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Review article

Machine learning – A new kind of cultural tool? A "recontextualisation" perspective on machine learning + interprofessional learning

David Guile

UCL – Institute of Education, 20 Bedford Way, London WC1H 0NT, United Kingdom

A R T I C L E I N F O

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A B S T R A C T

The paper argues that (a) Machine Learning (ML) constitutes a cultural tool capable of learning through perceiving patterns in data, (b) the kind of learning ML is capable of nevertheless constitutes a more circumscribed kind of learning compared with how that concept has been interpreted in sociocultural (S-c) theory; and, (c) the development of ML is therefore further extending and distributing the complex relationship between human and machine cognition and learning. The paper explores these contentions by firstly, providing a broad-based account of the conception of cultural tools in S-c Theory. Secondly, offering a genealogy of ML, including the model of learning that underpins ML and highlights the challenge that a cultural too capable of some kind of learning presents for the extant S-c conception of a cultural tool. Thirdly, identifying the new human-machine working-learning problem the ML model of learning is generating. Finally, argues the concept of *recontextualization* offers a way to address that problem by providing a holistic perspective on the relationship between ML and IPL models of learning. In making this argument the paper distinguishes between the ML predictive and the Chat GPT answer to question(s) model of learning.

1. Introduction

In *The Cultural Origins of Human Cognition*, Michael Tomasello (1999, p. 2) observes the "basic puzzle" about the development of *Homo sapiens* is that there has been insufficient time for the normal processes of biological evolution, involving genetic variation and natural selection, to have created the cognitive skills we require to "invent and maintain complex tool-use industries and technologies" and complex "forms of symbolic communication and representation" and "social organisations and institutions characteristic of modern societies." Hence, he concludes there is only one possible solution to this puzzle "social or cultural transmission." Drawing attention to three types of cultural learning that evolutionary anthropologists and development psychologists have identified facilitated the development of *Homo sapiens* – imitative learning (treating others as intentional agents to acquire their store of cultural knowledge), instructed learning (discursive cultural transmission) and collaborative learning (sharing and developing concepts and their implications for action) – Tomasello (1999, p. 5) argues they collectively culminated in "a single very special form of social cognition." The distinguishing feature of this form of cognition was the ability of individuals to understand "conspecifics as beings *like themselves* who have intentional and mental lives like their own" and this involved "learning not just *from* the other but *through* the other (*ibid* italics in original)" because the tools, symbols and cultural practices they produced for example, language, text, art,

E-mail address: d.guile@ucl.ac.uk.

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transformed their inherited biological mechanisms of cognition. Consequently, human cognition was freed "from the immediate perceptual situation" as our capacity to *infer* what follows enabled "reference to things outside the situation" as well as "multiple simultaneous representations of each and every, indeed all possible, perceptual situations" to become possible (Tomasello (1999, p. 9).

The paper argues Tomasello's insightful account of the mediated relationship between, and development of, cognition, language and tools (C-T-L) and shared intentional and inferential activity, can be seen as a prequel to, what it defines as, a sociocultural perspective on the C-T-L relationship. The paper uses this term to encapsulate the generality of insights from Cultural-Historical Activity Theory (see inter alia. Blunden, 2015; Ekbia & Nardi, 2014; Kaptelinin & Nardi, 2006; Karanasios et al., 2021; Miettinen & Paavola, 2018) and Situated Cognition/Learning (see inter alia. Erstad, 2013; Hasse, 2020; Ludvigsen et al., 2010; Mäkitalo et al., 2019; Säljö, 2010; Sorensen, 2009) and Distributed and Extended Cognition (Hutchins, 1995a, 1995b; Clark, 2003, 2011) about the aforementioned relationship rather than specific formulations within those traditions, for example, Vygotsky's (1978) argument about tools and signs.

The paper argues that broadly speaking the sociocultural perspective has assumed that although a) mind is formed in society, rather than being merely a product of biological inheritance, it is nonetheless bound by skin; and b) cultural tools are endowed with 'learning', in the sense they constitute the ongoing accumulation of humankinds' cultural evolution, they are themselves incapable of learning. The paper, however, points out the second assumption started to be debated when Artificial Intelligence (AI) emerged from the 1950s onwards, and that debate has escalated since the development of Machine Learning, specifically "Deep Learning" (Cardon et al., 2018). At first sight, the claim that a machine which has been interfaced with data can learn from data appears to anthropomorphise the former. While some zealots foresee ML as a major step towards the eventual arrival of the "Singularity" (Kurzweil, 2006) or a new age "superintelligence" (Bostrom, 2014), and sceptics in social sciences fear ML is an inhuman power (Dyer-Witheford et al., 2019), diminishes aspects of human labour (Ekbia & Nardi, 2014) or constitutes a surveillance technique for labour and society (Zuboff, 2019), a much more caveated and nuanced interpretation exists in some parts of the Machine Learning (ML) literature. Marcus and Davis (2019, p. 121 and 149) have acknowledged that although ML algorithms interfaced with specialist data, for example, from fields such as architecture (Tamke et al., 2018), engineering (Willard et al., 2022) and health (van der Schaar, 2020) discerns on the basis of statistical probability patterns in that data and generates predictions based on those patterns, which some writers claim "bring the future into the present", for example, ML's in the production of vaccines to combat Covid (Nowotny, 2021 p. 5–9), this is not equivalent to learning inferentially through and from others.

The common thread in the above discussions is that ML is capable of *some kind* of *learning* because it generates predictions. This suggests it is timely to revisit the sociocultural conception of cultural tools. In light of this contention there is a two-fold argument animating this paper. The first is the creation of cultural tools capable of learning introduces an entirely new dimension to the notion of learning from and through others: others now could, in certain circumstances and in certain ways, include nonhumans. The second is the emergence of these new circuits of human and nonhuman interaction or ecologies suggests it may be helpful for writers in the sociocultural tradition to operate with a broader conception of the C-T-L relationship that accepts humans will in future learn from, and through, a nonhuman source.

The paper explores this two-fold argument in the following way. It starts by presenting Tomasello's conception of the C-T-L relationship, including acknowledging its Cultural-Historical Activity Theory provenance, before extending this discussion through reference to Wartofksy (1979) typology of cultural tools, which has been widely embraced by sociocultural writers (see inter alia. Cole & Derry, 2005; Geström, 1987; Kaptelinin & Nardi, 2006; Säljö, 2010) to present a more rounded sociocultural conception of the C-T-L relationship. Next, the paper argues that this conception retains the sociocultural assumption that although mind is formed in society it is nonetheless bound by skin and, as such, has only tangentially engaged with Clark (2003, 2010, 2011) and Hutchins (1995a, 1995b) respective arguments that the C-T-L relationship has always been "extended" and "distributed". The paper therefore uses their work to broaden the sociocultural concept of the C-T-L relationship to include the possibility people may learn, in principle, from nonhumans. It explores this contention by firstly, identifying the assumptions that underpin the ML deep learning inductive inferential model of learning (Guttag & Suresh, 2019; Pasquinelli, 2019) and the constitution of algorithms, which are the pivotal element, in that model (Jaton, 2020), and illustrating that model's malleability by presenting two different examples – supervised and unsupervised learning – of the way the ML deep learning model can be interfaced with data to generate predictions. Secondly, identifying the new human + machine working-learning relationship the model is ushering in by discussing Van der Schaar (2020) "interpretability, explainability, trustability" triplex. The paper concludes by turning to Guile (2010, 2019) concept of "recontextualization" to argue that it offers the sociocultural tradition a way to understand and analyse the working-learning challenge set by the deployment of a cultural tool capable of generating predictions from data in professional contexts, such as architecture, engineering and health. In doing so, the paper notes, but does not explore, the difference between the deep ML model of learning that generates predictions from data, compared to the ChatGPT model of learning that generates answers to questions.

2. Cognition, tools and learning: a sociocultural perspective

To explore the cultural basis of cognition, Tomasello interpolates his evolutionary anthropological research with idea from a number of "classic theorists" who have discussed the "fundamental processes of social coordination that made human culture and language possible" and "role of culture and artifacts in making possible certain types of thinking in different historical eras" (Tomasello (2014, p. 2 and 1). In the case of cultural tools, Tomasello main source of inspiration was Vygotsky. His great insight, according to Tomasello (1999, p. 1), was to reveal that human children grew up with the tools and symbols of their culture, "including especially the linguistic symbols that preorganise their worlds for them", and by internalising the use of these tools via the "law of genetic development" develop the "kind of internal dialogue that is one prototype of human thinking." In the corpus of his published theoretical and empirical work, Tomasello (2019, p. 301–2) culminates his investigation into the cultural origins of human cognition by producing, what he defines as, a "neoVygotskian account" of that process. This account presents the development of the higher mental functions, for example, textual and mathematical symbolisation, meta-cognition etc., through the creation and internalisation of cultural practices involving the use of tools and symbols, as "cognitive prostheses" (ibid) and the externalisation of cultural tools via labour and inquiry, as the result of the development of collective intentionality, social cognition and cultural learning.

Acknowledging Vygotsky's preoccupation to show the crucially important role of culture and tools in human cognitive ontogeny led him to gloss over the special skills required to participate in cultural practices, Tomasello turns to Mead and Wittgenstein's different, but nonetheless complementary, arguments that social interaction (their way of conceptualising activity as will be explained below) is a prerequisite for human development throughout the life-course. Specifically, Tomasello (2014, p. 2) draws on Mead's (1934) insight that participation in cultural practice enables humans to imagine themselves in the role of the other and, as such take on that person's perspective, and Wittgenstein's (1953) argument that the use of a linguistic convention is predicated upon the existence of shared cultural practices and judgements (forms of life). Tomasello demonstrates how these skills of social co-ordination are developed in conjunction with our use of cultural tools in ontogeny as we move from "individual intentionality" (i.e. self-regulated way of doing things with cultural tools),via "joint intentionality" (i.e. participants' social role influencing the way they deploy cultural tools) to "collective intentionality" (i.e. cultural practices based on conventions, norms and institutions influencing the collective use and development of cultural tools). In making this argument about social interaction and collective intentionality, Tomasello can be interpreted as indirectly engaging with, on the one hand, Leont'ev (1978) concept of object-oriented activity since he is acknowledging that the development of cognition is influenced by the purpose of an activity and the way in which cultural tools are used to realise that purpose; and, on the other hand, the situated cognition/learning tradition which emphasises that access to the "technologies of practice" are vital to participation in any form of practice (Lave and Wenger, 1991).

Despite acknowledging the way that the "ratchet effect" of collective activity produces cultural tools with "accumulating modifications", Tomasello (1999, p 38) skates over discussing the implications of the qualitative differences that exist between different types of cultural tools and social interaction for cognition. This issue has, however, always been central element of any sociocultural perspective on cognition, tools and learning as Marx Wartofksy (1979) work in historical epistemology has demonstrated. Written nearly twenty years before *The Cultural Origins of Human Cognition*, and drawing on the lineage from other classic theorists, in this case Aristotle to Marx, who were concerned with the relationship between making (production) and doing (communication), Wartofsky clarified the relationship between different types of cultural tools and social interaction for the development of cognition. Defining his task as the systematic construction of the genesis and historical evolution of the "modes of cognitive praxis", that is, perceiving, judging and acting, necessary to address the issues and challenges humans faced collectively, Wartofksy (1979, p. xiii and xiv) argued, in common with Tomasello, that we create cultural tools which "not only go beyond the biologically evolved and genetically inherited modes of perception and cognitive action, but which demarcate human knowledge from animal intelligence." Hence, these models "are representations to ourselves of what we do (*ibid*)."

From Wartofsky's perspective, (ibid) the nature of knowing changes historically, in other words, "how we know changes with changes in our modes of social and technological practice, and with changes in our forms of social organization." In making this argument, Wartofksy (1979, p. 205) anticipated Tomasello's subsequent answer to the puzzle of human development by arguing that the "*artifact* (hereafter cultural tools) is to cultural evolution what the gene is to biological evolution." Thus, it follows, for Wartofsky, that firstly, human intention is embodied in the tools used in production, the skills developed to support such tool use, and the ensuing forms of symbolic communication. Secondly, perception is a highly evolved mode of human action mediated by the forms of representation associated with different cultural tool, rather than only being biologically or physiologically rooted (Ivarsson & Säljö, 2005).

To explain the complex interplay between cultural tools, perception and the development of human cognition, Wartofsky produced a three-tiered – primary, secondary and tertiary – typology of tools. In his typology, Wartofksy (1979, 202–209) distinguished between different types of cultural practices, their ensuing cultural tools (artifacts) and cognitive modes of action. The outcome of: (i) material production is primary tools – originally they would have included knives, spears and pots; however, in a more contemporary vein they include aircraft, automobiles and computers – which facilitate our cognitive capacity to transform our environment to support our continued existence; (ii) symbolic production is secondary tools, that is, representations of the modes of action associated with primary tools, which include such constructs as, abstractions, models etc., methods to record and transmit them, for example, writing and printing, and heuristics we use to plan, manage and evaluate our tool-based activities in occupational fields; and (iii) is tertiary or abstract tools, in other words, imaginative, integrative representational structures, including works of art, theories and models (scientific, technological, social scientific etc.) which allow us to reimagine the purpose of tools, modes of action and the shape and direction within a society.

In developing this differentiated account of cultural tools as the linchpin of cultural mediation, Wartofksy presents a parallel sociocultural argument on the one advanced by Tomasello and that is embraced by the sociocultural tradition. Wartofksy accepts that, on the one hand, there is no inherent characteristic of a tool, which will determine its role and function: tools point, as Tomasello (1999, p. 9) observes to the "problems they were designed to solve and to the affordances they offered to solve other problems"; and, visual symbols point to modes of communication they were designed to represent, and subsequently to new modes of communication. On the other hand, Wartofsky, echoing Leont'ev (1978) unconsciously, acknowledges more explicitly than Tomasello that the nature of knowing changes historically with changes in our modes of social and technological practice as well as with changes in our forms of social organization. Hence, Wartofsky drew attention to the "function" of a cultural tool by noting that the part they play in the production, reproduction and transformation of the human species (Cole & Derry, 2005, p.11).

Writing after Wartofsky but in a similar vein, Tikhomirov was one of the first sociocultural writers to recognise that the development of digital technology changed the function of cultural tools. Digital tools enabled cultural practices and experiences to be transferred not only to other people, "but also to information technology, for instance, in the form of computer programs" Tikhomirov (1990/1999, p. 358) and, as such, would continue to affect the way in which people could gain access to "social memory" and represent memory (Säljö (2010, p. 56). The implications of digital technology have subsequently been pursued in a variety way in sociocultural research (see inter alia. Ekbia & Nardi, 2014; Kaptelinin & Nardi, 2006; Hasse, 2020; Miettinen and Paavola 2016; Suchman, 2007). These sociocultural responses nevertheless still tend to follow the Tomasello-Wartofsky framing of the sociocultural tradition presented above. They therefore conceive of mind as bound by the skin and digital cultural tools as being incapable of learning and, moreover, some writers are sceptical about claims that cognition exist external to the mind (Kaptelinin and Nardi, 2006, p. 203).

3. Cognition, tools and learning: an "extended" and "distributed" sociocultural perspective

One way to broaden the sociocultural lineage discussed so far in this paper is by considering Clark (2011) work on the "extended mind" and Hutchins (1995a, 1995b) work on "distributed cognition" and their associated conceptions of learning. They have both, on the one hand, acknowledged Vygotsky's influence on their respective thinking about their extended and distributed conception of the C-T-L relationship (Clark, 1998; Hutchins, 1995a, 1995b); and, on the other hand, had connections between their work and the sociocultural tradition affirmed (see inter alia. Cole & Engeström, 1993; Derry, 2013; Dixon Keller, 1996) or in Clark's case (1996) acknowledged the affinities between Tomasello and their perspective on the above relationship. Moreover, despite some theoretical differences, they are both, as Hutchins (2013, p.4) has acknowledged, concerned with the "interaction of persons with their immediate material and social environment" therefore [author] "the intersection of distributed cognition with extended mind is substantial."

Echoing Vygotsky, Clark accepts, like Hutchins, that cognitive processes have always involved humans thinking through and with technologies that are external to their biophysical selves. Clark (2006) however extends Vygotsky's mediated conception by arguing that the boundaries of our minds have always extended our skin and include tools we interact with in our environment and explored this contention through his concept of the "parity principle." This refers to the idea that "if, as we confront some task, a part of the world functions as a process which, were it to go on in the head we would have no hesitation in accepting it as part of the cognitive processing," then it follows it is part of our cognitive process (Clark and Chalmers, 1998, p. 8). Subsequent explorations of the extended mind thesis appeared in *Natural-Born Cyborgs* (2003) and *Supersizing the Mind* (2011). In the former, Clark highlights how our growing use of AI-based cultural tools is extending and embodying our minds in new ways. Noting the complex feedback loops that connect action-commands, bodily motions, environmental effects and multisensory perceptual inputs via internet-based technologies, such as tele-presence, Clark (2003, p. 114) concludes the "two-way flow of influence between brain, body and the world" has become "the basis of which we construct (and continually reconstruct) our sense of self, potential and presence." Pursuing this new possibility in *Supersizing the Mind*, Clark (2011, p. 437) invokes the concept of the "Principle of Ecological Assembly" to denote the way in which we recruit "whatever mix of problem-solving resources will yield an acceptable result with minimum effort", and employs the term "canny organizer" (Clark 2011, p.437–8) to refer to the human activity responsible for creating the ecological assembly that facilitates the extension of mind internet-based technologies have facilitated.

The activity of the canny organizer is however underpinned by two meanings of the term assembly: control of the process and the location of cognitive activity once the process is up and running. They reflect, according to Hutchins, 2011, p. 438), a tension in Clark's work between the cognitive activity required to actively initiate and control the assembly process, and the distributed and extended nature of the ensuing assembled cognitive systems. This tension leads Clark to err towards, according to Hutchins (2011, p. 440), a naturalistic interpretation of the term ecology. Consequently, Clark's rich description of ecological assemblies, based on the way in which individuals combine the opportunities provided by feedback loops and use their active sensing body to create or respond to, for example, multimodal data and engage in iterated bouts of exploration and intervention, glosses over the reason this array of possibilities exists.

This is a significant oversight for two reasons. The first, as Hutchins (2011, p. 441) points out is that it is our cultural practices which "shape active sensing and ways of seeing the world by highlighting what to attend to and what to see when attending." In making this case, Hutchins (2011, p.443) is extending and refining the sociocultural conception of perception inspired by Wartofsky. It is our participation in occupational cultural practices, according to Hutchins, which transforms our socialised perception into different forms of "professional vision" (Goodwin, 1994), in emergent and dynamic distributed systems of cognition and also contribute to how we organise our thinking, acting and feeling in situated activity. The second reason is that once we focus on cultural practices, we can understand not only the way in which "all instances of cognition *can be seen* (italicisation in original) as emerging from distributed processes" Hutchins (2014, p. 3), but also how cultural practices create and sustain distributed processes and, in the process, facilitate learning. From Hutchin's perspective therefore, it is cultural practices and cultural tools which give structure to our collective actions and cognition by providing a form of orderliness and organization to "reduce entropy and increase predictability" (Hutchins, (2013, p. 5). Hence, the human-machine relationship is "symmetrical" (Kaptelinin & Nardi, 2006, p. 202).

To explain how such cultural practices and tools are internalized and externalised symmetrically by individuals Hutchins (1995, p. 283–5) elaborates and extends Vygotksy's law of genetic development. The cornerstone of his argument is that many of the external interpsychological functions, in other words, cultural practices, associated complex distributed systems are too complex to be internalized by single individual and therefore are distributed between individuals and cultural tools. This process therefore not only constrains human perception and action, but also shapes the types of necessary embodied skills that humans need to develop to successfully perform in a distributed cognitive system. The paradigmatic example of such systems, for Hutchins (1995), is navigation: nautical and aeronautical. Achievement in both rests on the coordinated efforts of people facilitated by the constructed tools and devices of their trade. To understand how such coordination occurs, Hutchins (1995, p. xvii) argues that learning is best viewed as "local adaptions in a dynamic system of co-ordinations of representational media". These media include human minds, material artifacts communicative routines and behavioural practices integrated for the accomplishment of specific ends" (Dixon Keller, 1996, p.47). Distributed cognition is therefore, a "system where tasks are performed as representational states pass from one node to another" (Kaptelinin & Nardi, 2006, p. 2003) and, as such, this flat perspective accepts that cognition can be applied equally well to any system or to any of its nodes.

Viewed from the sociocultural C-T-L perspective outlined at the start of the paper, Hutchins' conception of the C-T-L relationship and the process of learning appears, as Kaptelinin and Nardi (2006, p. 203) have observed to "wipe out the very notion of human cognition and replaces it with the idea that anything can potentially cognize." Alternatively, the critique that Hutchin's concept of distributed cognition and learning as propagation, and by extension Clark's ideas about the extended mind accept that anything can potentially cognize and therefore learn, offers a way think differently about the C-T-L relationship. This possibility exists in Hutchin's case because he poses a different kind of question compared to the sociocultural C-T-L conception outlined at the start of the paper. Hutchins (2013, p. 3) is concerned with "how a process we call cognitive emerges from the interactions among elements" in cultural ecosystems and how it is ongoingly reorganised. Returning to his focus on the dynamic and adaptive alignment of the components and practices of ecosystems, Hutchins (2013, p. 13) argues cognition occurs in such systems as we use cultural practices to hold in place certain ways of thinking, acting and problem-solving, and we develop those cultural practices as a result of human and technological feedback loops thereby enabling human-machine self-monitoring and revision process to occur. It is a short step from here to accepting some elements in a cognitive system might, potentially, be capable of learning, though, not necessarily equivalent to human cognizance and learning.

This issue is however a little more complex than it might appear at first sight, because technologies such as ML have been embedded with cognitive resources via the cultural practices of "system designers" who provide algorithms with their mode of operation, aesthetics and functionality and "choice architects" who determine the purpose a digital technology will serve and interface algorithms with data to serve that purpose (Frischmann & Selinger, 2018, p. 94). This process of technological development is, therefore, broadening the provenance of the distributed cognition thesis to include system designers and choice architects. For this reason, it is necessary to identify the conception of the 'cognitive' that they build into ML algorithms and its implications for the ML model of learning.

4. Machine learning: a cultural tool with a mode of perception and model of learning

The ML, that is deep learning, model of learning emerged, as Woolridge (2019, p.168–187) has acknowledged, as a result of three separate developments. They are the a) reconfiguration of the architecture of the perceptron model via the creation of neural nets, b) creation of big data sets facilitated by the creation of multi-dimensional vector space, and c) growth of computational power. Since the first two are integral to the ML model of learning; the paper focuses on their respective development and assemblage into the aforementioned model.

In the case of the perceptron model, it emerged from the complex association between computationalism and connectionism and AI (Childers et al., 2023). The first stage of this developments was, according to Woolridge (2021, p. 174–5), McCullough and Pitts (1943) mathematical modelling of neurons as electric circuits to support computation and its subsequent refinement by Rosenblatt (1958) to create a simple decision device – the perceptron model – capable of replicating a computational perspective of how a human brain recognised patterns in data sets. Predicated on a relationship between processing units (i.e. neurons) and the connections between neurons (i.e. synapses) and the way in which neurons operate in parallel and transfer among themselves over synapses, Rosenblatt's simple neural nets were capable of deciding whether an input belonged to a certain class of things (Alpaydin, 2016, p. 86–7). Subject to criticism for failing to capture certain characteristics of data, for example, an image, it had been trained to recognise (Minksky and Papert, 1969), the model lay dormant until Rumelhart and McClelland (1986) transformed the original into a multi-layered neural net that eliminated the above errors. In the last decade, however, "something akin to a Copernican revolution" (De Sautoy, 2019, p. 67) has occurred in the field of AL. ML initiated a shift away from top down and towards bottom-up approaches to programming because "learning algorithms" (Domingos (2015, p, 6.), which had been inscribed with a self-directed capacity to revise the way they function based on what they discover in the data they are analysing, began to be written.

This occurred after firstly, Hinton and colleagues developed an algorithmic technique called "backpropagation" (Marcus and Davis (2019, p. 51). Backpropagation resulted in the inauguration of Deep Learning (Woolridge, 2021), that is, convolutional or multilayered nets which detect structures or features of their input, for example, statistical data or complex images, at an increasing level of abstraction, but with minimum human contribution, before subjecting the outcome to a checking process (Marcus & Davis, 2019, p, 51–2). Secondly, convolutional neural nets were enhanced by their inputs – data (statistical or visual) – being coded via a "new cultural tool a purely digital vectorial representation" often referred to as "word2vec" (Cardon, Cointet and Mazières, 2018, p. 23). This process enabled images to be curated via cultural practices by, for example, reducing a "labelled face to numerical values" in a vectorial space to enable a neural network to perceive and classify those numerical values, closely followed by words and eventually combinations of images and words (Jaton, 2020 p. 249 and 272).

The reason the above classification processes were possible, as Crawford (2021, p. 106) observes, is because the establishment of the internet enabled people "to upload their images to websites, to photo- sharing services, and ultimately to social media platforms." This development was given particular momentum when "Professor Fei- Fei Li decided to build an enormous dataset for object recognition. 'We decided we wanted to do something that was completely historically unprecedented,' Li said. 'We're going to map out the entire world of objects' " (Crawford, 2019, p. 107). This development unleashed a global desire to convert "*images* into *infrastructure*" (italicisation in original) and in the process establish a way to create resources that now informs "how machine intelligence is recognised and produced from university labs to the tech industry" (Crawford, 2019, p. 97). Consequentially, it became possible to turn all types of artifacts – images, text, statistical patterns – into data.

The cumulative effect of the above developments has been the assemblage of an ML model of learning - expressed in sociocultural terms a new kind of cultural tool – which is capable of generating predictions from data. The model consists of, as Guttag and Suresh (2019) and Pasquinelli and Joler (2019) have observed, three elements – Data + Algorithm + Model. This pivotal element of this new cultural tool is an algorithm because its formation enables data to be read and a model and its predictions generated. Algorithms can be viewed, following Jaton (2021), as being constituted by three intertwined cultural practices. They are the: (i) the identification of a "ground-truth", in other words, the issue to be investigated (Jaton, 2021, p. 24); (ii) "programming" of an algorithm on the principle of inductive inference to follow a "machine-readable list of instructions" to discern patterns in the textual and/or numerical data pertaining to the issue being investigated (Jaton, 2021, p. 54 and 89); and iii) "formulating" (Jaton, 2021, p. 234–5), in other words, curating that data in accordance with the mathematical functions built into an algorithm so it can create a prediction "model" (Alpaydin, 2016, p. 14) which will evolve as the algorithm observes more evidence and adjusts its expectations and predictions accordingly. The ML model of learning is, from a socio-cultural perspective, underpinned by three further cultural practices which operate as inter-linked modalities of operation. They are defined by Pasquinelli (2019, p. 6) as, "pattern abstraction", "pattern recognition" and "pattern generation" and are possible since system designers and choice architects (i.e. ML experts) have embedded higher mental functions, such as abstraction, clustering etc. into algorithms. These modalities are a feature of the types of deep learning – supervised, reinforcement and up-supervised learning – that generate predictions, and irrespective of the algorithmic architecture underpinning each type, for example, Analogizer, Bayesian, Connectionist, Evolutionary, Symbolist (Domingos, 2015) or context of deployment: professional assemblages (the focus of the paper) or Silicon Valley.

To clarify how ML inductive inference model of learning operates, two ideal typical depictions of supervised and un-supervised learning are presented below.

In supervised ML, an algorithm is trained with curated data that has been labelled, that is, each point in a data set has been categorized into one or more groups pertaining to aspects of its content, and unlabelled data which functions as an "evaluation" dataset (Jaton, 2020, p. 54). Labelling and evaluation are cultural practices that facilitate the pattern abstraction modality by enabling an algorithm to discern how its training data has been structured, and to use this knowledge to abstract, that is, construction a function that maps inputs to outputs of natural or cultural patterns it has perceived in, for example, a finance or health dataset. As new input data is fed into the statistical model, the pattern recognition modality determines whether it falls within or outside the input-output relationship and then generates an appropriate representation. This process of determination is possible because the cultural practice of the "confirmation of the model or an issue for further deliberation" has been embedded in the algorithm (Pasquinelli and Joler, 2020). Finally, the pattern generation modality facilitates predictions about the perceived patterns discerned in the previous stage, for example, with financial date to predict the types of firms predisposed to bankruptcy (Alpaydin (2014, p. 40).

In contrast, in un- or self-supervised learning an algorithm "learns without labels by detecting the characteristics that make data points more or less similar to each other" (RS, 2017, p. 20). This is possible because cultural practices such as clustering have been embedded in algorithms (Alpaydin, (2014, p. 112–3). Clustering facilitates the abstraction modality by allowing an algorithm to perceive and then group, or segment, datasets with shared attributes, prior to extrapolating or generating a model based on commonalities in, for example, customer segmentation patterns in an industrial sector. Having identified commonalities in data, the algorithm facilitates pattern recognition by reacting to the presence or absence of commonalities in each new piece of data. This, in turn, triggers the pattern generation modality as the algorithm creates a statistical distribution of a pattern that otherwise would not have been generated, and detects anomalous data points (i.e. not fit existing pattern) for further consideration (Jaton, 2020, p. 275–8). In the case of finance, an algorithm may, for example, identify a niche in the market that a firm decides to explore (Alpaydin (2014, p. 112).

The ML model of learning is therefore a "*method* that requires data and a *tool* (italicisation added) that enables uses of it" (Royal Society, 2017, p. 48). The model's disembodied 'cognitive' mode of action operates however in a very different way from how learning has been conceived in the sociocultural tradition: an algorithm is unable to learn from and through the others, for example, other algorithms or people, or to reimagine the task it has been set. This has led some members of the AI community to argue that the reason the ML is incapable of this type of learning is because "that a lot of what is needed to interpret", for example, sematic phrases or clusters "is not explicit, and machines don't know how to deal with what isn't made explicit" and feel, consequentially, that ML should be continually scrutinised until it has been imbued with "common sense" (Marcus & Davis, 2019, p. 158).

The ML model of learning is nevertheless indisputably generating as writers, such as Pasquinelli and Joler (2021, p.1263) who while expressing reservations about the model, acknowledge some kind of new knowledge or information as it perceives "patterns and correlations through vast spaces of data beyond human reach". One way to define this new output is to borrow Knorr Cetina's (2010, p. 178) concept of "information-knowledge." She coined this term to refer to a form of quantitative data that has not been verified by normal scientific procedures, protocols and standards; but is instead produced as an algorithm undertaking an inquiry and identifying patterns and correlations in data before generating conclusions for humans to consider. The algorithmic-generation of information-knowledge, however, is continually creating a problem because when ML generates patterns and correlations "programmers haven't really got a clue how it has come to this conclusion" (Du Sautoy, 2019, p. 74). Referring to the implication of this issue in the field of health, but the observation applies equally to other professional fields such as architecture, engineering, finance and so forth, The Lancet (2018, p. 801) has stated that ML can be referred to as "a black box—data goes in, decisions come out, but the processes between input and output are opaque."

There is an interesting difference of view about how to respond to this dilemma in the ML community. One position, which is held by some of the leading figures in that community, maintains that ML users should adopt "self-supervised learning, things that are not trained for a given task but are trained generically [because: author insertion] a lot of those problems will essentially disappear …. [because humans: author] don't have discrete symbols. We have patterns of activities in neurons" (Leucin quoted in Monroe, 2022, p. 12). This reflects LeCun' (2018) and colleagues such as Geoffrey Hinton and Yoshua Bengio's adherence to a strict neuroscientific-connectionist conception of human cognition and faith in back-propagation to be continually updated to eventually be equitable with human cognition. An alternative position exists however among other members of the ML community. Christian (2021), echoing Tomasello's notion of learning through the other, has argued (2021, p, 269) that it is helpful to understand human learning in inferential" terms, that is, recognise that "we take actions *knowing* that another is trying to read our intention" thereby drawinf attention to the purpose, logic and tacit implications of communication.

In deviating from the strict neuroscientific view espoused by LeCun, Christian opens the door to a discussion about the new human-machine working-learning relationship, in other words, the new type of questions that have to be asked and cultural practices required to address them, that ML is ushering in. Intriguingly, this issue has been explored by van der Schaar (2020b) who, despite operating with a computational perspective on learning, has implicitly introduced a sociocultural perspective on the human-machine interface with her "interpretability, explainability and trustability" working-learning triplex (Guile & Popov, forthcoming). It is only when we are confident when we know how to approach the inter-relation between these three issues that we will, according to van der Schaar, 2020 (b p.1), be in a position to infer "why a recommendation was reached, how it was reached, what can be learned, and how the model will perform in a range of situations" and, moreover, why we should have confidence in the answers to those questions (ibid). To have this degree of confidence in the outcomes from any ML model of learning it will be necessary, according to van der Schaar (ibid), for firstly, interprofessional teams, comprising system designers and choice architects and domain user groups who have commissioned their services, in her case, medics in the field of breast cancer to (a) interpret the information-knowledge generated by a ML model of learning, (b) explain to domain user groups (i.e. oncology experts) the value of the information-knowledge generated by a ML model of learning and (c) for domain user groups to explain to beneficiaries (i.e. breast cancer patients and their families) the relationship between ML generated predictions and their decision about a treatment regime so they feel that they can trust decisions based on ML-generated data.

Van der Schaar, 2020b) offers therefore a way to strike a balance between the criticisms that some writers have levelled about the deficiencies of ML predictions, especially in relation to breast cancer (see inter alia. Wang et al., 2016), and the position adopted in this paper that the deep ML model of learning is creating new circuits of human and nonhuman interaction that have new implications for working and learning. What she does not provide however is a way to conceptualise the working and learning process that occur in the aforementioned circuits.

5. Interprofessional + machine learning cultural ecosystem: a "recontextualization" perspective

This lacuna offers the sociocultural tradition the following opportunity: how could the form of learning required to engage with an even more extended and distributed human-machine learning cultural ecosystem, where humans can learn from non-humans, even if it is producing a fairly narrow kind of learning, be conceptualised? Our starting point is Hutchins because we saw earlier that he conceives of learning as involving professionals undertaking local adaptions in a dynamic system of co-ordinations of representational media. This conception, which was formulated to take account of learning in extant systems of distributed cognition such as aviation, helpfully alerts us to the human-machine interface and its spatially and temporally distributed nature. What remains an implicit, rather than explicit, feature of Hutchins' account of co-ordination however are the cultural practices that facilitate inferential decisions about which elements in a system should be co-ordinated, why they should be co-ordinated, and how such decisions should be communicated to other members of the distributed ecosystem. These issues are probably taken-for-granted by Hutchins, because in the type of cultural ecosystems he has researched, for example, aeronautical aviation, the cultural practices that underpin the purpose of or tacit assumptions about aviation have been well-established for some time.

The new more extended and distributed human and ML models of learning that are being assembled in the type of professional contexts that are the focus of this paper presuppose, as we have seen, a whole new array of local adaptions in a dynamic system of co-ordinations of representational media, courtesy of the emergence of the two new cultural practice clusters namely ground truthing-programming-formulating and interpretability-explainability-trustability. What is required therefore is a way to conceptualise working and learning semantically and as a tool-mediated process. One way to do so is to view them as a process of "continuous recontextualization" (Guile, 2019), because recontextualisation is an "open" (ibid) sociocultural concept of learning, which can be modified to respond to the emergence of new challenges and cultural tools and how different communities learn to respond to them.

From a recontextualization perspective, all forms of activity have an object, in Edward's (2010, p. 5) term, a "problem space" where participants use extant, or develop new, cultural practices and tools to discuss, debate and then realise that purpose (Guile, 2019). Moreover, all forms of activity occur in a normative context – web of reasons – which provide criteria participants can use as resources to facilitate their decision-making processes (Guile, 2019). This conception of normative is indebted to Robert Brandom's argument in *Articulating Reasons* (2000) that forms of human activity, including its associated cultural tools are underpinned by reasons, in other words, activities and cultural tools are based on agreements that have been or are in the process of being built-up historically and culturally and, as such, classified in different ways. Although he follows Hegel and affirms that this is a universal principle that underpins all human activity, Brandom nevertheless accepts that activities are differentiated by their respective purpose and problem space. He invokes therefore the concept of "web of reasons" to encapsulate the relationship between the generality of his argument and particularistic expressions of that generality Brandom (2000, p. 45). By incorporating this nuanced formulation of the relationship between the general and particular into the concept of recontextualization, it is possible to distinguish between different types of webs of reasons: webs developed by specific professions enable them, for example, pharmacy, to create their own form of knowing, cultural tools and normative conventions of verification (Guile, 2014), whereas webs developed by interprofessional teams, for example, in the creative and construction industry, are contingent and developed situationally to assist team members to commingle different forms of knowing, cultural tools and normative conventions of verification (Guile, 2011a, 2011b; Guile & Wilde, 2023; Wilde & Guile, 2021).

From a recontextualization perspective therefore professionals work and learn in a web of reasons as they engage in an inferential semantic and tool-mediated 'what follows' practice (Guile, 2019). Typically, this practice would involve members of interprofessional teams: (i) listening to other members present or use cultural tools to model suggestions based on their interpretation of plans, data or issues arising from previous discussions and deliberations, and then recommending a particular interpretation or course of action; and (ii) engaging iteratively with that process by offering counter-interpretations or alternative suggestions based on their interpretation of data, or proposals to coordinate tools in an alternative way etc. before explaining or demonstrating the reasoning behind the suggestions they are putting to team members. The concept offers therefore a way for the sociocultural tradition to engage with the new working-learning issues, in other words, the cultural practices of ground truthing, programming and formulating and interpreting-explaining-trusting, associated with the new extended and distributed human + machine cultural ecosystems being assembled in professional contexts. This claim is explored analytically below.

Any interprofessional team comprising domain experts, system designers and choice architects will be working in their own problem space and using an ML prediction-generating model of learning to investigate a specific issue. From this perspective, they will be using the two aforementioned cultural practice clusters to continually recontextualise their extant form of knowing with the emerging ML-generated information knowledge, for different audiences.

In the case of the first cluster of cultural practices, an interprofessional team will be engaged in recontextualising their respective domain form of knowing, for example, about breast cancer and the ML model of learning, to create a web of reasons to enable them to work and learn together. This mode of recontextualisation will enable (a) the domain experts to share with the system designers and choice architects the assumptions underpinning and the parameters determining the scope of the issue that the former have identified for investigation, (b) the system designers and choice architects to infer how to programme a ML model's algorithm to investigate the chosen ground truth and (c) both groups to determine whether they feel that algorithm has been programmed and formulated effectively to read via a supervised or unsupervised process, the data it has been interfaced with in order to generate information-knowledge. By engaging in this mode of recontextualization, the team develops an understanding of the way in which the affordances and constraints that have they built into the ML model of learning's algorithm can be tweaked to facilitate, rather than distort, the investigation being undertaken.

In the case of the second cluster of cultural practices, the interprofessional team will further recontextualise their respective forms of knowing to extend the web of reasons that they have established to enable them to interpret, explain and eventually establish trust among themselves and user groups as regards the outcomes of their ML model of learning. This mode of recontextualisation will be enable domain experts, system designers and choice architects to, on the one hand, decide whether they intend to ask questions about the way they have designed an algorithm and whether it has enabled an ML model of learning to detect, rather than reproduce, biases that may exist in the data it is reading. And on the other hand, to explain to user group domain experts with cognate interests working in other contexts, in the case of breast cancer oncology experts in a hospital, how they have (a) interpreted the information-knowledge generated by a ML model of learning and inferred its validity in relation to the ground truth being investigated, and (b) urged user groups to voice any concerns that they have about the validity of the ML generated information knowledge..

This is however a pivotal moment in the recontextualization process, because the interprofessional team cease to be involved and the user group domain experts now 'pick up the baton' and recontextualise their new ML-mediated form of knowing to create a web of reasons with beneficiaries (i.e. breast cancer patients and their families). By doing so, they are able to explain the relationship between ML-generated information knowledge and their prior domain knowledge, and how they have drawn on both to infer a particular treatment regime. Beneficiaries are then positioned to infer from the explanation that they receive from user group domain experts whether to accept the treatment regime based on the recontextualization of ML-generated predictions or whether to question that recommendation.

Taken in combination, the concept of recontextualization and the two cultural practice clusters offer a more multifaceted way to analyse working and learning in the extended and distributed human-machine cultural ecosystems being assembled in professional contexts, because they are predicated on working and learning as semantic and tool-mediated process. Hence the concept can embrace the possibility that humans can learn from non-humans. It remains to be seen however whether, over time, trust is built through a long trend of empirical validation in specific domain areas and as a result explainability becomes a less pressing issue. This could wax and wane if the reasons for the good validation results are not transparent or explainable.

6. Conclusion

The paper has presented a number of interconnected arguments that are consistent with, yet differ from, the longstanding sociocultural perspective on the C-T-L relationship outlined at the start of the paper. The first is that ML constitutes a cultural tool capable of learning by perceiving patterns in data and generating conclusions from them, even though the ML connectionist model of learning (MLMoL) constitutes a much more circumscribed kind of learning compared with how that concept has been interpreted in the past in sociocultural theory. The second is that the MLMoL is resulting in the creation of new extended and distributed cultural ecosystems, which domain experts, comprise choice designers, system architect, professional user groups and beneficiaries, involved with the two new working and learning cultural practice clusters – ground-truthing-programming-formulating and interpretability-explainability-trustability. The third is that the concept of recontextualization offers a way for the sociocultural tradition to locate the narrowness of MLMoL generated outcomes in relation to broader sets of human-machine concerns that span the new circuits of human and nonhuman interaction among domain experts, user group domain experts and beneficiaries. In making the above multi-stranded argument the paper is supplementing the cumulative insights from sociocultural writers on learning, rather than follow a socio-culturally-influenced argument that the emerging human-machine interface presupposes the adoption of a "posthumanist" perspective on learning (Hasse, 2019). This claim nevertheless warrants sustained discussion in a subsequent paper.

Finally, at the time of editing the paper in response to peer review feedback, Chat GPT was launched into the AI marketplace accompanied considerable fanfare about its potential revolutionary implications for working and learning. It is therefore important to note, even if it is beyond the scope of the paper to explore, the difference between ChatGPT and the MLMoL discussed in this paper. The former is, as Ouyang et al. (2023) demonstrate, a model of providing answers to human-generated questions based on training language models to follow instructions. Although the training process is initially predicated on the use of supervised learning and subsequently supplemented with reinforcement learning, it operates with a very different model of, and has a very different outcome of, learning compared with the MLMoL explored in this paper. It is nevertheless important to note that ChatGPT is a further example of a cultural tool capable of some kind of learning and, as such, like the MLMoL has poses a challenge for the traditional socio-cultural conception of cultural tools.

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