Machine (network) learning in K-12 classrooms: Exploring the state of the actual with Actor-Network-Theory

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Abstract

In times when machine learning (ML) and other artificial intelligence (AI) technologies are expanding the role and definition of network learning in schools, this short paper reports from a practice-centred research project that explores how K-12 teachers affect and are affected by educational technologies with AI. Accelerated by the COVID-19 pandemic, data-driven and decision-making systems with ML are already entering various educational policy and practice realms, often underpinned by promises of automation and personalization. A growing number of research, drawing from the theoretical orientations and empirical approaches from Science & Technology Studies is increasingly unpacking such promises as well as addressing controversies directly related to the constitutions of ML AI in education. Still, little research explores the adoption of data-driven AI technologies in classrooms from a socio-material, networked learning stance. This short paper introduces such work (in progress) drawing on ethnographic fieldwork conducted in Sweden. Guided by the ontological and methodological approaches of *Actor-Network-Theory* (ANT), the study focuses on the *interactions* in K-12 classrooms between commercial ML technologies and teachers. Methodologically this means engaging with both human and non-human *actors* through ethnographic approaches striving for very specific descriptions of *interactions* within the *actor-network* and its enacted realities. Preliminary findings from the first of two envisaged case studies in which a ML-based teaching aid in mathematics was tried out in 22 classrooms indicate how compensatory and contradictory actions and accounts emerge within the *network* of heterogeneous *actors*. Human *actors* seem to compensate for the algorithmic actions of the specific educational technology with ML. This is however not a fait accompli but a continuous and unsettled process in the making between humans and the (non-human) technology. Preliminary results also suggest how controversies of ML algorithms in teaching aids, such as their lack of transparency and algorithmic "governance" play out in authentic learning contexts. In conclusion, the paper argues that theoretical and methodological principles of ANT grant for non-deterministic narrative of the heterogeneous nature of educational practice and have the potential to open the black-box of machine learning in the emerging networked learning settings of K-12 classrooms.

Keywords

Artificial intelligence in K-12. Machine learning. Networked learning. Automation. Actor-Network-Theory.

Research background

AI in education thrives on academic, political and commercial assertions of how machine learning (ML) in specific educational technologies can improve and personalize learning, augment and automate teaching while at the same time, transforming all dimensions of education (e.g., Luckin et al., 2016; Tuomi, 2018). Recent year's advances in ML also inspire future imaginaries of how new kinds of mathematical precision, through data analysis of educational activity, will provide "more fine-grained understandings of how learning actually happens" (Luckin et al., 2016 p. 18). Russel & Norvig (2021) describe ML as the scientific study of how computer systems can "learn" from data without being programmed in specific ways. However, ML can also be understood as intensive data processing that affects and alter the behaviour of individuals (Knox et al., 2020). Accelerated by the COVID-19 pandemic, these multifaceted technologies are already entering different realms of policy (e.g., Miao et al., 2021; WEF, 2020) and practice (e.g., Facer & Selwyn, 2021; Luckin & Cukurova, 2019). With their entrance, thousands of data points for each student are being captured within complex network learning infrastructures daily. This data is believed to reveal insights about individual students and their learning that (human) teachers are not able to see with the same accuracy (c.f. Luckin 2016; Selwyn 2019).

A growing number of recent studies drawing from the broad collections of theoretical orientations and empirical approaches from Science & Technology Studies scrutinize these AI promises by unpacking the close connections between research, the EdTech industry and policy and point to the problematic constitutions of ML AI in education (e.g. Knox et al., 2020; Lupton & Williamson, 2017; Perrotta & Selwyn, 2019). By challenging the ideas of education technology as an a-political tool in the service of teachers, many of the findings reveal complex and situated entanglements of "configurations" between social and material *interactions* (c.f. Jones NLEC, 2021, p. 331; Perrotta & Selwyn, 2019). However, accounts from empirical research of how these ML-based educational technologies are enacted in schools are few (Castañeda & Williamson, 2021). The recent emergence of ML in educational technology together with its poorly understood socio-material implications for practice (Hrastinski et al., 2019) sketches the backdrop of this explorative, teacher-centred research project.

Aim and research questions

Guided by the ontological standpoints and methodological principles of *Actor-Network-Theory* (*ANT*) (Callon, 1984; Latour, 1999; Law & Mol, 1995), the ongoing study aims to explore how two different educational technologies with ML affect and are affected by K-12 teachers by focusing on the complex *interactions* in classrooms. Here the term *interactions* is used to describe situations where social and material entities act or enact each other (Latour, 2007). With this in mind, the following tentative research questions (RQs) have been articulated:

- RQ1. How do human and non-human *actors interact* when two different ML technologies are introduced in Swedish K-12 classrooms?
- RO2. How do the two different ML technologies affect K-12 teachers' practices?
- RQ3. Conversely, how do teachers' practices affect the two different ML technologies?

These inquiries also have the potential to deepen the understanding of how technologies with ML shape and are shaped between human and non-human *actors* in network learning (NLEC, 2021).

Tracing with Actor-Network-Theory

Developed as a materialistic movement that explained scientific and technological innovation (e.g., Callon, 1984; Latour, 1999) ANT is used as a theory and method to trace the complex *interactions* between social and material *actors* from which all scientific and technological innovation is constructed. ANT can be positioned within the ontologies of *relational materialism*, where the focus lay on the relations that produce both the material and the social (Law & Mol, 1995). From a *relational materialistic* stance educational facts and artefacts like curriculum, routines or AI technologies emerge as temporary effects from what heterogeneous *actors* do in relation to each other in an everchanging *actor-network* consisting of teachers, students, teaching aid authors, AI-policy, educational researchers but also theories of how students learn, ML algorithms, a research design, paper tests, laptop computers, classrooms, interfaces, broadband, API:s, routers, ed-tech developers and much more. From this outset, a specific ML AI educational technology is a complex and messy infinite web of code, databases, infrastructures, platforms and interfaces, new technical settings, human experts, scientific and commercial settings founded of a vast proliferation of techniques that actively set up and construct specific ways of thinking about and acting upon other *actors* (Decuypere, 2021). The way these *networks* are composed is particularly visible when things go wrong. Conversely, these inter-connections tend to be hidden when things work smoothly. Thus, an AI-based teaching aid appears successful when the *actor-network* is stabilized and durable while concealing all the complex *interactions* between heterogeneous entities that created it and continue to maintain it. Methodologically ANT means to engage with the *actors* through ethnographic descriptions of *interactions* within the *actor-network* and its enacted realities (Latour, 2007).

Design and data production

The study is based on a *multiple case study* approach (Merriam, 1998). Two case studies are planned to address the proposed research questions. The main selection criteria for each one of the cases has been to study the "state of the actual" (Selwyn, 2010), that is to explore the *interactions* between commercial ML technologies and teachers in authentic classroom contexts. The fieldwork of the first case study draws on a Swedish innovation and research project in which an ML-based teaching aid in mathematics, here referred to as the *AI system* was tried out in 22 different classrooms. During two 6 weeks long interventions, students in years 2, 5 and 8 (age 8-9, 11-12 and 14-15) exercised mental arithmetic with the *AI system*, 3 times per week, each session lasting 10 minutes. The learning content consisted of five exercise modules, developed by the teaching aid author in collaboration with the project team. To work empirically and analytically the *actor-network* was "cut" (Fenwick & Edwards, 2017) around salient *interactions* emerging between the representatives from the project team, teachers, students, and the *AI system*. Of particular importance for the ethnographic writing up were field notes from four classroom observations and seven video-recorded and transcribed interviews with teachers and members of the project team. The analysis was made through an abductive process (Dubois & Gadde, 2002) where key events from the ethnographic fieldwork were selected to be included in the analysis as partly inductive reasoning partly sprung out from the posed research questions and selected *ANT* concepts; *actors, interactions, actor-network* and Callon's (1984) *obligatory passage point.* Thought as the narrow end of a funnel, the *obligatory passage point* is what makes *actors* converge on a certain question and can explain why "actors are obliged to remain faithful to their alliances" (ibid p.224). The set-up and data production for Case study 2 is still in progress and therefore not reported on in this paper.

Preliminary findings

Preliminary findings indicate how compensatory and contradictory actions and accounts emerge within the *network* of heterogeneous *actors* and (re)construct the technology promises of AI in education. Human *actors* (teachers, students, teaching aid authors, educators, and researchers) seem to compensate for unexpected and undesirable algorithmic decision-making(s) of the *AI system.* Fieldnotes from one of the classroom observations illustrate how these ideas are materialized in practice:

> A classroom with desks and chairs. The desks are arranged in three rows centred in front of a big whiteboard. 20 students aged 8-9, sit at their desks in pairs or groups of three, each student equipped with a laptop computer. They are exercising with the *AI system*. A teacher circulates the room, occasionally stops, and leans over some students. The *AI system* displays 64-56 on the white laptop screen of several students. The *AI system* then continues to recommend the exercises 51-42, 90-1, 22 + 17, 37 + 19 on one of the laptops. During their *interaction* with the *AI system*, some students demonstratively use their fingers to count. They seem concentrated when taping the numbers that appear in the small, coloured, empty box of the minimalistic interface. As soon as an answer has been inserted, the *AI system* displays the next exercise in the same manner. Some students work individually with the *AI system*, others consult their neighbouring peers to get the answer right. One student says "hello, this is too difficult". After 10 minutes, the teacher ends the activity, and it is time for a lunch break. The teacher later tells me that the students seem to get exercises that correspond to their abilities and thinks students are challenged in a positive way when they get difficult exercises. He adds that it would have never worked without his help or without altering the instructions prior to the exercise sessions. (Field notes, year 2)

The scene captures just a few of the many *interactions* between a group of students in second grade (8-9 years), their teachers and the *AI system*, during a math lesson. Their teacher expresses a certain conviction to the teaching aid and its ability to personalize. However, the idea of personalization does not appear as something that the *AI system* does. Rather the idea of personalization and automated teaching emerges as an effect from the entangled web of exercises, algorithms predicting and delivering the exercises, computers, desks, students trying to insert the correct answers through keyboards via specific interfaces and a supporting teacher in constant movement within a classroom space. For personalization to emerge the compensatory work of the teacher seems indispensable. Human compensatory *interactions* can also be traced in the dialogue between one of the other teachers and the researcher:

> Teacher: Sometimes it felt like the students got the same or similar exercise for a very long period, but I think it is because they were not so good at it then or that they inserted wrong answers…But above all, it was that they could not write anything in the small box, as if it froze a bit.
>
> Researcher: Mmm… and what did you do?
>
> Teacher: Eh well... then we switched to the next module, as there were different modules that you needed to complete. (...) And then this extra module came with more exercises that especially some students used. For some, it was too difficult. The problem here was that they had to write the numbers in ways that did not work…

Rather than abandoning the *AI system* the teacher persuades her students to exercise in different modules when the *AI system* stops delivering numbers. As new modules are added by the teaching aid author, she directs her students to try these out. Hesitant to whether the *AI system* is adapting to the student's ability, the teacher seems aware of which students benefit from this kind of adaptive exercising and for whom the new modules are too difficult. This suggests that in the established *actor-network* the *AI system* recruits co-workers according to its interest, as other *actors*- here a teacher – are enrolled to do its work. The teacher is in fact the one constantly monitoring *interactions* between the students and the *AI system*, providing differentiated content accordingly. As for the suddenly frozen screens, an explanation later given by human *actors* from the project team relates to the decision-making actions of the *AI system.* When a student completes a task correctly at speed, the *AI system* predicts that the individual is very likely to complete the task again and will stop displaying numbers. This "algorithmic governance" together with the lack of transparency in the decision-making process suggest how controversies of ML algorithms, also reported on in other domains (e.g., Katzenbach & Ulbricht, 2019) can play out in authentic learning contexts.

Concluding remarks

Despite its limitations to one case study, the preliminary findings empirically show how ML AI in education is a complex social and material phenomenon in the making emerging from the *interactions* between heterogeneous *actors,* all with their different interests and goals (Callon, 1984). Rather than suggesting that human *actors* will always be needed to compensate for technology-enhanced learning or that teachers' tasks cannot be automated, the empirical data production indicates that these technologies are deeply relational and that the way *interactions* occur is a temporary and negotiated process. *Interactions* are not deterministic which make them well as the emerging effects unpredictable. Future ethnographically oriented research is however needed and envisaged in order broaden the understanding of how ML-based teaching aids are appropriated and constructed in Primary Education classrooms. The sensibilities of ANT grant for a holistic and non-deterministic narrative of this construction, offering methods and theoretical concepts to open up the black-box of ML in the emerging networks learning settings of K-12 classrooms.

References

Callon, M. (1984). Some Elements of a Sociology of Translation: Domestication of the Scallops and the Fishermen of St Brieuc Bay. *The Sociological Review*, *32*(1_suppl):196-233.

Castañeda, L. & Williamson, B. (2021). Assembling new toolboxes of methods and theories for innovative critical research on educational technology. *Journal of New Approaches in Educational Research*, *10*(1),1-14.

Decuypere, M. (2021). The Topologies of Data Practices: A Methodological Introduction. *Journal of New Approaches in Educational Research*, *10*(1), 67-84.

Dubois, A. & Gadde, L. E. (2002). Systematic combining: an abductive approach to case research. *Journal of business research*, *55*(7), 553-560.

Facer, K. & Selwyn, N. (2021). Digital technology and the futures of education – towards 'non-stupid' optimism. Paper commissioned for the UNESCO Futures of Education report (forthcoming, 2021).

Fenwick, T. J., & Edwards, R. (2017). *Actor-network theory in education* (2nd ed.). Routledge.

Hrastinski, S., Olofsson, A.D., Arkenback, C. et al., (2019). Critical Imaginaries and Reflections on Artificial Intelligence and Robots in Postdigital K-12 Education. *Postdigital Science Education 1*, 427–445.

Katzenbach, C., & Ulbricht, L., (2019). Algorithmic governance, Internet Policy Review, *Alexander von Humboldt Institute for Internet and Society, Berlin, Vol. 8,* (4), 1-18.

Knox, J., Williamson, B., & Bayne, S. (2020). Machine behaviourism: future visions of "learnification" and "datafication" across humans and digital technologies. *Learning, Media & Technology*, *45*(1), 31-45.

Latour, B. (1999). On recalling ANT. *The Sociological Review*, *47*(Suppl 1), 15–25.

Latour, B. (2007). *Reassembling the Social: An Introduction to Actor-Network-Theory.* Oxford: University Press.

Law, J. & Mol, A. (1995). Notes on materiality and sociality. *The Sociological Review*, *43*(2), 274–294.

Luckin, R., Holmes, W., Griffiths, M. & Forcier, L. B. (2016). *Intelligence Unleashed: An argument for AI in Education*. Pearson Education, London.

Luckin, R. & Cukurova, M. (2019). Designing educational technologies in the age of AI: A learning sciences-driven approach. *British Journal of Educational Technology, 50*, 2824-2838.

Lupton, D., & Williamson, B. (2017). The datafied child: The dataveillance of children and implications for their rights. *New Media & Society*, *19*(5), 780–794.

Merriam, S. B. (1998*). Qualitative research and case study applications in education* (2nd ed.). San Francisco, CA: Jossey-Bass Publishers.

Miao, F, Holmes, W, Huang, R. & Zhang, H.) (2021), *AI and education: guidance for policymakers*, UNESCO, Paris.

Networked Learning Editorial Collective (NLEC)., Gourlay, L., Rodríguez-Illera, J.L. *et al.* (2021). Networked Learning in 2021: A Community Definition. *Postdigital Science Education 3*, 326–369.

Perrotta, C. & Selwyn, N. (2019). Deep learning goes to school: toward a relational understanding of AI in education, *Learning, Media, and Technology*, *45*(3), 251-269

Russell, S.J. & Norvig, P. (2021). *Artificial intelligence: a modern approach.* (4th edition.) Hoboken: Pearson.

Selwyn, N. (2010). Looking Beyond Learning: Notes Towards the Critical Study of Educational Technology. *Journal of Computer Assisted Learning 26*(1), 65–73.

Selwyn, N. (2019). *Should robots replace teachers? AI and the Future of Education*. (1st ed.) Polity Press.

Tuomi, I. (2018). The Impact of Artificial Intelligence on Learning, Teaching, and Education. Policies for the future Publications Office of the European Union, Luxembourg, JRC113226.

Williamson, B. (2017). *Big data in education: the digital future of learning, policy, and practice*. London: Sage.

Williamson, B. & Eynon, R. (2020). Historical threads, missing links, and future directions in AI in education, *Learning, Media and Technology, 45*(3), 223-235.

World Economic Forum (WEF) (2020). *Schools of the Future Defining New Models of Education for the Fourth Industrial Revolution,* (Report REF 09012020).

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