Research paper

High school students exploring machine learning and its societal implications: Opportunities and challenges

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A B S T R A C T

The increased use of AI and machine learning (ML) calls for a general AI literacy, in particular regarding understanding how ML works, the process behind creating ML models, and reflecting on its implications. Where existing learning tools focus on the first two, we explore opportunities and challenges for meaningfully engaging students in understanding and reflecting on ML in their everyday life. We designed VotestratesML, following a Constructive Design Research approach, as an ethics-first learning tool that allows students to explore implications of ML for democratic elections. Based on deployments of VotestratesML in two high school social studies classrooms, we found that safely exploring ML from a concrete starting point helped students reflect and form opinions about its use, that promoting iterative exploration through collaboration and competition motivated them to explore, and that foregrounding ethics in the design and grounding ML in a well-known subject area allowed them to engage with ML on a personal level.

1. Introduction

The increased use of Machine Learning (ML) in almost all aspects of our lives (O’Neil, 2017; Pasquale, 2015) increases the necessity of a widespread AI literacy (Druga, Vu, Likhith, & Qiu, 2019; Long & Magerko, 2020). AI, and subsequently ML, is part of the infrastructure of many everyday technologies in ways that are often opaque and difficult to comprehend (Burrell, 2016; Shneiderman, et al., 2016). Understanding how AI and ML work is important not only for those pursuing a career in STEM (Science, Technology, Engineering, and Maths) fields but, arguably, for all children, as these technologies are increasingly pervading all aspects of our lives (i.e., education, leisure, and work). Thus, AI literacy becomes a precondition to fully participate in society, whereby the term literacy denotes that the goal is not simply to develop children’s instrumental skills, but also a critical understanding of manifestations of power and ideology in AI technologies, and consequently, its personal and societal implications (Van Mechelen, Wagner, Baykal, Smith, & Iversen, 2021).

The importance of a critical understanding of technologies has also been echoed in recent studies on Computational Thinking (CT). Researchers (e.g., Brennan & Resnick, 2012; Grover & Pea, 2013; Iversen, Smith, & Dindler, 2018; Kafai, Proctor, & Lui, 2019; Tissenbaum, Sheldon, Seop, Lee, & Lao, 2017) have argued that traditional CT competencies (e.g., decomposition, abstraction, automation, etc.) should be complemented with critical perspectives on the personal, social, and political consequences of digital technology. In these broader and more comprehensive approaches to CT, students learn about technologies and computational infrastructures, not just in order to become better programmers or designers, but also to enable them to engage with political and ethical questions about technology in the real world. As Kafai et al. (2019) put it, these approaches see the “cognitive understanding of underlying concepts of CT and its uses in the world as key to becoming a more critical practitioner of computation”. We agree with the critical approaches above, and align ourselves specifically with the notion of Computational Empowerment (CE) (Dindler, Smith, & Iversen, 2020; Iversen et al., 2018); a perspective on computing education rooted in Scandinavian participatory design values of democracy and skillfulness that aims to develop children’s critical understanding and informed decision-making with regards to the role of digital technology in their lives and society more broadly (Iversen et al., 2018). Using CE as an approach to AI literacy raises the question as to how ML learning tools can qualify and support children’s critical reflection and understanding of ML, including its personal and societal implications.

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With this awareness of the need for students and the general public to understand AI and ML, researchers have started exploring what K–12 students ought to know about ML. Touretzky, Gardner-McCune, Martin, & Seehorn (2019) in order to become AI literate (Long & Magerko, 2020). The understanding needed can be summarised as belonging to three main areas; (1) what is a ML system, (2) how are ML models developed, (3) and what are possible implications of ML applications? An important aspect to consider here is what Blikstein (2013) terms selective exposure, i.e., which aspects of the technology should be foregrounded to children, and how to maximise what can be achieved with the technology through a certain tool. In current research we often see the former two areas emphasised in educational tools and practices (Kahn & Winters, 2018; Williams, Park, & Breazeal, 2019; Zimmermann-Niefield, Turner, Murphy, Kane, & Shapiro, 2019), while the third is either neglected or only briefly touched upon (see e.g., Zimmermann-Niefield, et al. (2019), which seeks to engage ML novices in interactive model building, but leaves notions of empowerment to future work). This trend is also demonstrated by Giannakos, Vougari, Papavlasopoulos, Papamitsiou, and Vannakakis (2020), who identify several projects/games for teaching AI/ML, where most focus on the first two areas (e.g., ML4Kids1 and AI4Children),2 while a few include the third area (e.g., The Moral Machine).3 This aligns with findings of Van Mechelen, Baykal, Dindler, Eriksson, and Iversen (2020), who, based on a systematic review of child–computer interaction research, concluded that design ethics (i.e., the personal/societal impacts of technology and its qualities in use) has been underdeveloped in the literature, both as an overall concern and an explicit learning goal for children.

Thus, while interesting work has been done that can inform the design of tools and activities to teach students about ML; to our knowledge, no studies have taken a CE approach to learning about ML, which entails a more equally distributed focus on all three main areas. With the aim to do so in this paper, we explore the following question: What are the opportunities and challenges for a CE approach to meaningfully engage students in understanding and reflecting on ML? To explore this question, we have reviewed existing literature on designing ML curricula and tools for teaching it with regards to how to support CE. Additionally, we have designed VotestratesML; a prototype of an interactive, collaborative learning tool for ML, aimed at supporting high school students in exploring and reflecting on the role of data and ML in political campaigns. VotestratesML was iteratively developed in a Constructive Design Research (CDR) process (Krogsh & Koskinen, 2020; Stappers & Giaccardi, 2017), and serves both as a proposal for a high school learning tool for ML, and as a means to explore the design space of ML learning tools in high schools. The process was realised through six user-interventions in two social studies high school classes. To inform the future design of learning tools for ML, we herein present our findings and how they formed the design of VotestratesML.

With this paper, we address Eriksson, et al. (2019) call to open up new frontiers for research that carries child–computer interaction (CCI) beyond the foundation and legacy of Papert and Harel (1991) in order to embrace the entire education system with a broader, more critical perspective on 21st century learning, and encompass diverse issues related to children's use and understanding of emergent technologies, such as ML (Eriksson, et al., 2019), a need more recently identified by Van Mechelen, et al. (2021) who note that critical notions of empowerment are only marginally represented in CCI. More specifically, our contribution is a synthesis of what students should know about ML as seen through the lens of CE, as well as the design of VotestratesML and the ways in which this tool can engage students in learning about ML and critically reflect on its impacts.

The paper is structured as follows; In Section 2 we review existing literature on ML curricula and learning tools. Then in Section 3 we present VotestratesML. Here, we describe a typical use scenario in a classroom, then we detail the VotestratesML prototype and user interface (UI) and highlight certain aspects of the design of the tool. Finally, we provide the overall design rationale behind the tool. Following this section, we present our design process and study in Section 4. In Section 5 we present our findings, before discussing them with regards to our research question in Section 6. In Section 7 we discuss limitations of our study, and finally in Section 8 we conclude the paper and point to future work.

2. What students should learn about machine learning

Here, we review existing literature about teaching ML to K–12 students, divided into three main areas that correspond to current research trends about what these students should understand about ML (Long & Magerko, 2020; Touretzky et al., 2019); (1) what a ML system is, (2) how ML models are created, and (3) what possible implications of ML applications are. Often learning tools for ML address the first two areas and to a lesser extend the third, but we argue that a focus on CE requires a specific focus on the third area in combination with the former two.

2.1. What is a ML system?

We see in the literature a focus on teaching what a ML system is. Along these lines, Touretzky et al. (2019) emphasise how computers learn from data and maintain models/representations of the world based on this data. Similarly, Long and Magerko (2020) state competencies such as distinguishing between artefacts that use and do not use ML, understanding the strengths and weaknesses of ML system, and recognising how ML systems reason and make decisions as core in developing a literacy about ML and AI. This approach is reflected in most tools for teaching ML. Many block programming languages include this such as AI Snap! blocks (Kahn & Winters, 2018) that allow students to build ML applications in the Snap! block-programming language, using predefined ML blocks. Similarly, Cognimates (Druga, 2018) and Machine Learning For Kids from IBM allow children to experiment with speech recognition, object recognition, etc., through the Scratch programming language. Other tools specifically designed for teaching ML have a similar focus. The popular Teachable Machine (Carney, et al., 2020) by Google, allow users to input data and train ML models for image, sound and gesture recognition. Popbots by Williams et al. (2019) introduces the basics of ML systems, such as training a classifier by labelling data input. Cozmo, a robot from Anki, allows children to play and experiment with built-in object and marker detection, face recognition, etc.

While understanding what constitutes a ML system is important, it is not enough to understand the whole of ML, and from a CE perspective, not enough to develop the capacity for critically engaging with the implications of ML. Understanding what a ML system is, will help students recognise ML systems in-the-wild, and with reasoning about what tasks ML a technology is suitable for addressing, and importantly which it is not. However, it does not help students in deciphering and challenging assumptions implicitly built into the system by its designers and the implications these might have for the people affected by the system.

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1. https://machinelearningforkids.co.uk/  
3. https://moralmachine.mit.edu
2.2. The ML process

Another current focus is on teaching the process of creating ML models. Here, Long and Magerko (2020) emphasise the different steps involved in creating ML models and the role humans play in doing so. Several learning tools focus explicitly on this aspect of ML. Hitron, et al. (2019) introduce the Gest system, a ML-based gesture recognition system designed to teach children aged 10–13 about data labelling and evaluation of ML models. They conclude that children are able to understand ML processes, specifically data labelling and evaluation of models, and that children are able to apply this knowledge in other contexts. Zimmermann-Niefield, et al. (2019) deploy learning tools for ML into a high school context. They design and evaluate AlpacaML, an iOS application building models of athletic moves through sensor-input for use in physical education in high schools. They found that students developed their own theories on what constituted a "good" model and were focused on the performance of their particular model rather than whether the model was true to what it modelled. Kaspersen, Bilstrup, and Petersen (2021) and their Machine Learning Machine try to encompass the entire process of building ML systems, from collecting data to training and to evaluating a model, and the iterative nature of doing so.

Understanding the ML process is another central aspect of developing AI literacy from a CE perspective. An understanding of the ML process entails understanding what steps are involved in creating an ML model and importantly the choices made by humans in these steps (for a further discussion of this see, e.g., Enni and Assent (2021)). In combination with an understanding of what ML is, understanding ML processes will allow students to further pick a part of any ML system, and go beyond the face-value of the system to reflect on and discuss how it came to exist.

2.3. Implications of ML

Finally, there is a focus on the implications that ML systems might have on society and in our personal lives. Long and Magerko (2020) stress that students should understand that “data cannot be taken at face-value” and that some systems have the ability to “physically act on the world”. Finally, they point out that students should be able to “[i]dentify and describe different perspectives on the key ethical issues surrounding AI”. Similarly, Touretzky et al. (2019) present the idea that AI and ML systems “can impact society in both positive and negative ways” and that this is a important to teach. We also see this in research on learning tools, albeit to a lesser extent. Bilstrup, Kaspersen, and Petersen (2020) engage high school students in designing ML systems in a card-based design workshop which engages them in discussions of the ethical dilemmas in applying ML to solve real-world issues. Similarly, Skinner, Brown, and Walsh (2020) explore children of colour’s perception of fairness in ML/AI systems in a co-design workshop in which 9–14 year old children design a “fair” AI librarian.

Understanding the possible implications of ML implies viewing ML systems as socio-technical systems that engage in complex social and technical structures in our society. Seeing ML systems this way allow students to look beyond the system itself and reflect on the way it affects people around it in direct and indirect ways.

2.4. Three areas of ML

In summary, we see that what students should understand about ML can be divided into three areas; what ML is, the ML process and implications of ML, and that focus on them are different between different learning tools. Table 1 presents an overview of how a selection of different tools and activities address them (the selection includes a limited but broad view of both popular publicly available tools and recent research prototypes). Focusing on one area is not sufficient as, e.g., understanding the ML process requires knowledge of ML concepts and vice versa. E.g., in a later paper, Zimmermann-Niefield, Polson, Moreno, and Shapiro (2020) expand AlpacaML to integrate with Scratch allowing students to build gesture-controlled interactive media and to engage more with understanding different components of a ML system and how they fit together. Similarly, tools targeting the first two areas, sometimes include reflections on ML implications; Hitron, et al. (2019) also investigate if children after using Gest are able to reflect on situations where it is inappropriate to use ML, and find that about half of the participants were able to identify issues about privacy, intimacy, and safety. Kaspersen et al. (2021) propose scenarios explaining how the Machine Learning Machine could be used to explore ethical issues of ML, such as data representation and biases, but do not evaluate this aspect. These aspects are, however, most often not presented as a core aspect of the learning tool design, but as an addition that requires a separate discussion.

From a CE perspective, understanding and being able to reflect and act on the implications of ML is the most important of the three areas, and should be at the core when designing ML learning tools. However, to be able to do so requires some insight into what ML is and the process of creating ML models and humans’ role in doing so. Thus, all three areas must be covered, at least to some extent, by learning tools aiming to support children in becoming computationally empowered, and research is needed that explores how to do so. In the following section, we present VotestratesML, which as a learning tool embodies our exploration of how a balance between the three areas could be struck.

3. VotestratesML: A collaborative learning tool for teaching ML

VotestratesML is a web application enabling students to collaborate in real time on iteratively building models for predicting voter behaviour using voter profile data, and which aims to scaffold class-wide discussions about ML. Data from a survey of the Danish national election in 2015 (Møller Hansen, 2017) is used in the prototype to make predictions about real world voters. VotestratesML and the rationale behind it embodies our suggestion for how to teach ML with an emphasis on CE, although other researchers might design such a tool differently.

3.1. A VotestratesML use scenario

In a typical use situation of VotestratesML, students are introduced to the tool and how it supports building ML models. Next, students are divided into groups of 3–4 people. Each group member logs into VotestratesML on their laptop gaining access to the collaborative ML tool, see Fig. 1a. The teacher then asks groups to create the best possible model for, e.g., predicting if a person will vote for The Social Democratic Party. Each group chooses the Votes for The Social Democratic Party-label available in VotestratesML. The groups go on to discuss which features to include in their model. Here, students can draw on their existing knowledge from social studies class. For example, according to the Michigan Model for voter behaviour (Jensby, Pedersen, & Brøndum, 2017), which students are taught in advanced social studies, voting behaviour is affected by family, and thus, it might be important to choose features describing how the parents of a person voted. Once students agree on a set of features, they need to choose an algorithm, and to determine its parameters. Once
Table 1

<table>
<thead>
<tr>
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<tbody>
<tr>
<td>What ML is</td>
<td>Training data, ML models, training</td>
<td>Training data, ML models</td>
<td>Training data, ML models, hyper-parameters, training</td>
<td>N/A: Children were asked what AI and “fair” meant.</td>
<td>Training and test data, training and evaluation</td>
</tr>
<tr>
<td>The ML Process</td>
<td>Data gathering, labelling, cleaning and analysis, evaluating models</td>
<td>Data gathering and labelling, evaluating model</td>
<td>Data gathering and labelling, evaluating models</td>
<td>N/A</td>
<td>Entire process, from training to evaluating models</td>
</tr>
<tr>
<td>Implications of ML</td>
<td>N/A: Authors suggest to explore it in future work</td>
<td>Explored in post-interviews, but is not part of the learning tool design</td>
<td>N/A</td>
<td>Design and discussion of what constitutes “fairness” in an AI Librarian.</td>
<td>N/A: Authors suggest activities, but do not evaluate them</td>
</tr>
</tbody>
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3.2. Collaboratively building, evaluating and reflecting on ML models with VotestratesML

Below, we describe in detail the design of VotestratesML as it played a central role in the knowledge generation leading to the contributions of this paper. This is explained further in Section 4.

To support real-time collaboration, VotestratesML is built in Webstrates (Klokmose, Eagan, Baader, Mackay, & Beaudouin-Lafon, 2016), which synchronises DOM elements between multiple clients in real time. The students each work on their own laptop, but collaborate with their group through a shared Webstrates-based website, making the interface of VotestratesML inherently collaborative between group members’ laptops. Every group member has full control over the application and they must communicate to coordinate their work, the intention being that students will divide tasks with different focus points between them.

VotestratesML consists of three interdependent components that support different types of class activities through providing different functionalities and model views. The relation between components is illustrated in Fig. 1.

Using the Collaborative Component, students collaborate in groups by building, testing and improving the group’s ML model for predicting voter behaviour. VotestratesML conceptualises the process of building ML models in a series of steps as illustrated in Fig. 2. First, students process the data-set by shuffling the data and splitting it into a training data-set and a test data-set (see Fig. 2a). Second, they explore the properties of the data-set, which ranges from age and gender to voters’ attitudes towards environmental issues and tax policies, and choose one label and as many features as they like (see Fig. 2b). Finally, they choose between two ML algorithms; K-Nearest Neighbour (KNN)\(^4\) or a Feedforward Neural Network (FNN)\(^5\) and set the parameters for the chosen model (For KNN: value of k, for FNN: layers and number of iterations at the training step), and train and evaluate a model to see how it performs on the test dataset (see Fig. 2c). Students are provided with the model’s accuracy and f1 score, which they can use to compare their model with earlier attempts or other groups’ models. Students can freely jump between these steps and group members can work on different steps simultaneously. The interface is designed to support students in following

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Fig. 2. The VotestratesML Collaborative Component in detail; (a) shows the Data Screen that allow students to experiment with their input data, (b) and (c) shows the Features and Labels screens (conflated as they are similar in design), that allow students to determine what data their model should consider (features) and what it should look for (label). Finally, (d) shows the Model Screen that allow students to select the model type, configure its parameters and train a model.

this process, even if they do not fully understand ML. It does so, by only allowing actions that bring the application to meaningful states, greying out buttons and hiding UI elements when not relevant. Thus, students can work on creating functional ML models from the beginning and can explore ML further by tinkering with data and model parameters to improve the predictive ability of their models. The Competitive Component has a single view, see Fig. 3a, which is projected on a shared screen in the classroom and provides information about the scores of each group’s model. Models are pushed to the Competitive Component by each group as they iteratively try to improve them. Using this component, students can share their models with the classroom, and see how well they fare in comparison with other groups’ models. Finally, the Discussion Component also has a single view which is projected on a shared screen and used to mediate a joint discussion in the class. This component is used to inspect students finished models when the teacher ends the activity of building them. The Discussion Component provides full information about each model, see Fig. 3c, and lets the teacher use students’ models to predict the behaviour of different personas, see Fig. 3b. This is used as an anchor point for discussions about the implications of ML for elections and broader discussions about ML in society.

3.3. Design rationale: Machine learning for social science

VotestratesML differentiates itself from similar learning tools in a number of ways. First, it combines the three areas of what students should know about ML; what a ML system is, the ML process and the implications of ML (with an emphasis on the latter). Second, instead of starting by introducing ML concepts, VotestratesML takes departure in the social studies subject as a tool for analysing voter behaviour. The tool is designed to support typical social studies class activities; Students work in groups on tasks assigned by the teacher, followed by a discussion based on
the group work. The available data categories were chosen based on models of voter behaviour taught in Danish social studies classes (Jensby et al., 2017), allowing students to explore how ML models can predict voter behaviour, compare theoretical models with ML models, and discuss ML models from a social studies perspective and how they are already used actively to affect the outcome of democratic elections (Anstead, 2017; Nickerson & Rogers, 2014; Ribeiro, et al., 2019).

By focusing the design of VotestratesML on making predictions about people’s voting behaviour based on properties like age, income, gender, etc., students can draw on their prior knowledge to explore the extent to which their knowledge and preconceived notions are supported by real-life data. Thus, their prior knowledge and interest in the topic of voter behaviour can bootstrap their exploration of machine learning methods and the implications of these.

In addition, the design of the interface aims to scaffold students in building ML models, even with a very limited understanding of ML. Through experimentation with building models for predicting voter behaviour and iteratively improving these models, students gain experience with the trial-and-error process and begin to gain an understanding of ML models. The KNN and FNN algorithms were chosen because they exemplify the extremes with regards to ML complexity; KNN being simple and FNN being complex. KNN was used to illustrate the basics of ML, while FNN was used to illustrate how ML can become almost too complex to understand. As such, students were not expected to understand the FNN algorithm, rather they could experience how difficult it can be to explain its predictions.

By providing a collaborative interface in which groups are forced to negotiate design choices internally because all group members have full control of the application, VotestratesML aims to scaffold reflections on the process of building ML models. Similarly, the competitive aspect of VotestratesML aims to scaffold students in considering how their models can be improved, and VotestratesML allows students to do so through trial-and-error, which is analogous to how ML models are often improved in real-world situations. Thus, students experience first-hand the design choices and potential issues embedded in ML models. The design of VotestratesML aims to actively scaffold insightful discussions about the implications of ML and to motivate students to further explore ML by interacting with the tool.

4. Method

VotestratesML is the result of a constructive design-research (CDR) process and was evaluated and iterated on through several real-world deployments. In this section, we present the methodology behind our work, the design process leading to the design of VotestratesML as well as how it was evaluated in the field.

We adopted a Constructive Design Research methodology (Koskinen, Zimmerman, Binder, Redstrom, & Wensveen, 2011; Krogh & Koskinen, 2020) in order to investigate how ML learning tools can be designed for K-12 classes and how they can support critical discussions and reflections around the use of ML. According to Bang, Krogh, Ludvigsen, and Markussen (2012), CDR can be seen as a way of iteratively making and testing hypotheses, where knowledge-generation revolves around the construction of an artefact (e.g. a product, a service, media etc.) (Koskinen et al., 2011; Stappers & Giaccardi, 2017) and experiments with this (Bang et al., 2012; Krogh & Koskinen, 2020). In this work, VotestratesML is the central artefact, and our findings are based on the different experiments leading to the version of VotestratesML presented above as well as the lessons learned from the in-situ deployments of VotestratesML. The design process led us to the final version of VotestratesML as presented in this paper (see Fig. 4 for an overview), and to two central hypotheses (similar to the two central arguments of our design rationale); that grounding ML in an existing subject (i.e. social studies) can engage students already interested in the subject but not in ML, and second that collaborating in groups and competing against other groups can be an effective way of scaffolding students’ reflections about ML.

4.1. Participants

We collaborated with two social studies teachers from a public high school, located in an upper middle class area in a mid-sized Danish city, each inviting us to work with one of their classes. We consented 30 students in one class (A), and 31 in the other (B), aged 17 to 20. All participants under the age of 18 were asked for the consent of their parents or legal guardians. Consent forms were collected by the researchers at the beginning of the interventions. All students from both classes had elected into a 3-year social studies class. Students from class A were in their third year, while those from class B were in their second year. In both classes, the gender ratio was approximately equally distributed.

4.2. Intervention protocol

VotestratesML was designed in an iterative design process with three main phases (as illustrated in Fig. 4). In each phase of the design process, each class participated in an intervention with the dual purpose of teaching students about ML and informing the design of VotestratesML, which was introduced in phase 2 and iterated on in phase 3. This resulted in a total of six interventions (see Fig. 5 for an example of the intervention setup). All interventions took place during regularly scheduled social studies class, with each intervention lasting 90 min. Two researchers and a teacher were present during each intervention. The researchers took over teaching during the intervention, while the teacher focused on helping students with exercises and contributing during class discussions.

All interventions were structured similarly; a brief introduction was given about the subject of the particular phase, followed
by the students doing group work, and ending in a general discussion in the classroom. The first phase focused on introducing ML to social studies students and informing the first version of VotestratesML. We did so by introducing students to central ML concepts and letting them work with these in a collaborative Jupyter Notebook, based on Google Collaboratory. We used common interactive elements, such as sliders and drop-down menus to allow students to engage in building ML models without prior programming knowledge. While this was effective in engaging the few students who were already interested in ML, it did not motivate the rest. Thus, in the second phase we explored how to contextualise ML for a social studies class, by deploying the first iteration of VotestratesML. It was also in this phase that the competitive element was introduced, to see what effects this would have on the students’ motivation. We introduced new concepts integral to using VotestratesML, in particular the K-Nearest Neighbours (KNN) algorithm, and let students work in groups using VotestratesML to build social-studies specific ML models, such as creating a model for predicting who will be voting for the Social Democrats. This was also in this phase that students used ML concepts and their experiences with VotestratesML to identify societal implications of ML in discussions in intra-group and class-wide discussions. Regarding collaboration and competition we focused on students’ engagement and frustrations, how they discussed design-decisions while using VotestratesML and for breakdowns with the prototype.

4.3. Data gathering and analysis

Throughout the interventions data was collected in the form of observations and field notes, sound recordings and photography. We made observations and field notes with an open ended approach in which we in particular noted critical incidents related to students’ use of ML concepts in discussions and group work, students’ engagement in discussions and group work as well as frustrations and break downs during the group work with VotestratesML. During the introduction to each phase, one researcher did the introduction while another made observations and wrote field notes. During group work and discussions audio recordings were made by placing recording equipment at the desks of the student groups, and both researchers made observations and field notes as well as taking photos of the students working.

The data was analysed deductively by the first two authors, with the two CDR-hypotheses (see above) as sensitising concepts (Blumer, 1954; Miles & Huberman, 1994) guiding the analysis. Following each intervention, a write-up (Miles & Huberman, 1994) of observations and field notes was produced and discussed between the two researchers present at the interventions. Audio recordings of students’ intra-group discussions during group work and of class-wide discussions were reviewed by the first two authors, and excerpts that informed the sensitising concepts were selected and later transcribed. With regards to grounding ML in social studies, we particularly looked for ways in which students used ML concepts and their experiences with VotestratesML to identify societal implications of ML in discussions in intra-group and in class-wide discussions. Regarding collaboration and competition we focused on students’ engagement and frustrations, how they discussed design-decisions while using VotestratesML and for breakdowns with the prototype.
Between interventions, these analyses were used for designing the following iteration of VotestratesML, with each iteration embodying the findings from the previous intervention (Carroll & Kellogg, 1989), as described above. Following the interventions, the first two authors did an analysis similar to the above, but across all three design phases, the results of which is presented below.

5. Findings

As argued, we see a need for CE learning tools that support students in understanding ML, the process of creating ML models, and in reflecting on the implications of ML and how it should form our future lives and societies. Here, we present and discuss the findings from designing and evaluating VotestratesML.

5.1. Making ML personally meaningful

VotestratesML frames ML as a social studies tool for predicting voter behaviour, that can be used to achieve goals in the social studies subject. With the tool, students can utilise theoretical models from social studies or test their own intuition about who votes for whom. In this way, students can engage with ML both from the perspective of the ML technology and its concepts and processes, but also approach it from a well-known subject area. In particular, the narrative around ML and the models of voter behaviour built by the students inherently frames the discussions in terms of potential societal implications of ML.

This design is based on our experiences in phase 1, where we observed that many students did not see themselves as individuals who could or should understand the technical aspect of ML. The exercises in Jupyter notebooks were centred around basic components of ML, such as features, labels and training- and test-data. From observations made during group work in these interventions, we found that students quickly distanced themselves from the exercises with comments such as “I’m not very good at math” and “This looks very complex” before having invested any time with the prototype. As one student put it in a conversation between them and one of the researchers present: “For this to be really exciting, you probably need to be interested in the subject [ML].” Although students were eager to discuss ML, they did not draw on ML concepts in their discussions.

In contrast, in the interventions with VotestratesML, students’ models and their predictions were used as basis for class discussions in which students’ arguments were grounded in social studies theory and in their existing knowledge of voter groups, or based on their experiences from trial-and-error processes with the prototype. Different types of arguments led to different discussions concerning the use of ML. For instance, in phase 2, students role-played as advisers for the Social Democratic party, and were asked to advice, based on ML models, how to best persuade voters from another party. The exercise spurred discussions about the ethics of using ML in political campaigns, e.g.: “The Social Democrats do vote-seeking [in the role-playing exercise]. But I don’t have much respect for that. I would rather go for policy-seeking...”. In another discussion about how micro-targeting could make democratic parties focus on single issues instead of prioritising coherent ideologies, one student argued: “It is a democratic problem, if you [democratic parties] focus on single issues rather than a coherent ideology or harmony in their policy... it will lack coherence and will not work”. Furthermore, the predictions of the personas’ behaviours spurred technical questions about ML, which could be verbalised using students’ models about, e.g., how models with high accuracy sometimes make poor predictions or why models with more features are not always better.

5.2. Supporting reflection through collaboration & competition

The iterative process of building ML models combined with collaborative and competitive aspects of VotestratesML spurred reflection on and discussion about ML during the activities. While competing in small groups in phase 2 and 3, students collaborated to build the best possible model in order to beat the other groups. Students were observably motivated by the competitive aspect of the exercises and the option for each group to compare themselves to the other groups seemed to give students a sense of ownership, and pride in their models, motivating them to keep improving it. For example, groups regularly cheered after having tested their new model and some students would make exclamations such as “Share it, share it, share it! We need a group name! It’s a great start, nobody is close to us” or “We should choose this features, nobody else has used this one!”.

The audio recordings of students’ intra-group discussions during group work with VotestratesML showed that students were eager to supersede the models of other groups. Students would eagerly discuss how to gain an advantage over their competitors, and these discussions were, although based on students’ understanding of social studies and their personal prejudices, discussions about ML, e.g., whether a new feature was important prior to selecting it:

Student A: “What about this one [a feature]: ‘Supports a political party.’ It could be good”.

Student B: “Yes.. But isn’t it very typical for young people to issue-vote? Like, just voting for what you feel?”

Student A: “Yeah.. You might be right about that”.

Student B: “Can you try train it? [the model with the new feature]”

The discussions and experiments with different features during group work, observably spurred students’ curiosity about ML, leading them to ask questions to the authors present such as “What is a good score?“ and to ideas about why other groups’ models performed better than theirs; “What if we have trained our model too much, so it now has become bad?”. On the other hand, the competitive elements of VotestratesML made some reflections superficial due to the high pace of the competition. Often, students could be seen brushing over otherwise curious results in order to have time for another attempt to beat their peers.

The experience of building and optimising models by any means, however, also led to nuanced reflections on the issues around ML after the group work and to students taking critical stances towards the technology. For example, from the audio recording of a classroom discussion in phase 3 one student argued: “It is against our culture, where you are not allowed to generalise by any means. That is outright what this is built on…”, while another argued: “Machines only look at what we ask them to look at. If they have made a model, it is us who decide, what they should be looking for. Humans are better at marginalising than machines are. If we do not make them marginalise groups, they won’t do it!”... Another student recognised problems with ML models on how to choose which norms should guide the models’ decisions:

“It is very different from person to person, which values you find most important. [...] It is just very different, and it [an ML model] may not be able to predict this”.

5.3. Conceptualising ML for K-12 students from a CE perspective

Where other tools focus mainly on what ML is, and the process of creating ML models, we have worked towards exposing the implications of ML through the interaction with and activities around VotestratesML.

This approach worked well for engaging students in understanding ML and for reflecting on its implications, but we also experienced that students formed misunderstandings about ML, which hindered their reflection: During phase 2, we observed that students had difficulties understanding the connection between the data and the voter behaviour predictions of their models. If choosing a feature did not have the expected effect or a model made an unexpected prediction, most students rejected what the model actually stated, and instead wrote it off as a problem with the data, rather than reconsidering the veracity of their expectations. Especially the generalisability of predictions seemed to be difficult for students. To explore this, in phase 3, we asked students to use VotestratesML to predict how the researchers present at the interventions would vote. While working on the models, students asked the researchers questions such as: "What do you [the researcher] think of this?" or "How do we know, what topics you [the researcher] care about", indicating that students thought of the models as being able to predict the voting behaviour of a specific person or group of persons, rather than as general models for predicting voting behaviour. We believe this misunderstanding about the role of data stems from the data-set being relatively black-boxed in VotestratesML. As argued above, this was done to scaffold students in quickly building ML models, but might have hindered their understanding of the data-set and what each row in the data-set represents. This highlights the importance of finding the right concepts to black box and the right ones to glass box, something also noted by prior research in ML learning tools (Hitron, et al., 2019), and that a good balance between black and glass boxes is not trivial to achieve.

6. Discussion

In this section, we discuss the findings above as they relate to our research question: what are opportunities and challenges for a CE approach to meaningfully engage students in understanding and reflecting on ML?

6.1. Implications of machine learning: Foregrounding ethics and grounding ML in a well-known subject area

VotestratesML aims to teach the implications ML could have on our lives and on society. It does so through two measures: foregrounding ethics in the design of the learning tool itself and the activities with it, and by grounding ML in social studies.

VotestratesML is not unique in including ethics when teaching ML. It is stated as future work for AlpacaML (Zimmermann-Niefeld, et al., 2019) and the MLM (Kaspersen et al., 2021), and Hitron, et al. (2019) evaluate if their participants are able to reflect on ethical ML dilemmas after using the Gest system. However, none of these systems are designed with an ethics-first approach, and aim at teaching ML first, while treating ethics as a sort of after-thought. In contrast, VotestratesML was designed with the intention of foregrounding ML ethics and teaching ML as a means to that end.

VotestratesML does so, by presenting ML as a tool for predicting voter behaviour in social studies, making learning about ML a necessity for becoming a better social studies student. This provides the tool with relevance in a social studies classroom, even if teachers or students initially do not see ML as relevant for the subject. Iversen et al. [12] argue that being able to judge the relevance of a given technology is important for CE. When designing learning tools for CE, we argue that this relevance should be communicated in the design of the tool, allowing students to use the tool for achieving meaningful objectives for the subject and for themselves in general.

This approach seemed to increase students' motivation to engage in activities with ML. Instead of requiring students to “be good at math” or have an initial interest in ML, VotestratesML allows students to utilise ML for achieving meaningful objectives and advance their proficiency as e.g. social studies students, while learning about ML along the way. We argue, that the framing of CE learning tools as belonging in existing subjects is an effective way to engage students with different subject-related backgrounds and knowledge in working with technologies. Zimmermann-Niefeld, et al. (2019) take a similar approach, by framing AlpacaML as a tool for physical education, but do not discuss the critical aspects of introducing ML in athletics with students.

6.2. Exposing the ML process through collaboration & competition

The ML process consists of a series of steps involving human choices such as data gathering and analysis, selecting a model type, optimising the model, evaluating the results, etc. Enni and Assent (2021) Other learning tools such as AlpacaML (Zimmermann-Niefield, et al., 2019) and the MLM (Kaspersen et al., 2021) aim to teach students about this process by letting them create and manipulate data in an iterative fashion. However, they do not engage students in the steps involved in creating ML models between data gathering and analysis and evaluating the model.

VotestratesML, on the other hand, aims at exposing the “messiness” of the entire ML process and to have students experience how it is based on human choices, judgements and trial-and-error. VotestratesML still black boxes some of the underlying ML mechanisms, but aims at exposing the ambiguous choices and the complexity embedded in the ML process. It supports this by allowing teachers to set clear and comparative goals for students (e.g., build the best possible model for predicting if a voter will vote for the Social Democratic Party), and by allowing students to explore and experiment with different strategies for selecting features, model types and model parameters through an interface that is designed for fast iterations and collaboration.

In our study, we found that collaboration and competition were effective means of engaging students, something Iversen et al pose as a major challenge for CE (Iversen et al., 2018). The Collaborative Component of VotestratesML motivated and supported students in reflecting on and discussing different choices while improving their model, and each group seemed to take pride in their models, motivating them to keep improving upon it. The competitive aspect of VotestratesML motivated especially students who were not initially motivated by either ML or predicting voter behaviour.

In line with Iversen et al. (2018), we find motivational factors important aspects to explore when designing learning tools for ML, in order to engage all students in the learning activities. However, discussions during group work were sometimes superficial, as the competition and improving their model, for some students, became more important than understanding how their decisions had affected their results.

This highlights the importance of striking a balance between motivational measures, such as competition, and encouraging reflection. While VotestratesML perhaps does not strike that exact balance it does provide insight into how students can be motivated to engage with and reflect on complex aspects of the ML process.
optimising technical skills, but we argue that while these skills are important, the ability to take a critical stance, to discuss and reflect upon such technologies as ML are even more important skills for a majority of students. Thus, while we should not abandon traditional CT and computer science education, we agree with Hviersen et al. (2018) that CE is an important addition.

When exploring new ways of teaching ML designers and educators should consider the balance between the three areas of ML (see Section 2) and be especially mindful that teaching implications of ML does not become an afterthought, but instead central to the design of the learning tool/activity. We hope that our reporting on VotestratesML, its design and our findings from deploying it can contribute to future explorations of how to teaching ML from a CE perspective.

6.3. What a ML system is: Safely exploring ML from a concrete starting point

We argue, that the conceptualisation of ML (and other technologies) for CE learning tools is a central challenge for CE. Other research emphasises design and fabrication with technology as the core approach to empower youth (Joshi, 2016; Lee, et al., 2012; Tissenbaum, et al., 2017). However, when working with advanced technologies, such as ML, which rely on many other technologies and are integrated into larger infrastructures, fabrication may not expose all its implications. Instead, VotestratesML responds to recent calls on ‘pulling back the curtain’ of intangible and abstract computational systems (Kafai et al., 2019), by providing a concrete starting point for discussing ML. VotestratesML aims to achieve this, by having students build interactive ML models, seeing how they fare when predicting voting behaviour, and discussing this from a social studies perspective. To support this, we designed VotestratesML to allow students to build and configure these models. VotestratesML encourages experimentation with different parameters and models, by only allowing safe actions that result in VotestratesML ending up in meaningful states. VotestratesML black boxes many underlying ML mechanisms, and prioritises students’ exploration of higher level ML phenomena and their implications, by exposing the process of developing ML models.

Although students’ conceptions of ML were challenged, we also observed how their understanding of ML helped them reflect on, discuss, and form opinions about the use of ML in society, and argue for these opinions using terminology from social studies theory and from ML. We have aimed to illustrate for high school students, that ML is not just a powerful tool that can improve their lives; ML models have both positive and negative implications, and it is important that we, as a society, actively engage in discussions about, and take a critical stance towards it.

Furthermore, we chose to use the terminology used in typical ML activities (features, labels etc.) and while most students were able to use many of these terms in discussions, these also revealed misapprehensions in students’ understanding of the terms. We wonder if the use of these terms is an appropriate way to conceptualise ML in high school. It would perhaps be more apt to draw on concepts already known to students, such as dependent and independent variables, or it might be better to simply describe them as input and output. We encourage future research to explore what terminology is most appropriate for introducing ML in high schools.

6.4. Teaching ML from a CE perspective

In Section 1 we argued for the need for a CE approach to teaching ML and in Section 2 we argued for the shortcomings of many previous tools from a CE perspective. While VotestratesML is by no means a perfect CE learning tool, it embodies our best efforts to design a ML learning tool with a CE starting point, summarised in Table 2. This approach might not be ideal for optimising technical skills, but we argue that while these skills

<table>
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7. Limitations

This paper has a few limitations. First, the study has limited external validity: It involved only two social studies classrooms from the same high school in an upper middle class neighbourhood, making the participants a somewhat homogeneous group, and as the interventions took place during a regular social studies class, students might have been motivated simply by having a break from their regularly scheduled teaching. Finally, we acknowledge the risk of confirmation bias and of oversights in our data analysis due to only analysing the data deductively from the sensitising concepts that emerged during the design process and are aware that our findings are suggestive. We stress that the design VotestratesML is a specific proposal, that other tools for supporting CE might look different, and that studies with such tools might identify other, complementary opportunities and/or challenges.

8. Conclusion & future work

In order to promote a general AI literacy in high school students, we set out to explore opportunities and challenges for a Computational Empowerment approach to meaningfully engage students in understanding and reflecting on ML and have done so through a Constructive Design Research approach, by proposing and evaluating VotestratesML; a collaborative learning tool which embodies our approach for engaging students in learning about ML by allowing them to explore ML and its implications for democratic elections. The design of VotestratesML, is based on the notion that students should learn what a ML system is, the ML process and the implications of ML with a particular focus on the third area, to support them in becoming computationally empowered. With VotestratesML, we explored how to design ML-learning tools that qualify and support students in reflections and discussions about the implications of ML. Based on the design process and the deployment of VotestratesML in two social studies classes in a Danish high school, we have identified some key opportunities and challenges; Letting students explore ML and its implications from a concrete starting point and in a low risk way helped them reflect, discuss and form opinion about its use. We also found that VotestratesML’s collaborative and competitive nature helped motivate students to explore and experiment with different options for improving their model. Finally, we found that designing VotestratesML as an ethics-first learning tool and grounding ML in a well-known social studies allowed students to have personally meaningful discussions and to advance their proficiency as social studies students. VotestratesML exemplifies our approach to “pulling back the curtain” of otherwise intangible and complex computational systems in order to engage students with different subject-related backgrounds and knowledge in working with ML as well as other
emerging technologies. We believe that the opportunities presented in this paper hold true for other emerging, computational technologies such as the internet of things, augmented/virtual reality, and blockchain. Further, we find that more research is needed on conceptualising these technologies for high school students to allow them to understand and discuss their implications, especially with regards to which concepts to black box and which to glass box and with regards to the terminology used.

9. Selection and participation

The participants were chosen by their high school teacher volunteering the entire classroom. While most participants were legal adults, a few were under the age of 18. All participants were consented by their respective Social Studies teacher, who asked them if they would sign a standard consent form worked out by the employing university of the authors. All consent forms informed participants about how their data would be collected and stored as well as how to withdraw their consent. All participants under the age of 18 were asked for the consent of their parents or legal guardians. The consent forms were collected by the researchers at the beginning of the interventions.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Magnus Hoeholt Kaspersen reports financial support was provided by Villum Foundation. Karl-Emil Kjaer Bilstrup reports financial support was provided by Villum Foundation. Maarten Van Mechemen reports financial support was provided by Villum Foundation. Niels Olof Bouvin reports financial support was provided by Villum Foundation. The authors do not have permission to share data.

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Data availability

The authors do not have permission to share data.


