Introduction

This begins by noting the rise in big data within educational policies, and the tendency within educational research to ignore increasing datafication. This risks educational agendas and day-to-day experiences being shaped by arrangements of software and code, rather than academic research. This paper seeks to analyse how data science methods have been used to reformulate contemporary conceptions of 'learning', using Biesta's (2005) 'learnification' model in regard to marketising and disrupting conceptions of the learning process.

Machine learning (ML) is the particular focus of this article, examining how ML techniques frame learning in ways which are significant for the datafied education sector, as well as learners within this sector. Firstly, ML influences educational activity using technical expertise and behavioural psychology, seeking to promote an environment which creates the greatest value reward in terms of data collection. Secondly, behavioural economics is used in educational software to promote optimal outcomes in the behaviour of learners, nudging them in the direction deemed appropriate. New persuasive computing (Yeung, 2017) techniques subject human learning to further governance in digital environments, reflecting the increasing power of data science in education. Finally, the future goals of ML-influenced education are examined, suggesting a move towards machine behaviourism over student autonomy, extending learnification across human and mechanical systems of datafication.

The learnification of education

This section details Biesta's (2005, 2006, 2013a, 2013b) concept of learnification, stating that there has been a turn towards framing education as 'the provision of learning experiences' (2005, 55), rather than privileging teaching. This creates a self-directing, autonomous 'learner'. This learner is a consumer, while the teacher is the provider, and education is the commodity. Learnification, according to Biesta (2005), is caused by a number of factors, such as the acceptance of constructivist and socio-cultural theories in the psychology of learning; the postmodernist critique of the project of education and its Enlightenment ideals; and the individualisation of learning through informal or non-traditional means, in which the individual becomes the site of learning. This is, of course, furthered by neo-liberalism and its persistent commodification of anything that moves.

Biesta suggests that the language of learning leads to two problematic assumptions. First, he claims that learners do not come to education fully understanding what their needs are. Rather, Biesta claims that educational institutions should equip learners with the tools to recognise these needs, while learnification suggests that educational institutions merely respond to learners' needs. Secondly, the transactional nature caused by this first assumption means that the only meaningful questions within education are technical i.e. questions about efficiency and effectiveness of the educational process, ignoring questions around education's broader role in society and how this relates to existing power structures. These critiques are important for this paper as they help show how the educational landscape has become more amenable to data-intensive practises, and how learning practises get measured as a consequence of this.

The 'datafication' of education

The datafication of education is said to align largely with learnification here, while also influencing learnification in turn. The use of ML in education, along with learning analytics (LA) have influenced educational policy agendas towards learnification, so one cannot be said to drive the other; learnification and datafication work in tandem in learner-centred practices.

LA-based literature has a tendency towards seeing itself as a technical discipline, as a ‘data science’. This indulges in Silicon Valley solutionism which positions data-work as revolutionary and disruptive to sectors (Morozov, 2013). However, Biesta (2013a) highlights that learnification means educational landscapes were already transactional arrangements in which datafication could thrive. Thus, ‘business intelligence’ systems in education are not just the result of LA systems but are also the result of increasingly commodified educational practices and materials. Additionally, LA only works if there is already an interest in a centrally important ‘learner’. There must be a desire to ‘penetrate the fog’ of educational activity through data (Long and Siemens, 2011), which tacitly assumes blind spots which can only be clarified by data. Learnification thus helps to explain existing conditions which facilitate the rise of LA in education, including a desire to create a model learner (Pea, 2014).

Datafication of education does require moves away from the learnification of education though; again, they are not one in the same. One example given is the technology used to collect data and model the ideal learner: software platforms. The semiotic move from a course management system to a virtual learning environment and then a dashboard highlights the move towards learner-centred software, which harvests student data to provide actionable feedback to teachers and administrators. Essentially, rather than a purely consumerist-bent within education, we also now see the dominance of data-driven decision making. This actually reasserts some kind of centralised control which ‘learning’ resists, with educators now not only being facilitators of learning but also subject to systems of data analysis.

The move to a data dashboard, from the VLE, once again signals a new view of the ‘learner’. Student data is now needed for the analytic engines of education, meaning learner behaviour is a commodity within the platform’s ML: students’ learning is learned by the machine learners (Mackenzie, 2017). For a system to become more accurate, and thus more valuable, it therefore requires more data. This moves students from being learner-consumers to being prized products for algorithmic systems. Here, we do not see a student-centred platform but a data-centred platform which positions students as the product of consumerist analytic technologies. Further, the internet of things (IoT) means that environments are no longer passive and pliant to the needs of the learner, instead becoming an active producer of data, extending beyond traditional data capture means to include bodily or physical effects. This moves learning from the self-directing, autonomous learner to non-conscious behaviours, both mental and physical. This signals a return to behaviourism and the work of BF Skinner, in the form of behaviour modification and behaviour engineering (Zuboff, 2019). This type of behaviourism seeks to actively modify and determine learning through control of the environment, seeing the learners as a passive blank slate, rather than an active and self-knowing individual.

The learnification of machines

One of Biesta’s (2013b) contentions is that learning is presented as inevitable, allowing for learnification to extend into all elements of life, beyond formal education systems. Datafication expands learning beyond the human, to the machine in the form of ML. ML tends to be understood as a purely technical process in which computers learn from data, rather than the formal structuring of a human programmer (Berry, 2017). MacKenzie (2017) claims that ML is the accumulation of data practices, moving beyond statistics or computer science, into every field, and creating learning algorithms which set the scope and limits of knowledge production. Mackenzie also claims that we should not see ML as a solely mechanical process but as a human-machine assemblage, with computers ultimately relying upon man-made technical infrastructures. This means what machines can learn is also limited by human specification, generally in the form of mathematical functions transformed into classifiable data, which can then be fed back into the algorithm of the ML.

Alpaydin (2016) identifies three forms of learning present in the ML process: supervised, unsupervised, and reinforcement learning. These draw from behavioural psychology and psychological learning theory. Supervised learning builds predictive models through initially using training datasets; unsupervised learning looks for patterns in data and creates algorithms to analyse this data 'in the wild'; and reinforcement learning teaches the algorithm through rewarding positive actions. It is then reiterated that we therefore cannot see ML as a wholly mechanical process but one which is inherently bound up with human actors.

Reinforcement learning is the primary focus here, as it relies least on human-generated data. The example of Google Deep Mind's AlphaGo is given, in which the program taught itself how to play Go without any human behavioural data but through a self-play reinforcement learning system; learning solely from its own behaviour. It is claimed by Silver et al (2017) that this could result in the ML outperforming humans in this context but also in other, real-world problems. Reinforcement learning has the potential to reshape learning processes, differing from a teacher in that it does not tell the student what to do but how well they did in the past (Alpaydin, 2016). This type of feedback is concerned only with predefined values for 'winning' and 'losing', which is basically stated to be an inhuman way of treating students and their education, playing on animal psychology and dopamine rushes for 'winning'. Reinforcement learning is not an isolated technique though, forming only one part of an overall ML approach and requiring monitoring from human actors. This, once again, makes reinforcement learning and ML a human-machine assemblage.

Learning as 'nudging'

Behavioural sciences have become prominent in governmental authority in the 21st century, replacing the idea of the citizen as a rational, utility-maximiser with the citizen as an emotional, irrational, yet predictable agent, who favours immediate gratification over future planning (Feitsma, 2018a). This has resulted in a governmental approach in which citizens are 'nudged' to behave in a more normative fashion; responsibilising citizens for supposedly problematic behaviour, rather than addressing any underlying causes (Feitsma, 2018b). One means of nudging people is through environment design or 'choice architectures' in which choices are framed in certain ways to make them seem more or less desirable.

Computational theories around reinforcement learning have been utilised to create choice environments in education, with examples being given from the UK Department for Education and the UK Office for Students adopting behavioural design in their approach to students. The most prominent form of educational nudging is seen in the constant tracking of students and subsequent prediction of behaviours, using the IoT to create a guinea pig economy (Whitehead et al, 2018) and reinforce surveillance capitalism (Zuboff, 2019). Here, students are assumed to be irrational subjects whose emotions, habits, and other non-cognitive functions can be optimised for academic learning through nudging (Lavecchia, Liu, and Oreopoulos, 2014).

Examples of this can be seen in apps such as ClassDojo or Panorama Education which measure emotional wellbeing of students to predict a need for behavioural intervention. These types of apps seek to promote 'grit' and a 'growth mindset' as long term behaviours or characteristics, again reinforcing the man-made nature of ML assemblages. In a potentially more extreme manner, biometric technologies such as wearable devices can measure factors such as mood, engagement, or attention in real time and nudge students through haptic touch. This includes measuring seemingly unconscious flickers of facial expressions, measuring emotions students are not consciously exhibiting (Zuboff, 2019). Even devices like the Amazon Alexa or Google Home have modes to train children to use polite language, measuring mood through voice tone and word choice, training children to act deferentially and obediently to machines. This results in hypernudge techniques, seeking to shift students to a more positive and rewarding state (Yeung, 2017).

Overall, this shows a reconceptualisation of learning in terms of psychologically quantifiable, affective characteristics, which are to be nudged into the pre-determined, normative position. 'Across this shift, this paper has attempted to emphasise the entanglement, rather than the simplistic 'disruption', of educational technology within the political economy of education, drawing attention to the ways data processing not only intensifies the marketised and performance-driven vision of the institution, but also offers heightened forms of governance and surveillance.'