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AI in the age of technoscience

On the rise of data-driven AI and its episteme-ontological foundations

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Each new piece of miraculous apparatus has been heralded as the essence of a new (but usually short-lived) 'age' in the history of mankind. In its turn each machine metaphor has opened areas of both insight and radical blindness as it becomes a means of interpreting what happens in our world

Langdon Winner, Autonomous Technology (1977, 45)

I am interested in the narratives of scientific fact – those potent fictions of science – within a complex field indicated by the signifier SF [science fiction; the authors].

Donna Haraway, Primate Vision (1989, 5)

Is there any point in understanding noisy data?

Noam Chomsky, Where Artificial Intelligence Went Wrong (2012)

This chapter offers a critical discussion of the epistemological and ontological foundations[1] of AI. It begins with a short history of AI focused on the epistemological and ontological premises foundational to the three AI approaches that have dominated its historical development, namely, symbolic, connectionist, and data-driven AI. It then presents some early and more recent critiques of AI technologies that are informed by (critical/feminist) science and technology studies, including more recent developments in algorithm and critical data studies. After discussing some thoughts on how we are to understand the rise of data-driven AI, it concludes with some critical remarks about the current call for 'ethics in AI'. The overall aim of the chapter is to contribute toward a reflection on the all-too-often implicit assumptions entailed by AI per se and by its new instantiations, thus laying the analytical groundwork for shaping alternative AI technologies in the future.

From symbolic via connectionist to data-driven AI

Until recently, the history of AI has often been described as oscillating between two different approaches: symbolic AI as the dominant rational-cognitive approach on the one hand and connectionist AI, or 'sub-symbolic' approaches, on the other.

The former is based on formal logic and mathematics and draws on representation, causality, and deduction (Newell/Simon 1976). One of its central assumptions is the concept of the physical symbol system, according to which any intelligent system – human or machine – "must operate by manipulating data structures composed of symbols" (Russel/Norvig 2010, 18). Expert systems – artificial systems whose purpose is to reproduce knowledge – can be regarded as a classic example of this kind of AI: AI researchers sought to extract knowledge from experts by interviewing them and encoding the knowledge thus gained into logical rules to make it computable. It soon became clear, however, that static knowledge systems are rather difficult to build and are not especially robust (Norvig 2011). For this reason, as far back as t he early 1980s, many regarded expert systems as a failure (Brooks 1986; Pfeifer/Scheier 2000).

The connectionist approach ranges from artificial neural network research to genetic algorithms and behavior-based robotics, and is rooted in, as well as inspired by, biology, psychology and the neurosciences. These approaches draw on correlation, induction, abduction and bottom-up strategies. They focus on behavior, learning, and self-organization while some work with concepts such as situatedness and embodiment. Warren McCulloch and Walter Pitts' artificial (learning) neural network (1943) is an early example of the biologically inspired approach. Another connectionist approach, Rosenblatt's famous 'Perceptron' (1962), which was a simple form of neural network, was vehemently criticized by Minsky/Papert (1969). Their critique heralded a lengthy period, from the late 1960s onward, in which the biocybernetic, connectionist approach lay dormant.

In the 1980s, however, the biocybernetic approach was revived in fields such as Artificial Life, biorobotics, and parallel distributed processing. In the course of this development, the focus of AI increasingly shifted from knowing to learning, from understanding reasoning as a high-level form of symbol manipulation toward solving problems with machine learning using so-called common-sense knowledge as a basis. It sought increasingly to deal with uncertainty and the 'theoryless' (Valiant 2014), a development paralleled by the introduction of new flexible databases (NoSQL), statistics-based methods of machine learning (e.g. genetic algorithms), and the usage of massive data that were now gathered from websites, search engines, online marketing, and similar sources.[2]

Data-driven AI is the dominant AI approach taken nowadays. It is based on machine learning (ML) from examples extracted via the analysis of massive amounts of (online) data, rather than building on logical rules.[3] More specifically, as one of the central pillars of data-driven AI, ML is "a method for finding patterns in data that are usefully predictive of future events but which do not necessarily provide an explanatory theory", as machine learner Leslie Valiant explains (2014, see 8). Its application is aimed primarily at aggregating “as much data as possible, in order to mine them for relevant patterns that allow the profiler to anticipate future behaviours” (Gutwirth/ Hildebrandt 2010, 7). As the chances of finding ‘relevant’ patterns increase with the volume and size of the data collection, efforts are undertaken to (re)combine more data from diverse categories and multiple (online) sources in order to find new correlation patterns. Algorithm studies scholar Louise Amoore describes this logic of ML as the “imagination of possibilities” (Amoore 2013, 24). Interestingly, induction and abduction are used here instead of deduction to target the realm of the so-called theoryless (Valiant 2014) and not the traditional realm of the physical world:

> *Machine learning is concerned with machines that improve with experience and reason inductively or abductively in order to optimize, approximate, summarize, generalize from specific examples to general rules, classify, make predictions, find associations, propose explanations, and propose ways of grouping things.*
>
> (Kovacs 2012, see 938f, emphasis added)

Reason, that is, classical rational-cognitive analysis, is only used in the post-processing and post-analysis phase of machine learning but not in its methodological grounding (Erni/Fröhlich 2010; Valiant 2014). Today, most ML applications are not used to target phenomena in the physical world but social or cultural phenomena that occur in everyday life. The applications range from analyzing the preference behavior of consumers to identifying fraud strategies in credit card transactions to identifying ‘terrorists’.

STS scholar Andrew Pickering has claimed that the biocybernetic approach is “an instantiation of a different paradigm from the one in which most of us grew up – the reductive, linear, Newtonian, paradigm that still characterizes most academic work in the natural and social sciences (and engineering and humanities, too)” (Pickering 2002, 413f). For him, “[c]ybernetics is all about this shift from epistemology to ontology, from representation to performativity, agency and emergence” (ibid., 414). Can this biocybernetic shift from logic to probability, from linearity to emergence, be regarded as a shift from classical Newtonian science to a new technorationality that seeks not so much to understand (fundamental principles) as to effectively engineer in the sense of developing the best solution possible for practical problems (Weber 2010, 2011)? Following Pickering’s argument and keeping in mind the recent merging of biocybernetic AI approaches with probabilistic, data-driven approaches, the question arises: how do these epistemological and ontological changes in AI affect our understanding of the world and of ourselves? What are the foundations of these frameworks of thinking; what are their implicit norms and values and their societal impacts?

It seems important to understand these epistem-ontological shifts, their logics, effects, and consequences (Weber 2011), if we want to engage critically with AI.

Early critiques

Early symbol-processing AI was criticized for its belief that every aspect of human thinking could be reduced to logical formalism, i.e. that human thought (and everyday language) is computable (Weizenbaum 1976). The argument was that it ignores the fact that people learn through their embodied, language-mediated practices which are embedded in the everyday world and include implicit, context-bound knowledge that ensures they are able to find orientation in that world (Dreyfus 1972; Winograd/Flores 1987; Adam 1998). Although language has been increasingly technicized and technology today is mainly (computer) language-based, it is not the symbolic that AI is working with but formal languages involving numbers and processing rules, whose logic is different from that used to think, talk, and produce meaning. Turing machines and formal languages might be concise and coherent, but they are not meaningful (Weizenbaum 1976; Mersch 2006).

STS scholar Donna Haraway's work on technoscientific developments, which is at once optimistic and critical of their entanglement with the sociomaterial relations of power,[4] has inspired a diverse body of research on artificial intelligence and robots. This work enables us to better understand the changing "sociomaterial grounds of agency and lived experience of bodies and persons, of resemblance and difference, and of relations across the human/machine boundary" (Suchman 2008, 139). It demonstrates not only that AI is modeled on hierarchical, gendered assumptions (as, for example, when humanoid robots are given the highly stereotypical shape of women, infants, or pets) but also that gendered ontological, anthropological, and epistemological premises are enacted in the theoretical concepts that form the basis of AI development.

Feminist STS scholars Lucy Suchman, Barbara Becker, Alison Adam, and others have pointed out that symbolic AI works with a limited concept of intelligence, one equated solely with cognition. Thus, they shed light on the cultural assumptions enacted in the design of humanlike machines, particularly regarding the 'nature' of the human. They depict AI as a deeply conservative project that draws heavily on long-standing Western philosophical assumptions regarding the nature of human intelligence by focusing on the individual 'cognizer' as the point of origin of rational action, while under-privileging affectivity and bodily states as crucial to the specificity of the materially embodied and socially embedded subject. In this framework the 'cognizer' is modeled as the universal figure of 'man' rather than as an embedded and materially embodied subject (Suchman 1987; Becker 1992; Adam 1998).

The problematic nature of this assumption already becomes apparent at the methodological level. For example, AI expert Alison Adam argues with regard to Herbert Simon's path-breaking book, Human Problem Solving, that the experiments conducted for his so-called general theory of intelligence, or 'information processing psychology', were:

based on the behaviour of a few, technically educated, young, male, probably middle-class, probably white, college students working on a set of rather unnatural tasks [formal logic; chess playing; the authors] in a US university in the late 1960s and early 1970s.

(Adam 1998, 94)

With regard to the early connectionist approach, Adam notes further that while there is a perceptible move away from strong rationalism – for example, knowledge is no longer modeled as propositionally structured (ibid., 45) – nevertheless, the system is still disembodied as the (implicitly male) operator supplies all the meaning for both input and output, including an understanding of skills and bodily knowledge, so that the system may be trained.[5] In her own research on social robotics, one of the authors (Weber 2005) also identifies a growing concern with questions of sociality, emotionality, and interaction within recent trends in robotics and the conceptualization of the human–machine relation. She argues that, while the 'weak' approach of so-called social robotics seeks to create machines capable of simulating emotions and sociality, it holds on to the traditional hierarchical master-slave relation between the expert/user and the machine. The 'strong' approach to social robotics, by contrast, seeks to create self-learning autonomous machines and builds on the highly gendered caregiver-infant relation between the user and the machine, thereby reifying traditional concepts of care and child-rearing. Modeling the human-robot relation in this way not only serves to exploit the user's time and dedication in helping the machine develop but also obscures the roboticists' own authorship of the humanrobot relation. Sherry Turkle (1996) reaches a similar conclusion when describing a shift from rule-based to emergent models within the field of AI, according to which computers are imagined as developing children that learn from experience and interactions and thus build their intelligence from the bottom up. Whereas Turkle concedes that these connectionist computer systems no longer need to be programmed by means of centralized sets of rules but through 'learning-by-doing', Weber argues that every intelligent machine will still be based on rules, as rule-oriented behavior forms the material basis and makes up the fundamental functionality of these machines (2005, 214).

If we follow this argument, it means that the standardization of human behavior is a precondition for every computer model and software application, and this in turn gives rise to the question of which behavior is identified and enacted as the norm (i.e. as 'normal'), which human behavior is excluded from this conceptualization, and how both of these elements are intertwined with gendered, racist, classist, and ableist structures and symbolic systems. At the same time, new field of biologically inspired robotics pays great attention to the unpredictable and to chance. With iterative strategies of trial and error, biorobotics tries to support developments that might result in unpredictable but controllable machine behavior on the basis of emergent, or evolutionary, processes. Traditional ideas regarding the objectivity, neutrality, and reproducibility of experiments are increasingly called into

question. The presumed selforganizing principles of the living are increasingly sought to be integrated into a new 'bottomup' technique of control.
Before turning to the more recent critique of data-driven AI, it seems sensible to take a look at the structural setting within which AI is situated, as this has been problematized from its early days.

Sociopolitical context of AI

Although Donna Haraway takes an optimistic stance toward her analytical figure of the cyborg, "a cybernetic organism, a hybrid of machine and organism, a creature of social reality as well as a creature of fiction", she also remarks pointedly: "The main trouble with cyborgs, of course, is that they are the illegitimate offspring of militarism and patriarchal capitalism, not to mention state socialism" (2004 [1985], 10). The development of AI technologies has been heavily funded to date by military, defense, and intelligence organizations. A current example is the recently suspended cooperation between Google and the US Pentagon in Project Maven, a joint project to develop AI for interpreting video imagery that could be used to improve the targeting of drone strikes. While Google pulled out from Project Maven after an employee's protest letter against the participation of their employer in the development of warfare technology, tech giants are continuing to compete for multibillion-dollar defense contracts (Shane/Wakabayashi 2018). As this case shows, corporations active in the so-called new economy are gaining significance and influence when it comes to advancing AI technologies, as they control vast amounts of big (social) data as well as the technological infrastructure for generating, storing, and processing these data on which the development of AI depends today (boyd/Crawford 2012; Lyon 2004). Whereas critical data scientist Jim Thatcher (2014) argues with regard to the expanding data industry that big data are structured by capitalist interests, it is equally clear that, when it comes to the development of AI today, it is structured by both capitalist and military interests. Moreover, AI must be seen as the center of a military-industrial complex that US President Eisenhower warned against in his famous farewell address of 1961 (Eisenhower 1961). Media theorist James Der Derian (2009[2001]) even speaks of a rapidly growing military-industrialmedia-entertainment network in the 21st century, which includes new digital media, the game and simulation industry, and other actors.
Taking further into account that its influential (corporate and military) actors are located for the most part in countries of the so-called global north, AI must be understood additionally as being situated within (post-)colonial structures (Hagerty/Rubinov 2019). This structural setting of AI is mirrored in the composition of the workforce responsible for developing AI as well as for whose perspectives and interests are taken into account in the development of AI technologies.
The workforce responsible for conceptualizing, designing, and developing AI is highly homogeneous: it constitutes a 'virtual class' consisting predominantly of relatively young, welleducated, socioeconomically privileged, white (Caucasian) or Asian men (Barbrook/Cameron 1996). At the

same time, the largely invisible, less glamorous, low-skilled and low-paying work of so-called content moderation and simple data handling is done by a mostly anonymous (online) workforce comprised largely of people from the global south. Thus, the very foundations of AI are both gendered and globally divided, with many people around the world lacking the educational opportunities necessary to gain the skills required to participate in designing AI (Hagerty/Rubinov 2019, 5). In addition to this, of course, there is all the unpaid work done by those of us with access to digital media technologies, which we hardly ever consider as work, given that it seems we are just ‘using’ these media technologies; in actuality, we are sharing data and creating content that can then be mined, repurposed, and traded. As “digital housewives” (Jarrett 2015) we provide unpaid (re)productive consumer labor for capitalist companies to exploit, but we also take part – albeit often unknowingly or even unwillingly – in creating big data sets that are at the heart of today’s AI developments.

The data sets that are central for developing smart AI technologies today are, however, often unrepresentative of large parts of the world’s population – namely, the elderly, the less affluent, the disabled, women, people of color, and those from the so-called global south – because there is a penchant for data that originates in and ‘represents’ North America and (Western) Europa as well as data on ‘privileged’ members of these societies. Thus, the data sets that are foundational to AI developments reinforce the exclusion of the interests and needs of vulnerable social groups across the globe, and, in doing so, reproduce historically established relations of dominance, marginalization, and subordination (Lyon 2004; Hagerty/Rubinov 2019). As a consequence, for example, while algorithms used in medical research are improving the identification of skin cancer, they are doing so only in relation to lighter skin-tone samples.

Current critique of (big) data-driven AI

With the rise of so-called big data, promoted as establishing a new regime of truth (for a critical assessment, see Beer 2016), data-driven AI has gained additional momentum in recent years. Advocates of big data analysis promise that more and better knowledge will be produced:

> *Before big data, our analysis was usually limited to testing a small number of hypotheses that we defined well before we even collected the data. When we let the data speak, we can make connections that we had never thought existed.*
>
> (Mayer-Schönberger/Cukier 2013, 14)

As this quote rather pointedly states, the concept of big data promotes the idea of a “data-driven rather than knowledge-driven science” (Kitchin 2014, 1). It thereby renews “the primacy of inductive reasoning in the form of a technology-based empiricism” (Mazzocchi 2014, 1250) and idealizes a data fundamentalist approach to knowledge production, as critical data scientist Kate Crawford (2013) has called it.

This data fundamentalism rests on at least two equally controversial premises: first, “the belief that life can be captured and modeled by data or even fully transformed into it” (Thatcher 2014, 1768) and, second, the assumption that objectivity is the result of a subject-free and therefore neutral production of knowledge. Both ideas have been heavily criticized within STS as constituting specifically modern ideals of science.[6] Proclaiming that “raw data is an oxymoron”, Lisa Gitelman (2013) – and other scholars engaged in Critical Data Studies – have more recently revived the debate on how to understand data as a sociocultural, and highly political, construct. In contrast to the idea of data simply depicting and, thus, representing reality or nature, data is conceptualized as being the product of numerous practices of categorization and classification, the production of comparability, and the demarcation between what gets to be included and what does not, between what is considered as relevant and what is not – in other words, as a necessarily selective reduction of (social) reality. In their influential book, Sorting Things Out, STS scholars Geoffrey Bowker and Susan L. Star (1999) argued that data is never independent of the categories and stratifications that make up the sociocultural order of society and is therefore easily coupled with hierarchical differentiations and power relations. As a result, the focus on modeling, abstraction, and standardization that is central to any formal epistemology tends to ignore aspects of reality that do not fit the definition of the norm(al). Regarding the quantification of care work in hospitals, for example, they argued further that the quest for numbers led to the neglect of emotional work, which is usually done by women and ‘other Others’, as Haraway coined the term, such as the small talk conducted between a nurse and her (or, less often, his) patient, or a smile directed at them – work that is difficult to quantify and model using data. Others draw comparable lessons from historical experiences of quantification in human geography or social physics: the call for numerical representation is considered to favor mechanistic conceptions of the world that focus on singular codifiable components of reality, ignoring their interrelatedness, complexity, variability, and disparity (Barnes/Wilson 2014, 10). Numerical approaches to knowledge production have further been criticized as being less suited to capture relations of power, inequalities, or cultural and symbolic phenomena (Kitchin 2014, 8; Mazzocchi 2014). Additionally, it has been argued that data is ‘performative’: it constitutes the very ‘reality’ it supposedly merely represents. Building on these arguments, it has been proposed that data and society should be conceptualized as being co-constitutive (Houben/Prietl 2018).

The naïve promotion of a data fundamentalist approach to knowledge production within data-driven AI[7] also seems to ignore the long-standing insights of critical STS according to which there is no such thing as neutral and objective knowledge production but only “situated” truth claims that are highly contingent, depending on the sociomaterial context as well as on the subject producing the knowledge. Feminist work in STS has further argued that the modern Western ideal of science rests on the notion of a rational, non-situated, and bodyless subject of knowledge that has been constituted in contrast to the notion of emotionally bound and physically situated 'others', namely, women and people of color. Thus, the notion of objectivity has to be considered as a 'view from nowhere' that is ultimately androcentric as well as Eurocentric. Such a view has long served to legitimize the exclusion of women and people of color from academia and continues to marginalize forms of knowledge and modes of reasoning that are based on lived bodily experience and oral traditions (Haraway 1988).

Another characteristic of data-driven approaches to AI is the correlationism underlying machine learning approaches. Data-driven AI implements a shift from understanding or explaining a phenomenon – that is, asking why or how questions – to generating probabilistic predictions about a phenomenon that supposedly make it possible to describe or predict its future occurrence, as Chris Anderson (2008) famously proclaimed in his editorial letter for WIRED titled The End of Theory: "Who knows why people do what they do? The point is they do it, and we can track and measure it with unprecedented fidelity". According to this idea, reasoning increasingly moves from "data gathered about the past to simulations or probabilistic anticipations of the future that in turn demand action in the present" (Adams et al. 2009, 255), thereby establishing a "regime of anticipation" (ibid.) that is based on "post-explanatory pragmatics" (Andrejevic 2014, 1675). Put differently, turning to machine learning techniques goes hand in hand with giving up on explanatory theories and using pattern recognition to predict future behavior. A key technique within this context is regression analysis: here, algorithms search for patterns in large data sets by calculating how different variables correlate within this data set. By devising a model of this relationship, it becomes possible to predict how the variables identified will likely co-develop in the future. Thus, data-driven AI operates on the assumption that patterns found in data from the past enable us to predict (and govern) the future. The correlationism underlying this approach offers the possibility of finding patterns that do not originate in stereotypical classifications (such as women being more social than men). As Geoffrey Bowker (2014) argues, however, this advantage quickly turns into a disadvantage when the knowledge generated fails to understand the correlations identified and instead (mis)takes them as positivistic expressions of the truth. In other words, when AI affirms existing sociocultural structures, it turns into a sociomaterial apparatus of self-fulfilling prophecies, thereby unfolding conservative tendencies rather than fostering more objective decisions (Prietl 2019b).

As noted previously, machine learning gives up on explanatory theories and uses pattern recognition to predict future behavior. The post-Newtonian rationality, or 'technorationality', informing ML (Weber 2011; Suchman/Weber 2016) is based on a mapping of our world that is as complete as it can possibly be due to the collection and mining of any and every data source available. It is based on the exploitation of the unpredictable and unknown as well as on automated practices of tinkering. As such, it does not analyze the problem and deduce a solution but rather maps out a search area, defines border conditions, and uses processes of trial and error to solve problems that need not to be understood but solved or engineered. In contrast to this, the classical natural sciences worked – at least according to their own view of themselves, though this was often not true for their practices –

with an experimental perspective on causal relations, a theoretical perspective on natural laws, and a mathematical perspective on general principles. They relied on empirical research conducted on the basis of measurement with instruments and well-established theories (cf. Cassirer 1957[1929]; Grammelsberger 2010). Starting from the diversity of phenomena, the purpose of the natural sciences has long been systematic observation and empirical-instrumental research with the aim of ordering the world in a rational way on the basis of theoretical concepts. Against this background, data-driven AI looks more like a 'theoryless' endeavor based on common sense as well as analogies and abduction, as it seeks to capture everyday knowledge that cannot be processed using mathematics or formal logic. Asking "what it is about common sense that logic fails to capture", Valiant argues that the problem is "a result of mathematical logic requiring a theoryful world in which to function well", whereas "[c]ommon sense corresponds to a capability of making good predictive decisions in the realm of the theoryless" (Valiant 2014, see 58). Mathematics and formal logic are devalued as the "idea that common sense is somehow superior to reason" (ibid., emphasis added) becomes fashionable.

Interestingly, this is turned into a theory of the general nature of the 'theoryless', when Valiant argues in his well-known book Probably Approximately Correct (sic!) that ML deals with the unsystematic, the non-linear, the affective, and the orderless. And, though this new pragmatic approach leaves traditional rational-cognitive foundations by the wayside, Valiant seeks to justify this by referring to evolution, claiming that 'humankind' has naturally used machine learning techniques throughout its entire history to cope with the 'theoryless' (Valiant 2014).

Last but not least, data-driven AI is deeply embedded within what scholar and publicist Evgeny Morozov (2013) has called techno'solutionism'. Research concerned with the digital avant-garde of Silicon Valley, one important birthplace of AI, notes that a "solutionist ethos" is prevalent among the relevant actors. The utopias being portrayed around digital data technologies depict the world as being full of 'bugs' that need to be 'fixed'. The preferred means to do so are technological ones, especially ICTs, digital technologies and, last but not least, AI. The core idea of the techno'solutionism' promoted here is that every problem, including social problems, can ultimately be reduced to a series of small and therefore manageable problems for which technological solutions can then be found. The optimistic belief in technological progress in combination with libertarian ideals and a deep distrust of established politics draws on the so-called Californian ideology that has become prominent throughout the second half of the 20th century (Barbrook/Cameron 1996). The Californian ideology sees 'politics' as an outdated form of democracy; instead of political debate and the building of public opinion, a virtual 'agora', a digital public space of public discussion, is to be established where everyone is supposed to participate and speak his or her mind freely and equally, thereby paving the way for democratization, decentralization, and emancipation. To make this vision come true, two things are needed according to high-tech solutionism: humans need to live up to their full potential, which is supposed to be enabled by networking, the distribution and sharing of information and, therefore, equal access to knowledge and technology. Additionally, all institutions that hinder or restrict the free unfolding of human potential, such as bureaucracy, are to be removed and a strict meritocracy is to be established. While this may sound good in theory, the protagonists involved seem to fail to recognize not only existing inequalities in access to education and digital technologies but also the reproduction of power asymmetries and social inequalities in virtual spaces (e.g. Paulitz 2005; Zillien/Hargittai 2009). Likewise, the well-documented effect that the meritocratic ideal stabilizes existing social inequalities due to its disregard of the deeply embedded structural inequalities in society (Becker/Hadjar 2017) is not problematized any further, but a deeply anti-political stance is fostered. As Barbrook and Cameron (1996, 49–50) argue, this may be due to the fact that the protagonists of the New Economy themselves form a privileged "virtual class" that is rarely affected by racism, social inequality, or poverty. More importantly, however, this anti-political solutionism has profound consequences, as it privileges a focus on allegedly anti-political, purely factual aspects of reality and social life, thus ignoring the highly political and, therefore, inequalityrelevant notions of the world we live in. Remembering the lack of sensitivity toward power asymmetries and social inequalities of data-driven AI, one of the authors (Prietl 2019a, 10–21) argued that the current approaches in AI development run the risk of mistaking the perspective of a privileged view for a universal perspective, rendering those in marginalized positions (once again) invisible.

Thus, exposing data-driven AI to a (feminist) critique of rationality shows that its epistemological foundations are anything but neutral. On the contrary, they embody a specific approach to the world that transports certain possibilities of knowing and is itself not neutral but rather favors specific worldviews, perceptual styles, and the reproduction of existing social inequalities, as Donna Haraway has argued for technoscientific artifacts in general. Current forms of data-driven AI do so by (1) privileging phenomena that are easily transformed into (numerical) data and (distinct) categories and that are, therefore, more readily amenable to processing algorithmically; by (2) promoting the generation of probabilistic knowledge about specific possible worlds (and not others), instead of engaging critically with our contemporary world and questions of why specific phenomena have (not) come about; and by (3) favoring the presumably non-political analyses of so-called facts over sociopolitically informed, situated, and normative debate (Prietl 2019a, 22).

Discussion

Given the contemporary hype around data-driven AI, which often conflates it with machine learning, it seems important to ask how these new technologies can also be seen as the expression of specific societal formations and pressing issues – an approach philosopher Gilles Deleuze propagated in his famous 'postscriptum of the control society' (Deleuze 1992). He interprets technologies not as an a priori but as the expression of the zeitgeist, of the ontological selfinterpretation of a specific time and of a specific sociohistorical constellation of society, humans, and machines. According to this, we can ask why machine learning has become hegemonic in the last decade. Why are its forms of knowledge production – correlation, analogy, or abduction – so attractive? And how are power and knowledge entangled in the data-driven knowledge regime?

We find a renewed positivism built on the symbolic authority of data, which renders the results of such big data analyses extremely difficult to object to successfully (for the symbolic capital of numerical data, see Heintz 2010).[8] We are already familiar with this kind of authority in relation to statistics, which traditionally focused on the past while data-driven AI/ML focuses on prediction and anticipation – or even "premediation", as media theorist Richard Grusin argues: in the face of an "increasingly threatening future of geopolitical, environmental, and now economic dangers" (Grusin 2010, 134), people in Western societies are preoccupied with mediating every object, (inter)action, or event to "protect us from the kind of negative surprises that might await us in an un[pre; the authors]mediated world" (ibid., 127). Drawing on Foucault and Deleuze, Grusin argues that we are seeing a profound shift in the contemporary biopolitical regime toward a (neoliberal) governmentality with its strategies of control, management, and securitization. This move is accompanied by a "proliferation of networked media technologies so that the future cannot emerge into the present without having been premediated in the past" (ibid., 126). The cultural desire for anticipation and premediation thrives on and drives the development and use of networked media and – we would argue – especially that of data-driven AI. The monitoring of electronic interactions and the transactions of media networks that provide material for data analytics is supposed to register and prevent potential disruptions to the given sociopolitical order.

The mapping of a broad variety of possible futures via premediation, however, means that only specific options are offered, and some are more supported by the protocols and reward systems of AI (and other technological systems) than others. But processes of premediation could also be seen as technological discourses and practices which "turn open spaces of possibility into 'test environments preparing for techno- and sociological change'" (Kaerlein 2012). Premediation helps us to experience problematic political events, technological practices, or sociotechnical discourses as normal and regular. At the same time, the anticipation of possible worlds or events as well as practices of forethought fuels the production of ideas and innovations in (neoliberal) capitalism:

> *[T]he aim is to produce a certain anticipatory readiness about the world, a perceptual style which can move easily between interchangeable opportunities, thus adding to the sum total of intellect that can be drawn on. This is a style which is congenial to capitalism.*
>
> (Thrift 2007, 38)

Outlook

Throughout the last few years, reports of racist risk assessment tools employed in the US criminal justice system, of sexist recruiting tools, or of highly stereotypical digital assistants have highlighted the fact that AI programs are far from being neutral and objective.[9] In reaction to these numerous reports about discriminatory AI technologies and the ensuing public outcry, there has been a call for ethics in AI. So far this has mostly taken the form either of self-regulatory approaches, such as the implementation of ethical frameworks, guidelines, or boards that are supposed to ensure the development of responsible, non-discriminatory, and fair AI, or of endeavors to create moral machines and fair algorithms by building ethical considerations into AI technologies that enable them to act ethically themselves.[10] Design theorist Mona Sloane (2019) has criticized the hype around ethics as a panacea for remedying biases in AI, arguing that it functions as a smokescreen for carrying on with business as usual. Rather than initiating a genuine push toward social justice and equality, ethics are largely employed to gain a competitive advantage between companies, industries, or nations. And, last but not least, they are deployed because they are not enforceable by law and thus remain a gesture of goodwill.

The currently prevailing focus on ethics also appears problematic on an epistemological level due to conceptual shortcomings of how inequality/injustice is thought about in this context:[11] First, the focus on ethics assumes the existence of a rational and autonomous human being as the subject of (un)ethical behavior and, thus, takes a person's intent as key to identifying discrimination or wrongful doing. This idea of 'man' is highly andro- and Eurocentric. Focusing on the supposedly willful actions of individuals also means losing sight of the broader societal contexts within which actions take place. Put differently, a focus on free ethical choices for action largely ignores the social structures and symbolic orders in which people are situated and that pre-structure their choices, as well as the alternatives available to them in the first place. Second, the aforementioned understanding of (un)ethical behavior often translates into a rather narrow causal conception of discrimination, according to which efforts to construct nondiscriminatory AI focus on identifying errors to be fixed, i.e. specific data sources, technical features, or human biases that are understood as the discrete roots of the unfair result in question.[12] This causal thinking, again, largely ignores the social structuring of technology as well as its own structuring role and, thus, closes down the space for criticizing and challenging inequality as a complex, sociocultural, historical, and emergent phenomenon that is deeply intertwined with AI technologies. Third, disregarding inequality as a complex, multi-dimensional phenomenon goes hand in hand with a single axis thinking centered on disadvantage with regard to a rather small set of legally protected social attributes such as race, gender, or age. As a consequence, such efforts fall short when it comes to accounting for the intersecting effects of discrimination and the more complex coupling of AI with social inequalities. In addition, the focus on the (un) fair distribution of (material) resources ignores the question of what counts as a resource in the first place, what is considered to be fair distribution, and how these terms can be operationalized in order to meet the need for formalization, which is foundational to AI technologies. Instead, the ways that AI itself not merely informs decisions but is bound up in the production of sociocultural meaning and practices are black-boxed.

Considering these points of critique, a turn to critical (feminist) STS perspectives seems fruitful. This would imply a shift in focus from questions of justice to questions of inequality. This means focusing on understanding how AI is entangled with social relations of power and inequality as well as symbolic hierarchies, and how AI takes part in reproducing these sociocultural structures by pre-structuring the production of hierarchically positioned subjects, social practices, and ways of living. It means, among other things, asking: Who takes part in developing AI and in designing AI technologies? Which perspectives and whose wishes and needs are represented in the design of AI? Which norms and values become materialized in AI, and which ways of living are favored and privileged compared to others that are marginalized or ignored altogether?

Besides understanding the complex interplay between AI and social relations of power and inequality, a (critical/feminist) STS perspective demands that we take responsibility for the development, design, and implementation of AI technologies. In her Manifesto for Cyborgs, Donna Haraway (2004 [1985], 33) summons the marginalized and subordinated to seize “the tools to mark the world that marked them as other”. She depicts the vision of an “elsewhere”, a better world that no longer rests on hierarchical dualistic thinking, a world made possible – among other things – by the rise of technosciences that defy the illusion of stable dualisms such as human vs. animal, nature vs. culture, or men vs. women. This utopia, however, is not to be mistaken with claiming neutral objectivity for feminist perspectives; on the contrary, Haraway (1988) explicitly rejects the possibility of any perspective being ‘innocent’, as she understands that every knowledge and truth claim is “situated” within social relations of power. Nevertheless, she argues for starting with the perspectives of those who are marginalized and subordinated, because they are less prone to misunderstand their perspective as a universal ‘view from nowhere’. Haraway thus argues that we should reflect upon and make our own situatedness as a subject of knowledge a prerequisite for objectivity, because only this allows us all to be held accountable. With Haraway we can, thus, no longer hold on to the idea of neutral knowledge or artifacts, as these are always political in one way or another. Returning to AI, this means giving up the ultimately impossible search for non-biased technologies and instead focusing on how to intervene responsibly in their development and design; it means working toward taking into account a broad and diverse range of perspectives, needs, and demands in order to design AI technologies that are appropriate with respect to society’s heterogeneity and complexity; and it means striving for an AI that dismantles and reduces existing relations of power and binary dualisms rather than stabilizing and reinforcing them. Last, but not least, it means talking less about the technologies we can produce and more about those that we should and want to produce.

Notes

[1] Theory relies on meta-theoretical principles or orienting strategies. These principles or strategies contain epistemological premises as well as ontological options. The former give answers to questions such as how can knowledge be produced, what qualifies as knowledge/truth, how can truth claims be made, and what constitutes the subject of knowledge production. The latter lay down what set of things, entities, events, or systems are regarded as existing. Accordingly, ontology refers to these decisions and is not necessarily related to an essentialist argumentation. As AI centers around the question of knowledge production, considering the epistemological and ontological assumptions that go into its construction is paramount.

[2] Peter Norvig, AI expert and research director at Google, claims that: "The fundamental tools of A.I. shifted from Logic to Probability in the late 1980s, and fundamental progress in the theory of uncertain reasoning underlies many of the recent practical advances" (Norvig 2011).

[3] Although it is useful to differentiate analytically between these two approaches, it is important to keep in mind that many AI artifacts bring these frameworks together. For example, the Pitts/McCulloch approach of an artificial neural network, mentioned previously, can be seen as a hybrid of symbolic and connectionist AI because it is based on knowledge of basic physiology and brain structures but also works with propositional logic and Turing's theory of computation (Russell/Norvig 2010).

[4] For an overview of selected articles see Haraway 2004.

[5] For a critique of the "Sense-Act-Think paradigm" in these more recent approaches to AI, see also Hayles 2003.

[6] Historians of science have described how the idea that 'nature should speak for itself' became dominant throughout the 19th century in modern Western societies. Whereas personal judgement was considered an important prerequisite for any scientist in the 18th century, the new notion of 'mechanical' or 'non-interventionist' objectivity (Daston/Galison 1992) disavowed the scientist as the subject of knowledge production. In contrast to the machines and technical apparatuses of observation and measurement that were proliferating at that time, the scientist was portrayed as a source of prejudice and misinterpretation and, thus, as a threat to the supposedly pure image of nature. With the replacement of the human body with technical artifacts, numerical data became increasingly important for the production and communication of scientific knowledge. Since numbers can be communicated independently (or so it seems) from the individuals, places, times, and contexts of their production, they swiftly came to be regarded as the ideal manifestation of neutral objectivity (Heintz 2010).

[7] Interestingly, there appears to be a revival of promises of objectivity and neutrality in the context of big data analyses that have long been questioned even within AI and robotics research. Confronted with this discrepancy, one of the authors (Prietl 2019a: 22) has argued that the proliferating objectivity claims can be understood as discursive strategies for claiming epistemological authority in the course

of establishing and institutionalizing big data methods, whereas the limits of big data analysis are hardly ever openly discussed, because they conflict with dominant popular ideals of 'objective' science.

[8] Bettina Heintz (2010: 172) argues that an objection to numerical results requires either the availability of alternative numbers or a fundamental critique of the numbers in question, which in turn requires knowledge about their production.

[9] For an overview, see the pioneering book Weapons of Math Destruction (2016) by mathematician Cathy O'Neil; see also Redden/Brand (2019) https://datajusticelab.org/data-harm-record/.

[10] An analysis of statements about ethical AI development issued by key government, corporate, and civil actors in this field shows that they rely heavily on deterministic ideas according to which AI is inevitably coming and that it will disrupt the established social order and people's everyday lives. As a consequence, " 'better building' is [presented as] the only ethical path forward" (for a critical discussion, see Greene/Hoffmann/Stark 2019: 2128), leaving no room to discuss alternative developments.

[11] For a thorough critique from the perspective of moral and political philosophy, see Binns 2018; from the perspective of legal anti-discrimination efforts, see Hoffmann 2019.

[12] As a consequence, current approaches to fair machine learning focus on 'pre-processing,' 'in-processing,' and 'post-processing' techniques, with the aim of eliminating biases in training data, in the data-mining or machine learning algorithm, as well as in the resulting algorithmic (decision-making) system (Binns 2018: 79; Hajian/Domingo-Ferrer 2013).

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