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Vartiainen, H. (2022). Cross-boundary co-design for learning machine learning. In AI, data science, and young people. Understanding computing education (Vol 3). Proceedings of the Raspberry Pi Foundation Research Seminars.

Available at: rpf.io/seminar-proceedings-vol-3-vartiainen

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Introduction

Over the years, teaching computer science (CS) has been approached from different theoretical and pedagogical perspectives — both in research and in practice. As Kafai, Proctor, and Lui (2020) argued, some people focus on teaching foundational concepts and practices of the discipline, whereas others focus more on teaching computational design and engineering. Meanwhile, other approaches emphasise strengthening CS experiences that promote critical thinking and social justice, and aim to empower all children to become informed citizens in today's society. Each of these educational traditions has different theoretical underpinnings and priorities, as they typically place emphasis on either the cognitive process, on participation in the practices of communities, or on understanding the impact and influential role of computing in society (Kafai et al., 2020).

Similar questions and debates have also been emerging in terms of teaching artificial intelligence (AI) and machine learning (ML): should we develop pedagogical approaches and tools that support students in understanding the structures and the internal workings of ML? Should we develop pedagogical approaches that promote creativity and broader participation with the help of low-floor ML applications? Or should we focus on AI ethics and data literacy to enable the critical questioning of the practices of our data-driven society?

In the past few years, we have seen a rapidly growing number of initiatives for integrating such AI/ML topics into K–12 education (ages 5–18). However, the challenge is that there are no ready-made teaching practices or clear guidelines on what works when, how, and for whom. Another question regards in which school subject, or combination of subjects, ML should be taught. Moreover, the objectives, tools, and pedagogical approaches can be very different when working in diverse educational settings that range from kindergartens to high schools (Tedre et al., 2021). Research has also shown that what and how subjects are taught in schools is highly dependent on various contextual factors, such as national policies and curricula, as well as local school practices, goals, and values, which shape the everyday activities of teachers (Härkki et al., 2021). The development of new educational practices also requires responsiveness to the learning needs of teachers, as many of them are unaware of the mechanisms, opportunities, and impacts that ML already has on our societies, communities, and individuals (Vartiainen et al., 2022).

On the other hand, over the past decade, efforts by several interdisciplinary teams to conduct educational design-based research (DBR) have shown the significant promise of the strategy of engaging researchers, developers, and practitioners in a model of collaborative, iterative, and systematic research for the development of novel educational practices (Penuel et al., 2011). This approach highlights collaborative endeavours between researchers and practitioners, who work together in designing, implementing, and evaluating prototypes of learning environments, educational technologies, and pedagogical approaches aimed at addressing concrete educational needs (Penuel et al., 2011). From this perspective, we argue for the potential of cross-boundary collaboration and co-design as a strategy for bringing ML education into existence within school practices.

In this paper, we provide some reflections on our experiences of co-designing and piloting a ML project in Finnish basic education (ages 7–15). We describe how a learning project was co-designed by researchers from different disciplines in collaboration with local school teachers. We also present the pedagogical underpinnings and contextual factors that have informed our cross-boundary work and how these perspectives were transformed into learning activities, infrastructures, and scaffolding provided to school pupils. All this comes together in the closing section, in which we discuss how to support the contextual integration of ML topics into classroom practice.

Co-designing a pedagogical approach for ML: The case of Finland

Mapping local needs and design constraints

In Finland, like in many other countries, ML is a new topic in schools, and there is a significant lack of research and practices on how ML can be made part of our educational practices. In response to these knowledge requirements and challenges, we began our process of co-designing by organising joint discussions between researchers and participating school teachers. In accordance with an educational DBR approach, these joint discussions played an important role in framing local design constraints, such as how ML projects could be implemented in line with the Finnish national core curriculum, and how our intervention could be customised to serve the local needs and interests of the collaborating school. Although ML is not explicitly included in the Finnish National Core Curriculum for Basic Education (NCCBE), the curriculum's general frames of learning and teaching focus on the development of seven transversal competences:

- T1 – cultural competence, interaction, and self-expression;
- T2 – taking care of oneself and managing daily life;
- T3 – multiliteracy;
- T4 – ICT competences;
- T5 – working life competence and entrepreneurship; and
- T6 – the participation and involvement in and the construction of a sustainable future (T7).

These transversal competencies are to be introduced in local subject-specific curricula as well as through project-based studies that integrate several school subjects. From this perspective, our joint efforts to promote children’s agency and ML understanding through collaborative learning and design are well aligned with these national goals.

As a context-specific feature, it is also important to note that Finnish teachers are highly educated professionals who have a high degree of autonomy in their work. While the NCCBE is considered obligatory, the Finnish educational system does not involve standardised testing, auditing, or outside teaching supervision. Instead, the Finnish educational system emphasises trust in teachers’ professionalism, and teachers can decide on their teaching and assessment methods. Additionally, research-based approaches for developing educational practices are recognised in both the Finnish national strategies and teacher education (Niemi & Lavonen, 2020).

Making plans for joint action

As yet, there are no ready-made practices for teaching ML, so our joint planning of school projects focused on mapping the key elements of the desired activity system; together, these elements should enable the development of students' ML design skills as well as their understanding of the basics of ML. In practice, this meant negotiating 1) the objectives and learning tasks/problems that pupils face, 2) the tools, technologies, and materials provided, and 3) the forms of social organisation (e.g., individual, small group, and whole class activities) and the division of labour. This also required the creation of a shared understanding of the practical means through which we aimed to orchestrate relations among these elements in diverse stages of the project. These joint agreements were written down in a shared document that served as an externalised plan for the coordination of joint activities.

Implementation of the project through co-teaching

As our previous publications have described this intervention and the educational technologies employed in more detail (Vartiainen et al., 2021; Toivonen et al., 2020), we will now only briefly reflect on how the key elements of the designed activity system emerged during the implementation of the project. As one of the rationales for our pedagogical approach was to provide students with access to expert-like practices by working together with CS experts, we also elaborate on how CS researchers and teachers scaffolded the students' learning of ML.

In short, our pedagogical approach relied on design-oriented pedagogy, which aligns well with the national curriculum in Finland. Design-oriented pedagogy entails students building their conceptual understanding and new ways of thinking by creating digitally or materially embodied artefacts and projects with the support of technology (Kafai et al., 2020). Instead of scripted, build-a-thing tasks or step-by-step exercises, the students were instructed to work in small groups and were given open-ended learning tasks to generate ML solutions to real-life problems that they considered to be meaningful. In other words, the students had a large degree of freedom in terms of what to co-design within the epistemic, material, and social structures that support the learning of basic ML concepts and practices. Within the project described here, students' could learn to follow the basic epistemic functions related to ML workflow for problem-solving: how to collect data relevant to solving the problem, how to filter and clean the data, how to label the data, how to use those data to train a classifier, and how to link the classifier results with desired behaviours (in a web app, for instance), and evaluate the model (Tedre et al., 2021). While the development of conceptual understanding was deliberately addressed, we emphasised its creative uses with regard to solving everyday problems and gaining new insights into the ML-driven world students are already living in.

In terms of afforded technologies, students worked with Google's Teachable Machine 2 (GTM, see Toivonen et al., 2020), and our own in-house developed educational application for ML (Mariescu-Istodor & Jormanainen, 2019). At the beginning of the project, CS researchers demonstrated the ML workflow using GTM, which also gave the opportunity for the students to observe the processes through which experts make use of basic conceptual and procedural knowledge. As the CS researchers were verbalising their actions and thought processes, the students could also begin to build a mental model of the target processes that were required to accomplish the given learning task. Consequently, the students familiarised themselves with the possibilities of afforded tools. During this hands-on exploration, the CS researchers actively observed the students' activities, and they provided on-demand support by offering hints, guiding questions, conceptual reminders, and scaffolding (see Figure 1). At the end of the first workshop, the students were assigned an individual homework task, which asked them to search for and identify everyday problems that could be solved by using ML-based technologies.

Figure 1. Examples of social settings and support.

For the second workshop, we produced a design template with the aim of supporting the further development of ideas through collaboration. This template followed the GTM workflow and asked students to analyse what their own apps would do, what kind of data would be collected and from where (image, sound, poses), how many different categories the model should be able to recognise, and under what conditions the teaching data would be presented. Here, the idea was to provide scaffolding for the students to adapt basic ML concepts to the problems that they themselves were trying to solve. These externalised ideas were further defined in collaborative discussions with computer scientists who, for example, encouraged the students to reflect on their ideas, articulate the reasoning behind their dataset choices, and direct their attention to previously unnoticed aspects, such as the important role of background settings. In this way, the content of the expert scaffolding was immediately related to specific design ideas as well as emerging challenges that arose when the students were creating training datasets for their own ML applications.

Moreover, working in teams provided students with an additional source of scaffolding, in the form of knowledge and processes distributed throughout the groups. Developing their own ML models for applications also provided an important feedback loop, as the students could receive immediate feedback on the implementation of their own design ideas; that is, they could test the quality of their own data. GTM did not always work as students expected; hence, the students also had to analyse the relationship between their own input and the output provided by the responsive tool. Such a feedback loop also made it easier for the students to explore how the agent represents the world and perceives the information it receives and how it modifies its behaviour accordingly (Druga et al., 2019). In addition, each of the student teams worked on its own problem, and thus, they were also able to observe multiple ways in which this tool and the related conceptual knowledge can be applied.

On the other hand, even if such a low-threshold tool can support novice learners in familiarising themselves with ML, the implementation of such a design project revealed the importance of creating productive social settings and scaffolding around ML-based educational technologies. These technologies were actively used by the students in different phases of the project: when exploring the opportunities presented by these technologies in the first workshop, when creating datasets for their own applications in the second workshop, and when testing their own and other teams' applications in the final workshop. In addition, the collaborative discussions with their peers as well as with the CS teachers were constantly organised around these tools. Evidently, working with computer scientists was important as these experts had a deep understanding of the ML technologies being used and disciplinary ways of thinking, which helped them to be flexible in supporting and responding to the ideas and questions that students developed during the process. Meanwhile, the class teachers played an important role with regard to guiding the student teams in working together productively, engaging in respectful discourses and reflections, taking shared responsibility for the collaborative work, and displaying persistence in developing their understanding of ML. During these workshops, the students could also witness how their teachers were interested in learning about ML, and how they engaged in collaborative discussions to figure out how ML works. In this way, the teachers were also modelling how creative experts deliberately work at the edge of their competences and actively try to go beyond their current understanding (Bereiter & Scardamalia, 1993).

Reflection

Our process of co-design ended with reflections provided by all the actors involved. At the end of the project, each student team was asked to reflect on its own design and learning process. Such reflection deliberately challenges students to explain their own thinking and actions, and thus, these discussions provide information on how the process of co-design was actualised and experienced from the pupils' perspectives. Likewise, verbal explanations of the functionality of the application designs gave additional information about what kind of support pupils might need in their co-design projects. In a similar vein, joint discussions were held with the school teachers with a focus on how our co-designed activities, tools, and infrastructures supported the design and learning process of the students. In line with the DBR approach, various kinds of empirical data were collected, analysed, and reported in collaboration with the researchers from computer science and education.

Discussion

In this paper, the aim was to provide reflections on our process of co-designing and piloting ML learning projects in Finnish basic education (see Figure 2).

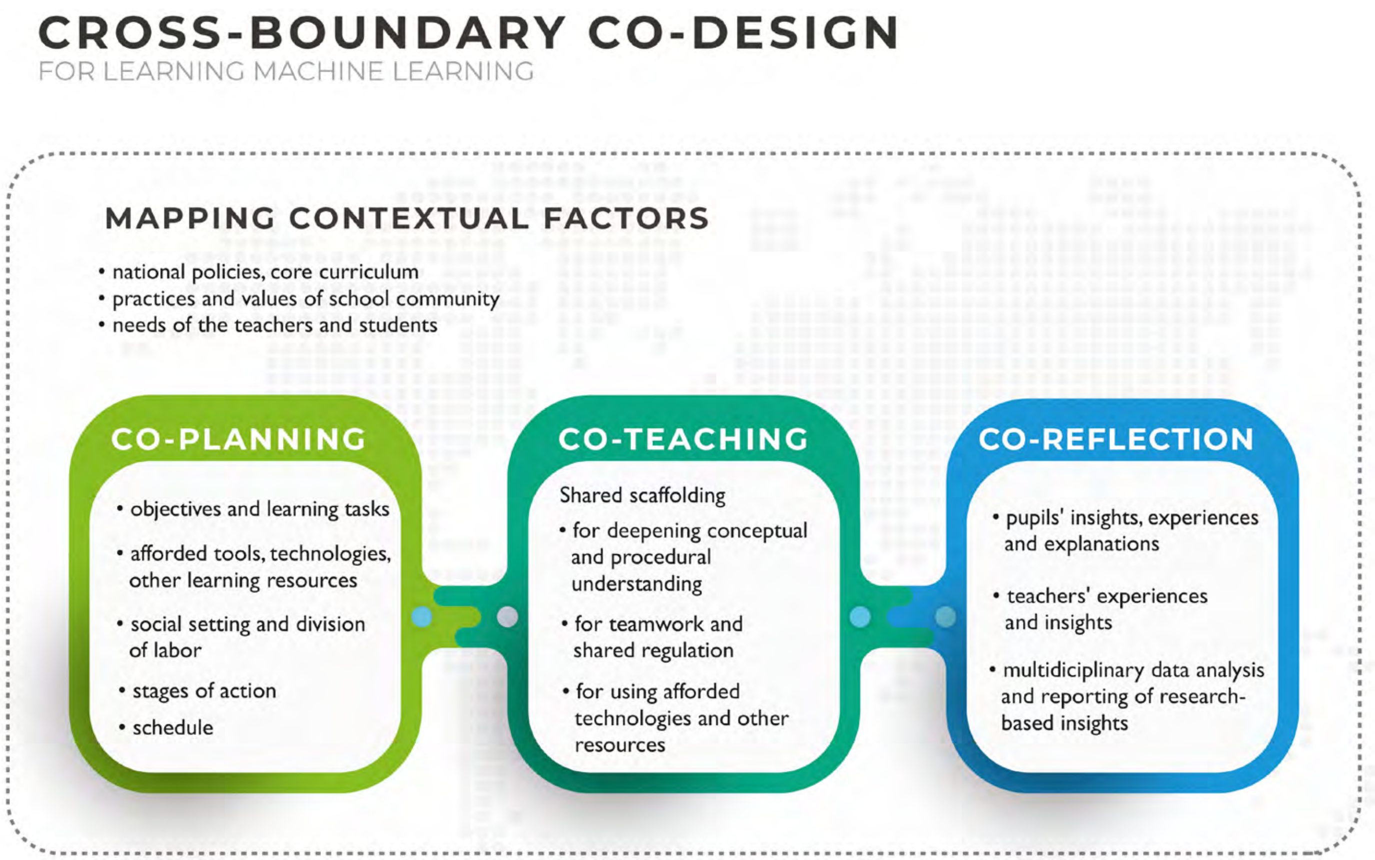

Figure 2. Cross-boundary co-design.

To conclude, our project illustrated how co-design between researchers and teachers was crucial for the success of the project. These joint efforts also provided indirect scaffolding for the emerging learning activities of the students, as the focus of the design was on the specification of the objectives and learning tasks that pupils pursue and the selection of appropriate technologies and forms of social organisation during the different stages of action. Overall, the design of novel educational practices, which were simultaneously relevant, appropriate, and capable of being realised, was crucially dependent on capitalising on complementary expertise. In this design process, the researchers from computer science contributed their extensive experience in computational thinking and ML educational tools, whereas the educational researchers brought theoretical and pedagogical ideas from the learning sciences. The teachers, in turn, provided their unique insights with regard to adapting the practices and educational technologies suggested by the researchers to serve their local contexts and the actual needs of their own students.

In a similar vein, the potential of cross-boundary collaboration was demonstrated during the implementation of the project as the CS researchers and schoolteachers all brought their unique knowledge, skills, and expertise to help scaffold students' learning and understanding. On the other hand, the arrangement of having researchers and teachers working together in a classroom is a unique setting and far from the reality of most schools. Yet, we believe that co-teaching may provide promising paths for teachers to develop and orchestrate novel practices for integrating ML topics in education. Our example also illustrated how disciplinary knowledge, pedagogical knowledge, and technological skills were all needed in the scaffolding of students' activities (Valtonen et al., 2019). While some studies and practices of design-oriented learning have created the impression that students can deepen their skills and understanding on their own, it is important to understand how pedagogical infrastructuring and contextual scaffolding provided by teachers and experts are a driving force for learning (Viilo, 2020).

Overall, the process provided promising results in terms of supporting middle schoolers to become co-designers and creators of their own ML applications in a manner that provided valuable learning experiences. Yet, the question remains as to how to scale up such practices and provide concrete resources for teachers to implement ML projects in various educational settings. Challenges also remain in terms of ML-based educational technologies. The use of low-floor ML-based educational technologies, such as those used in this project, may provide a promising entry point for novices looking to learn ML. Yet, students learn about ML workflows but not about the internal ML mechanisms (Tedre et al., 2021). While progress has been made in developing explainable AI for education, we should also develop learning tasks and processes that are responsive to students' evolving skills and understanding by increasing the complexity of skills and concepts. In a similar vein, we should make sure that children are able to extend and refine their creative abilities, critical thinking, and participation with regard to these evolving technologies. Accordingly, we will not only need ML-based educational technologies and learning materials, but also research-based understanding on how to create appropriate social settings and pedagogical infrastructures around these evolving educational technologies.

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Acknowledgements

We thank the January Collective for their continuous support as well as for the original idea for this study. The study presented here is a part of the research activities of the UEF DigS research community.

Raspberry Pi Foundation