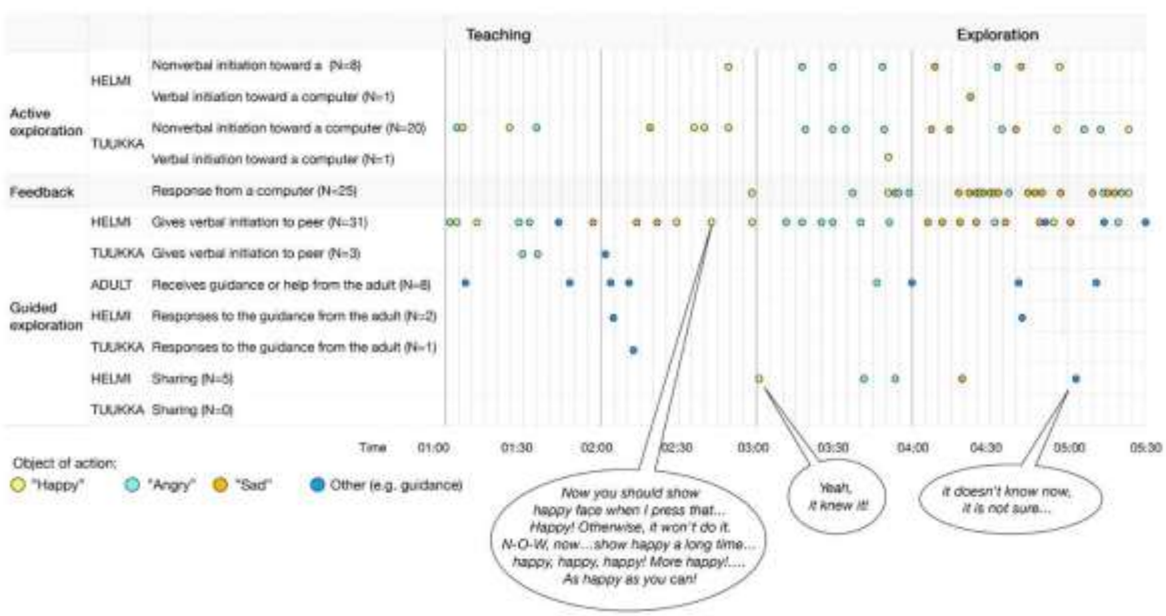

Figure 4. Co-teaching a computer.

4.3 CHILDREN’S EXPLANATIONS AND EXPERIENCES OF TEACHING.

With the Teachable Machine as a concrete point of reference for exploration, the first case shows that this 3-year-old child had no problem in identifying the animated and speech synthesized computer outputs to be a response to his own input given through bodily actions. What is even more interesting is that after 11 minutes of tool-mediated actions, a 3-year-old considered the emerging interactions both from his own and from the computer's point of view (what he sees vs. what the computer "sees"). This was evidenced when Toma was explaining these interactions afterwards:

Mother: So why does the [the computer] say it [word "happy"]?
Toma: Because I smile [smiles] then it says "happy"
Mother: Why is it [the computer] cheering [says the word "hurray"]?
Toma: Because I raised my hands up [raises his hands up and shows]
Mother: Well, what does the computer see?
Toma : It saw that I was cheering

Moreover, in this discussion, Toma used the same gestures when communicating his ML ideas and explanations to her mother. This presumably indicates that his mental images about ML were deeply grounded to his own bodily experiences and interaction with a computer.

Similarly, after about 6 minutes of interaction with the Teachable Machine, Kimi (8 years) explained: "It [computer] sees ... it sees ... um... what the computer is taught, so it sees that ". He further elaborated his explanation when giving guidance to her little sister:

Kimi: It [computer] recognizes those faces ... and it
Adult: yeah
Kimi:... and it recognizes those movements and it imitates them behind

Helmi's (8 years) interview confirmed that she clearly understood that the output on the computer screen was a response to her own input and the ML model she had taught. What is more, she also reflected on the amount of data that the computer needs for learning:

Mother: What about when you taught those emotions to it (computer)? So why did it say, for example, "happy"?
Helmi: Well, because we taught that to it
Mother: How did we teach that to it?
Helmi: Well, we showed that to it many times, a little over a hundred times ... and then it learned that

After guiding her little brother on how to use Teachable Machine, Helmi also evaluated if her brother had understood what he had taught the computer. This was done by asking about the ways that the animals in the .gif animations appeared on the screen, as shown in the following excerpt:

Helmi: What was a cat (gif animation)?
Tuukka: Green
Helmi: No, how was that cat done?
Tuukka: Two thumbs up (raises his thumbs up)
Helmi: Tuukka talk louder
Tuukka: Two thumbs
Helmi: What about a dog?
Tuukka: um ... One thumb down
Helmi: What about a rabbit?
Tuukka: um...by disappearing from the picture

What is more, the children also recognized that "being a teacher of a computer" was something new in terms of what they had experienced before. In general, the children described that teaching a computer was fun. Helmi described her positioning towards the Teachable Machine by referring to her previous experiences in school education: while earlier she felt that the computer had taught her, now she felt that she is teaching the computer—at the same time that process taught her too. She described the feeling as follows:

Mother: Well, how did you feel about teaching the computer?
Helmi: Pretty funny
Mother: Why was it funny?
Helmi: Well because the computer is taught even though the computer usually teaches us
Mother: yeah..well what have you learned from computer earlier, you said that
Helmi: well we have made those slideshows at school...
Mother: yeah
Helmi: … so there we had to search for information from the Internet from...I don´t remember what was the name
Mother: from Google?
Helmi: no
Mother: from Wiki...
Helmi: Yes, from Wikipedia!

5. CONCLUSIONS.

While machine learning is becoming a commonplace feature of people's everyday lives, so far there is a very limited body of theoretical or empirical studies focused on investigating learning machine learning from young children's perspectives. This understanding is, however, vital for enhancing children's participation and for supporting them to gradually develop computational fluency and data literacies that help them to understand the world they live in [40,59]. Machine learning has rapidly become the central technology for a range of applications, and its importance and application areas are growing fast – yet it is a poorly covered topic in computing education research, especially for young children. This exploratory study was aimed at addressing this gap by studying young children's early encounters with and insights to machine learning based technology.

Regarding the first research question, "What do the children teach the computer?", the results illustrate how, with the support of powerful tool and familiar tutors, young children explore the basic mechanisms of how machine learning works by training a model with data that they found meaningful—this time in the form of expressions of emotions. When teaching hyper generalized semiotic signs [cf. 59], the children could use their own previous knowledge and personal life experiences and thus explore this seemingly abstract phenomenon in a highly contextualized way. As such, the children were positioned as active subjects who were both producing the training data sets as well as testing the classifier they had trained, observing, exploring, and explaining the outcomes of their multimodal input. It is also worth noting that the same signs and gestures that children themselves decided to teach a computer, such as thumbs up and down or finger heart, also appear in various kinds of media texts and data-driven practices of contemporary media culture.

Regarding the second research question, "What kinds of interaction processes emerge when the children teach the computer?", the results further revealed that when the children themselves were instructing and controlling the Teachable Machine, the process of interaction with the computer became very quick-paced by nature; that was supported by immediacy of interactions enabled by the tool. While the object of action was in the expression of emotions, such child-driven, bodily interaction with quick interactional changes both sustained the interaction as well as enhanced the children to reason between their own bodily input and output of a responsive tool [see 38]. The results suggest that using easy-to-use ML tools that give children ample room for imagination helps young children explore and familiarize themselves with AI technologies as no writing, syntax, strict form, or programming experience is required [16,43]. The results of the study further indicated that the children themselves also recognized that the interaction design, which relied on quick-paced, multimodal interaction differs from a more traditional child-computer interaction in educational settings.

Regarding the third research question, "How do the children explain this unfolding process of teaching and learning?", one would expect young children to encounter great problems with explaining what happened with a machine learning system, especially when they are learning a black-box system by exploring without being instructed. However, the results illustrate that all children could explain the general idea of the output on a computer screen as a representation of their own bodily input interpreted by the ML model they had taught. Even the youngest, three-year-old participant was able to demonstrate the ways of instructing a computer, and, surprisingly, could distinguish between his own and the computer's "point of view" in the interactions that emerged. The apparent ability of a three-year-old to position oneself outside his own frame of immediate experience, and to look at the world as the computer "sees" it, warrants more research and analysis. What is more, the results of the study showed how children had no problems teaching their peers to explore the ML tool and some of them also reasoned on how to create a good data set and evaluate if the system was classifying the inputs correctly.

However, the exploratory nature of this study means that the observations above are not aimed at making claims about developmental trajectories. One of the main observations from the limited data is that when children's reasoning is supported by a powerful tool, they can, under some circumstances, provide rather informed explanations of their own interactions with machine learning technology. In socio-cultural terms, the results of the study illustrate the tool- dependent nature of human reasoning [27] and further confirmed that the practice of teaching a computer can be a generative fairway to explore the theoretical ideas associated with computation [36–38]. While Papert's visions fueled various kinds of efforts to bring computational thinking in the school curricula [59,60], critics have also pointed out that there is no significant empirical evidence that any of those highly-promoted pedagogical approaches in computing have resulted in improved outcomes for children's learning compared to other approaches [39,59]. Yet, the underlying educational philosophy of positioning children as active subjects and meaning-makers is also a common pursuit in contemporary early childhood research and practice. What is more, teaching children about the technology they daily interact with is one of the drivers of technology education and has merit per se [59].

The results also support previous research [16,23] that suggests that ML should be incorporated it into children's activities in a manner that supports their own socio-cultural practices, such as making, play and creativity. With a focus on child-centered, playful exploration, all the children were keen to show different kinds of bodily expressions and all of them described the process of teaching and exploration of the Teachable Machine as "fun" or "nice". While responses such as "fun" can arguably be considered as situational, conversational rhetoric between the children and adults [27,61], there were also a wealth of non-verbal signs of joy during the actual process of teaching and exploration. There again, it is also very likely that a large part of the excitement among the children was due to a new, highly interactive tool to play with. Be that as it may, such positive encounters and early experiences can play a key role in fostering children's intellectual curiosity to develop their computational thinking and understanding of machine learning.

6. DISCUSSION.

Given the paucity of research on the educational opportunities of machine learning technologies in K–12 education and especially for young children, this study offers new, early findings and pedagogical insights for future research, development, and education efforts. The results from this study suggest that embodied interaction with machine learning systems opens unforeseen research avenues for enhancing learning and computational thinking for beginners, especially with young children. As machine learning technology is slowly becoming the driving technology of a growing number of applications, there is a rapidly increasing need for teaching its basics to all. In the future, longitudinal pedagogical research can expand on understanding how computational thinking and understanding of machine learning develops in a process of learning, (co-)designing, experimenting, and participation. After exploring the basics, the children can, for example, proceed to co-design and build their own machine learning applications with the support of more experienced peers or adults. Through designing, experimenting, and playing, they can gradually develop a deepening understanding of, for instance, different machine learning techniques, data sets, under- and overfitting, and testing and improving their systems.

However, machine learning introduces learning pathways that are very different from those of traditional computing education. Computational thinking curricula typically proceed from simple linear algorithms to control structures, data types, and programming language syntax, among other computational thinking elements [62]—but as machine learning ideas and concepts are markedly different from the "classic" computational thinking concepts, the learning pathways, notional machines, and progression in machine learning also differ. Among the many clear and pronounced shifts are, for instance, the shift from rule-driven to data-driven thinking, from transparent and explicit to opaque, from deductive to inductive, and from sensitivity to syntax to brittleness of models and sensitivity to bias in training data. One of the central concerns with teaching computing, including machine learning, for all, is how to teach children about the role that computational thinking and design play in modern technology, sciences, media, and life in general [4].

While the findings of the study cannot be generalized to other populations, the knowledge of young children's insights and technology-enhanced meaning-making is important for future pursuit of equitable and inclusive AI education. Recognizing that even very young children are able to engage in the exploration of machine learning based technologies can encourage researchers, teachers and pre-service teachers to try out and further develop these new opportunities in diverse educational settings and for various purposes. After all, teachers and caregivers play a key role in bridging a child's present understanding with new understanding and skills in using specific cultural tools [28,29]. As machine learning is becoming emblematic of the current era, the importance of including its basics in the K–12 education system will parallel, and potentially surpass, the importance of programming and computational thinking. This study shows some early pedagogical results from teaching it to very young children.

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