



The Humanities and the Rise of AI

Implications of Cultural and Societal Engineering

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How is Artificial Intelligence Changing Science? Research in the Era of Learning Algorithms.

Andreas Sudmann, Anna Echterhölter & Jens Schröter

From its earliest days, artificial intelligence (AI) has been attributed with the power to radically transform our world. For many years, this transformative capacity remained a distant prospect (evoked by concepts like the technological singularity, Kurzweil 2005; Vinge 1993) or a speculative narrative of the culture industry. However, the widespread discourse surrounding an “AI revolution” suggests that this potential is now increasingly seen as an imminent reality, fueled by the rapid pace of current technological developments.

Such inflationary rhetoric of superlatives, which not only characterizes the PR talk of Silicon Valley’s leading tech companies, but also the beliefs of many computer scientists (Lynch 2017), almost inevitably prompts criticism. Indeed, when the discourse of AI as disruptive technology has become so ubiquitous, it is very tempting to question this assumption. In the humanities and cultural studies, distrust in technological futurism is deeply entrenched, mostly for good reasons. The critical monitoring of these developments is indeed a core rationale of the humanities. At the same time, we must be weary that this skepticism does not automatically lead to a dismissive ignorance towards the transformations facilitated by AI technologies in our very own disciplines. Without buying into the rhetorics of entirely good or bad technological revolutions, we set out to investigate partial shifts and concrete transformations. The challenge and important task of our time is to navigate this landscape, to remain curious about the complex dimensions of these socio-technological transformations, and to investigate them in their concrete empirical settings and with historical depth.

A few years ago, we established the research group “How is AI Changing Science” (HiAICS) to explore the epistemic and infrastructural role of AI in the academic production of knowledge through the lens of media studies, computer science, and the history of science, with a focus on specific research fields and projects (e.g. social science, film studies and climatology).^[1] The following text, mainly written in the first half of 2019, outlines some important research problems and analytical challenges we identified at the early phase of our project.

The historically new applicability of AI across various domains, whose current upswing can essentially be attributed to the machine learning approach of artificial neural networks (ANN), continues to fuel speculations about its future socio-technical potential, dangers, and ambivalences. Despite their current prominence in a wide range of applications (machine translation, image recognition etc.), ANNs are not a recent invention, with their foundations tracing back to the 1940s and 1950s through the work of scientists like Warren McCulloch, Walter Pitts, and Frank Rosenblatt (Sudmann 2018).

Nevertheless, their applicability has been limited to comparatively simple tasks in the past. In fact, they were considered a dead end in AI research.

In retrospect, this assessment, however understandable in its historical context, has proven to be incorrect. As it turned out, this specific approach of machine learning is now demonstrably permeating all areas of culture and society, including the practices and methods of academic research. In biology, ANNs are already used for making genomic connections. In art history, deep learning algorithms, as they have been called since the early 2000s, are used to analyze damage in artworks and aid in their restoration. In criminology, machine learning based AI systems are used for the purpose of predictive policing, i.e., to learn more about when and where a crime is likely to take place (Webb 2018; Adam 2019; McDaniel and Pease 2021).

While much evidence points to ANNs as the currently dominant approach in AI, it is crucial to recognize the multifaceted nature of this technology. Also today, AI encompasses a diverse range of approaches, from symbolic AI, which focuses on logical reasoning and knowledge representation, to evolutionary computation, which draws inspiration from biological evolution, to hybrid systems that leverage the strengths of multiple AI techniques.

Acknowledging the diversity of AI approaches, including the current dominance of ANNs, it is also essential to recognize that the current perceived boom has led to a revision of epistemological questions that have been present in the AI discourse for decades: Can we and how can we (eventually) delegate research in all its possible dimensions to AI? Is AI able to automate scientific thinking and working processes? Can AI contribute to or even autonomously and/or automatically generate new scientific insights? And should this be the case, would it be reasonable and desirable?

We are convinced that these questions have gained not only a new relevance at this very moment of history, but that they require a specific and critical socio-epistemological perspective across all disciplines. It is necessary to investigate how AI technology is already changing or amplifying the methodical practices of research in practically every field of science (including the social sciences and the humanities) and to explore how research is done *with* AI rather than *on* AI. Our focus is less on the future consequences of AI, but to critically evaluate the *current* conditions of using AI as a ubiquitous tool or as an epistemic medium, which alters or at least amplifies and enhances already existing methodological elements of academic research. Such a project requires not only a solid foundation in the current applications of AI, which we observe with ethnographic methods, but also a profound historical and theoretical analysis, partly because AI research itself, since its beginnings, has always been an inter- or transdisciplinary enterprise posing fundamental methodological questions beyond singular perspectives. We therefore have to take a closer look at how AI technologies are actively shaping and influencing the work of researchers, their academic practices and particularly empirical methods, how they are integrated into various infrastructures, platforms, and labs, and how these changes are being perceived and reflected upon by academic working in very different scientific fields.

In what follows, we will discuss, in a first step, some of the urgent epistemological and methodological challenges and potential framings of ANNs as opposed to the longer

process of digitalization of research. Recognizing that different methodological traditions vary in their response to AI-based tools, we begin by examining two prominent examples: data-abundant experiments and clustering practices. To further illuminate the epistemic potential of AI for academic research, we turn to particle physics, a field that has been at the forefront of using machine learning approaches. A historical case study within this domain will provide valuable context for understanding similar challenges emerging across academia. Assuming access to a substantial dataset, a key advantage of ANNs over mere digitization lies in their capacity for clustering, enabling self-learning systems to automatically identify patterns and classify data.

Finally, we examine the potential of clustering methods to contribute to scientific knowledge production. This focus on clustering stems from its capacity to facilitate the generation of novel hypotheses, particularly through its support of abductive reasoning. Abduction, often intertwined with deductive and inductive processes, allows researchers to formulate explanatory hypotheses based on observed patterns in data, including those that may be unexpected or challenge existing theories. AI-driven clustering algorithms, with their ability to identify complex patterns and relationships, can be valuable methods in this process. Consequently, they are increasingly recognized as important approaches for knowledge discovery across diverse research domains.

1. AI in academia

At present, it is fair to claim that the current AI boom has already affected basically every academic discipline. AI is not merely a topic of discussion in every field; it is also more and more widely used as a tool for practical research across an increasing number of disciplines. For example, only within the framework of our research group, we were early able to identify over 200 projects in Europe that are currently using AI in some form, just with regard to the selected six disciplines of our research scope.^[2] While machine learning methods and in particular ANNs have been applied early on in some disciplines such as physics or geoscience^[3], other academic fields, particularly in the humanities and social sciences, only recently began to explore their epistemic and practical potential. But also with regard to research in these areas, we have to highlight some important exceptions. Philosophy, particularly the philosophy of mind, has consistently engaged with the implications of neural networks including their computational models (Sudmann 2018). Furthermore, certain disciplines, notably computational linguistics within the broader field of linguistics, were early adopters of artificial neural networks, leveraging their prior experience with machine learning methodologies to explore new research avenues (ibid.). Especially the recent technical advances of ANNs in the fields of NLP like text and speech recognition (since about 2009) and image recognition (since 2012) have provided a boost in ever so many areas of academic research, including those which already have a long tradition of expertise in machine learning.

Given that machine learning methods are highly data-driven, there has been increasing talk of a new empiricism. In fact, as far as the relationship to research data is concerned, machine learning methods potentially transform the relation to data on all lev-

els: from the exploration and collection of data to its analysis and evaluation. However, the exact epistemic-technical status of AI procedures is quite different in all of its applications.

An important and widespread observation of machine learning's impact across disciplines is its capacity to optimize existing and established processes of scholarly work, and to automate practices previously performed (only) by humans.^[4] Furthermore, AI in general and machine learning in particular are meant to fulfill tasks that were previously impossible. But can machine learning approaches also formulate interesting or surprising hypotheses, enable new scientific discoveries or perform them independently?

Many experts believe that we have already entered this stage of development. DeepMind recently published a study that, according to its self-description, is supposed to demonstrate "how artificial intelligence research can drive and accelerate new scientific discoveries", referring to their system AlphaFold, which is able to predict the 3D structure of proteins based solely on their genetic sequencing (Senior et al. 2020). However, the possibilities of AI to discover something new are viewed critically by some scholars. For example, according to media philosopher and critical AI researcher Matteo Pasquinelli ANN are operating purely inductively. Since the corresponding models are always trained with known, existing data, they are therefore unable, as Pasquinelli argues, to perform what is called abduction in the sense of Peirce, in other words, they are ultimately incapable of generating something emphatically new (Pasquinelli 2017).

This is one position. At the same time, many computer scientists are motivated by the goal and do believe in the possibility of developing an artificial general intelligence. If the development of AGI (Artificial General Intelligence) is successful, then it is also quite likely that these systems would be capable of abduction.

Of course, a potential AGI does not have to be human-like. However, the question persists: what does it signify when machines contribute to and challenge scientific knowledge, devoid of the human attributes of passion, self-doubt, and the inherent thirst for understanding? This inquiry transcends a hypothetical future of autonomous AGI, extending to the current reality where AI increasingly participates in scientific pursuits.

In fact, for decades there have been attempts to breathe into machines those very anthropological characteristics that constitute the process of science as a human practice. Someone who has been working towards this ambitious goal for many years is the well-known AI researcher Jürgen Schmidhuber. In talks and interviews, he regularly mentions his childhood dream of developing an AI that would be better than himself, and he is one of the now famous utopists in the AI community who is deeply convinced that a machine capable of surpassing humans in all conceivable areas could become a reality in the not-too-distant future. Indeed, already in his final thesis of 1987, Schmidhuber was researching meta-algorithms capable of self-optimization. A few years later, he developed a general formal theory of fun, intrinsic motivation and creativity, which is based on the concept of maximizing intrinsic rewards for the creation and discovery of something new (Metzler 2017). And yet, it is not his work in the field of self-optimizing algorithms Schmidhuber's name is typically associated with. Rather, his central merit is

to have co-developed (together with Sepp Hochreiter) the so-called LSTM technology, a specific form of a recurrent neural network.

2. How to make sense of AI's transformative potential. Four analytic perspectives

Regardless, the critique of AI and the evaluation of its critical potential should not focus solely on future scenarios of its potential applicability. Meanwhile, there are already some important theories and theses that try to grasp the fundamental techno-epistemic shift connected to current AI technology beyond the concept of a technical singularity.

1) One of these concepts is the “end of theory”, as suggested by Chris Anderson in 2008, however, not in relation to AI in the narrower sense, but more generally about the epistemological role of big data. In fact, the article does not even explicitly mention AI or machine learning but speaks rather vaguely of “statistical tools”. Anderson: “The new availability of huge amounts of data, along with the statistical tools to crunch these numbers, offers a whole new way of understanding the world. Correlation supersedes causation, and science can advance even without coherent models, unified theories, or really any mechanistic explanation at all” (Anderson 2008). This is a bold and very general claim and our preliminary case study on particle physics (discussed below) shows that such a statement is hardly tenable. It is precisely through detailed case studies like the following that one can best discuss whether the grand theses so popular in AI discourse are sound or not. Hence it is important to study the concrete reconfiguration of data, models and theory and to consider that this reconfiguration varies in different disciplines, contexts and practices.

2) Nevertheless, in the age of learning algorithms, the thesis of the end of theory is gaining new relevance. Especially in view of a second thesis that claims to describe another ending, i.e., the end of code. Indeed, approaches of machine learning like ANN can master problems and solve tasks without being explicitly programmed to do so. Hence, scientists and engineers no longer just program machines, but train them: “First we write the code, then the machine expresses it. This worldview implied plasticity, but it also suggested a kind of rules-based determinism, a sense that things are the product of their underlying instructions. Machine learning suggests the opposite, an outside-in view in which code doesn't just determine behavior, behavior also determines code. Machines are products of the world” (Tanz 2017). However, in many current scientific contexts where learning algorithms are used, the training of such systems does not necessarily signal the end of programming. In fact, the configuration and fine-tuning of learning algorithms remains a form of programming, often involving traditional coding practices. Furthermore, in many contemporary applied AI scenarios, both within and outside academia, we observe the use of hybrid systems that combine automated machine learning techniques with classical symbolic operations.

While machine learning methods aim to automate certain tasks and reduce the need for explicit programming in some areas, we do not (yet) observe that they eliminate pro-

gramming altogether. Instead, they shift the focus of programming towards higher-level tasks like model design, data preparation, and evaluation. This shift introduces new challenges and considerations for the application of AI systems in scientific research, particularly in areas where transparency, interpretability, and control are crucial.

3) Another thesis related to the transformative potential of current AI technologies is very much focusing on a particular form of AI, i.e., systems of ANN. According to this thesis, ANN as a quasi-analog information technology representing a significant break with the functional logic of digital computers based on the Von Neumann architecture, which is still dominant today (Sudmann 2017, 2018).

The inherent parallelism of artificial neural networks, where numerous computational units operate concurrently, stands in stark contrast to the sequential nature of traditional Von Neumann computer architectures. This enables ANNs to excel at computationally demanding tasks, for example in the area of natural language processing, often outperforming traditional CPUs in terms of efficiency. This shift in computational paradigm extends beyond mere quantitative differences in processing power. It also signifies a qualitative transformation, enabling new types of algorithms and applications that were previously impractical or impossible with sequential processing.

The interconnected nature of ANNs gives rise to emergent properties that are greater than the sum of their parts. The complex interactions between neurons lead to learning and adaptation capabilities that are not explicitly programmed. While the extent to which this emergence mirrors the complexity of biological systems remains a subject of ongoing research, it undeniably marks a departure from the deterministic and predictable behavior of traditional computer programs. This signals a shift towards a more organic and adaptive approach to computing, one that embraces the inherent complexity and unpredictability of the natural world.

While the analogy to biological neurons is often invoked, it's important to recognize that the 'neurons' within ANNs are fundamentally mathematical constructs, implemented in software. Moreover, the opposition between ANNs and CPUs is not absolute. ANNs, as software entities, often rely on specialized hardware like GPUs to accelerate their computations.

Nevertheless, ANNs introduce a unique form of computation. Although they operate on a digital substrate, their use of floating-point numbers to represent connection weights allows for a nuanced and continuous representation of information. This quasi-analog nature enables ANNs to model complex relationships and patterns in data that are challenging to capture with discrete binary values. This capability is particularly valuable in scientific domains like drug discovery, where understanding the intricate interactions between molecules is crucial. This blurring of the line between analog and digital computation, facilitated by the use of floating-point representations, suggests a potential move beyond the traditional binary logic that underpins Von Neumann architectures. This hints at the possibility of a new era of computing, one that transcends the limitations of purely digital systems (Sudmann 2018).

In essence, while ANNs are built on digital foundations, their architectural and representational characteristics facilitate a form of computation that transcends the limita-

tions of traditional digital processing, opening a new potential for scientific exploration and discovery.

4) A final thesis we want to highlight, in view of the epistemic-technical potential of ANNs, is that they allow to address diverse problems of vagueness (e.g., visual, textual, acoustic) and uncertainty (prediction of future states, prediction despite missing information) on a new level. This technical-epistemic capacity is, in turn, closely linked to the properties of ANNs as a quasi-analog information technology, as described above (Sudmann 2017).

It is important to emphasize that the identification of these more general theses as a top-down perspective represents a complementary approach to the one we primarily adopt to adequately pursue our research interest: to focus on scientific practices and specific methodological applications of AI, i.e., to employ a bottom-up perspective that is closely connected with the self-descriptions and experiences of human actors in their respective scientific practices.

Our preliminary assumption is that all four theoretical perspectives are relevant to various degrees not only in adequately assessing the transformations in scientific fields brought about by AI, but equally to fathom the ensuing political and social dimensions of change, which we will address towards the end of this essay. But before doing so, we want to take a closer look at the field of particle physics and at the discovery of the Higgs-boson in 2012, because it is a revealing case study to discuss the epistemic-technical status of machine learning approaches in science.

3. A case study: machine learning in particle physics

Particle physics is a paradigmatic field for a preliminary case study, when asking for the role of machine learning, because in this field it was applied quite early, simply because of the gigantic volume of data generated in particle accelerators.^[5]

The search for the Higgs boson is the main example in a paper on the role of machine learning in particle physics. We quote in length from the paper in *Nature*:

Many known particles were discovered using detectors that made subatomic particles visible to the human eye. For example, bubble chambers filled with superheated liquids that boil when charged particles pass through them transform the paths of the particles into visible tracks of bubbles, which can then be photographed and analysed. The detectors at the Large Hadron Collider (LHC) are much more complex and record data at far greater rates than is possible using bubble chambers. For example, the LHCb experiment analyses as many events every six seconds as the Big European Bubble Chamber recorded in its entire 11 years of operation (1973–1983), and the datasets collected by the ATLAS and CMS experiments at the LHC are comparable to the largest industrial data samples. It is impossible for humans to visually inspect such large amounts of data; algorithms running on large computing farms took over this task long ago. (Radovic et al. 2018)

Obviously, the information processing capacities of humans are not sufficient to cope with the gigantic amounts of data. This becomes even clearer in the following quote.

The sensor arrays of the LHC experiments produce data at a rate of about one petabyte per second. Even after drastic data reduction by the custom-built electronics used to readout the sensor arrays, which involves zero suppression of the sparse data streams and the use of various custom compression algorithms, the data rates are still too large to store the data indefinitely – as much as 50 terabytes per second, resulting in as much data every hour as Facebook collects globally in a year. (Ibid. 41)

But why do these systems have to produce so much data?

Einstein famously related mass m to energy E via $E = mc^2$, where c is the speed of light in a vacuum. A powerful particle accelerator such as the LHC, which is 27 km in circumference, is therefore required to create particles orders of magnitude more massive than the proton, such as the Higgs boson. A Higgs boson is produced only once every few billion proton-proton collisions at the LHC. Many other interesting reactions occur orders of magnitude less often. To enable such data samples to be recorded in a reasonable time frame, the LHC collides nearly one billion protons per second. (Ibid.)

It is necessary to create so much data on so many events because the processes you are looking for are so extremely rare – as the theory predicts.

As stated above, a Higgs boson is produced only once every few billion proton-proton collisions at the LHC; however, the Higgs boson usually decays in ways that mimic much more copiously produced processes. The cleanest experimental signature of the Higgs boson involves its decay into two muon-antimuon pairs, which occurs roughly once every 10 trillion proton-proton collisions. (Ibid.)

Above all, that means the machine learning methods have the purpose to filter out the events which correspond to the predictions of the theory from the immense noise. But how do the machine learning systems know this?

The need to understand what signals will look like in the detectors and what other processes can mimic the signals has led to the development of high-quality simulation tools. Furthermore, the standard model provides accurate predictions of the rates and kinematic distributions of many of the processes that can mimic interesting signatures (referred to as backgrounds) and that contribute to particle-physics data samples, providing important benchmarks for validating the simulation tools and understanding their uncertainties. Therefore, simulated data samples are often used to train the machine-learning algorithms because in such samples all information is known by construction. (Ibid. 45)

Even if this is simplified and would have to be investigated in much more detail, e.g. by our project, it becomes clear: The analysis of the large amounts of data by the ML systems succeeds by training them with simulations according to the theory of the standard model. In a way, the AI systems ‘know’ what to look for. This shows that without the performative models of simulation, as Licklider had already called them in 1967, data analysis would not work (Licklider 1967). Simulation stands between the theoretical model, let’s say the theory of the Higgs-mechanism, and the raw data. Simulations perform the theory so that template-patterns can be generated that can be used to train the machine learning systems. This is an interesting result in itself: it shows that machine learning is applied in an ‘epistemic ecology’, in which it interacts with already established technologies and practices (here: computer simulation). Although the long-term implications of machine learning for scientific methodology remain uncertain, a complete replacement of existing approaches appears improbable. Instead, machine learning is likely to contribute to an evolving methodological landscape, where diverse techniques coexist and complement each other. Further research, particularly through concrete case studies across different disciplines, is crucial to understand these dynamics.

At its core, machine learning (ML) uses algorithms to identify patterns and relationships within large datasets (‘big data’). This pattern recognition enables the identification of complex structures and trends that might not be readily apparent using traditional analytical methods.

Still, there is a continuity to past scientific practices that were also already pattern recognition in (photographic) data but with the difference that today we have a lot more data – the systems find patterns that humans can no longer recognize. The ML systems are in turn trained with data, but data that – at least in the example here – is itself generated by simulations, simulations that are in turn based on theoretical models. The latter should be emphasized if we once again consider Chris Anderson’s thesis that big data and correlations substitute theory and (causal) explanations. Again, a longer quote:

“All models are wrong, but some are useful.” So proclaimed statistician George Box 30 years ago, and he was right. But what choice did we have? Only models, from cosmological equations to theories of human behavior, seemed to be able to consistently, if imperfectly, explain the world around us. Until now. Today companies like Google, which have grown up in an era of massively abundant data, don’t have to settle for wrong models. Indeed, they don’t have to settle for models at all. [...] The big target here isn’t advertising, though. It’s science. The scientific method is built around testable hypotheses. These models, for the most part, are systems visualized in the minds of scientists. The models are then tested, and experiments confirm or falsify theoretical models of how the world works. This is the way science has worked for hundreds of years. Scientists are trained to recognize that correlation is not causation, that no conclusions should be drawn simply on the basis of correlation between X and Y (it could just be a coincidence). Instead, you must understand the underlying mechanisms that connect the two. Once you have a model, you can connect the data sets with confidence. Data without a mod-

el is just noise. But faced with massive data, this approach to science – hypothesize, model, test – is becoming obsolete [...]. (Anderson 2008)

However, at least regarding the case study discussed here, we must disagree with Anderson's thesis. As one can see exactly at the LHC, data analysis needs models: 'Data without a model is just noise'. The main task of machine learning methods there was to find the tracks predicted by the theory in the noise of the collision events – if they are found, people might win a Nobel prize (as Higgs and Englert did in 2013). If not or if completely different events are found, at least historians of science might look at the failed models. 'Hypothesize, model, test' still applies.^[6] It is interesting, however, that physicists at CERN (and other research facilities) also hope for the discovery of phenomena that are not predicted by their models – since it is not known today which theoretical approaches of physics beyond the standard model, that are necessitated by several open problems (the role of gravity; dark matter etc.), are the right ones. Perhaps none of the existing models is correct, therefore unsupervised machine learning is used to detect patterns in the data that may point to new, unanticipated effects. "In principle, machine learning makes it possible to examine data series for signatures independently of models and theories, even those that do not occur in the standard model" (Gethmann et al. 2022, 32).^[7] In this sense the data can start the process of theory formation – if an unknown signature is detected, then the theorists have to adjust their models. But this cannot easily be used as a proof for Anderson's 'end of theory', because already in experimental and empirical science before machine learning, all in while unexpected results forced the construction of new theoretical models. The difference machine learning makes is again that it can handle far larger amounts of data and therefore, possibly, detect very rare and exotic effects.

Of course, the case study analyzed here cannot be applied unconditionally to other disciplines and academic fields. Especially in the humanities, one often does not operate with hypotheses that are tested experimentally or empirically. At the same time, it might be possible that machine learning techniques in other fields of the natural sciences have changed the importance of theoretical explanations and approaches. Therefore, it is crucial to investigate the relationship between theory and empiricism in the age of learning algorithms in concrete case studies, and this is exactly what we intend to do in our research project.

4. New Scientific Practices of Clustering: Revisiting the Debates on Data Driven Science and Abduction

But is there still a relation of theory and empiricism? Voices from the data science community have been quick to diagnose the end of theory and proclaiming a new era of empiricism around 2009. Instead, a data driven science will replace theoretical and deductive methods in the immediate future, when the fourth paradigm of data usage will have taken final hold. Theory is no longer the decisive driver of intellectual innovation. Knowledge production hinges on the availability of data, required for the training of

ANNs, before they even begin to make any sense. In a well-argued article, Rob Kitchin discusses the potential of data driven science for a wider set of disciplines in the natural sciences and the humanities. As a geographer, who advocates critical GIS and radical statistics, Kitchin identifies a new wave of empiricism and he aligns the onset of these data hungry approaches with what was labeled the “fourth paradigm” of data use (Hey, Tansley, Tolle 2009; Hey, Trefethen 2020). Similar methods have been advanced by Lev Manovich’s cultural analytics (Manovich 2020). According to the fourth paradigm it is no longer the search for knowledge which drives the development of the sciences in the present, but sheer availability of data. The solar storm of information unleashed by big data and new analytical “tools”, especially machine learning, is changing sciences as well as the humanities. The paradigm was formulated by some of Silicon Valley’s most acclaimed data architects, among them Tim Hey and the late James Nicholas Gray. They spoke from the heart of the world’s largest data nodes, from the centers of Microsoft Research’s eScience community, and they figured as diplomats of the brave new world of data in Washington D.C.

Grey embeds the first three paradigms of data use in a historical medley of experimentalism and empiricism. The epochs of empirical, theoretical, and computational science differ in that the procedures performed after the data collection become increasingly complex. Not everything in the four stages is concordant with the history of science’s findings about a (pre) history of big data, but the eminent impact of data availability cannot be denied. Access to statistics was not self-evident for researchers in the Early Modern period and if data were available, they often remained a state secret until the 19th century (Aronova et al. 2017). As Kitchin stresses, the fourth paradigm of data driven science is a generally shared belief of the eScience community.

What is remarkable in this discussion, however, is the implicit admittance that the status of data as evidence shifts with each new paradigm. The first paradigm in which data began to give rise to scientific method according to Gray is data collection and more precisely experimental science, where facts about nature are captured and simply represent or ‘describe’ the world (Hey, Tansley, Tolle 2009). Since the early modern period scientists learnt how to use these data for hypothesizing and modeling, a mathematical procedure culminating in the work of Kepler, Newton and Maxwell. Gray does not point to Bacon or the colonial origin of most of the empirical facts, channeled back to Europe by reporting routines of the navy, the chartered companies and various trading networks (Siebert 2003). But the inherent relation of data collection and colonialism is made more explicit in ‘information orders.’ Simon Schaffer retraced the origin of the data points given about global tides in Newton’s *Principia mathematica*. He was thus able to show the direct link of colonialism and empirical data collection, even for the physical theory of celestial mechanics (Schaffer 2009). If data as important empirical facts describe the early modern world, it is in a highly asymmetric manner.

The second paradigm takes data processing one step further. It is a little awkwardly called ‘theoretical science’ by Gray, and describes scientific modeling and generalizations performed from the Renaissance to the computer age. The third paradigm hinges on the availability of computational power, which sets on around 1950 and facilitates more than modeling. It leads to simulations (already mentioned above in the case of particle

physics), which build complex systems and are researched “as nature”. In this perspective, simulations also signify an end of analytical capacity, since the programmes shape and frame which questions can be asked and limit actual theoretical process.

In the fourth paradigm, eventually, eScience takes over. Scientists ‘look’ directly into data bases, all work becomes informatic with necessity, data are frequently published in and by themselves, and software costs dominate experimental research budgets. Detection and collection, as well as analysis and ordering, are automated and performed before scientists even try to begin to make sense of the data. Science then becomes tantamount with data management and curation of ‘statistics’.

Compared to approaches of new empiricism, which Rob Kitchin discussed in comparison,^[8] he credits the fourth paradigm of science to be more in tune with postpositivist and situated approaches to data. A relapse into simplified notions of data neutrality, objectivity and stable reference to nature is to be feared but not necessary. For example, the 19th century probabilistic revolution in statistics, which opens up the future for calculation, but deemphasizes the singular data point in its indexicality. This shift was observed in the case study from particle physics above. The chosen examples emphasized a shift from one, indexically recorded, ‘event’ to statistical distributions of many events (Krüger et al. 1987). Kitchin emphasizes the fact that new types of measurement have had the potential to change epistemologies and a profound impact on styles of thinking.

What is more, Kitchin goes beyond the theorists of the fourth paradigm by crediting AI based methods with innovation and hence fully capable automated thinking: it “radically modifies the existing scientific method by blending aspects of abduction, induction and deduction” (Kitchin 2014, 10). As we already discussed, attributing machine learning to the capability of abduction is not without a twist or a warning since with it intellectual creativity itself seems to be on the line. Charles Sanders Peirce and others reserved this late addition to the methodological vocabularies of induction and deduction for intellectual procedures of creativity, interpretation, and ingenuity from 1866 onwards (Peirce 1931). Abduction was carved out to be a stronghold of intellectual work as artists, intellectuals, theorists might see it: As unique products of trained minds, as unexplainable origination of truly new ideas, emerging from a “je ne sais quoi” of learning, adorned with a spark of originality. Abduction was coined as a philosophical notion and defined as the very moment in which a hypothesis is selected, which one might adopt for testing and further procedural, methodological work. Yet, it is here, where science is supplied with nascent theory, ideas, even new paradigms (Wirth 1999). This is why abduction is an interesting category to scrutinize the achievements AI approaches (Kelling 2009; Miller 2010).

Kitchin builds a questionable opposition between data-driven science and knowledge-driven science, which he sees confined and trapped in deductive and sterile approaches. As a consequence, machine learning, of all things, now wins the prize: It can bring the new, since it is capable of finding new patterns. This turns around the assumption by Pasquinelli and others that machine learning will be utterly unable to produce anything new and is incapable of any discovery in the proper sense. Kitchin avoids the term “discovery”, but stresses frequently how machine learning will help to identify patterns no human could have hoped to observe (as was also argued above in relation to

particle physics, when unsupervised learning might detect patterns not predicted by established theory). There is no reason why clustering and pattern recognition should not be understood as facilitating and improving abduction, as long as the closer cooperation between artificial and scientific minds is acknowledged. Before any AI can ‘recognize’ a pattern a good deal of programming, prompting and setting of parameters is invested on the part of human researchers. But the increasingly dialogical structure of AI is geared towards the discovery of the new. The best potential for abductive effects obviously lies with long-term data series or complex systems, which require supra-human capacities for analysis (Laubichler 2019; Laubichler 2014).

But what kind of data driven discovery and exploration is technically feasible, which would replace classical domains of theorizing? What ‘kinds’ of intelligence can we expect to emerge? (Malabou 2019) As we have seen, Chris Anderson maintained that correlation would supersede causation as a main epistemological practice (Anderson 2008). Correlations could be traced everywhere and seem to hinge on the area last conquered by informatics, namely automated pattern recognition within large data sets (like language or images).^[9] The potential for new results, which Kitchin chooses to describe as the machines’ ability to abductive inference, hinges on new correlations and on clustering. Just as data journalism starts out with a numerical irregularity and fills in the story later (Broussard 2018), it is plausible for Kitchin to point to the new abilities of algorithms, or increasingly ANNs, to identify patterns and to produce new insights.^[10] Kitchin’s term for this type of machine learning apart from abduction is “statistical exploration,” (Kitchin 2014, 2017) and some of the new developments he reports are less surprising when evaluated within the history of statistics. There is a slow development towards the immense distances between a factoid or data point and its eventual analysis in data driven science, which are bridged by various forms of processing and are currently turning data almost into a polyvalent abstraction such as money. The history of statistics allows us to trace several steps towards the production of this distance between empiricism and modern data usage. AI is generally described as having a decidedly “statistical anatomy”, (Alpaydin 2016) and thus constitutes the latest configuration of statistical methods.

In these, a crucial practice is data classification. The best researched example of the present changes in classificatory regimes within the history of statistics probably emerged within the history of the life sciences (Leonelli 2012; Bowker 2001; Rheinberger 2011; Seising 2018). Clustering has a longer history itself, but it is core to the recent technological success story of ANNs. The procedure learned by machines replaces classification.

Sabina Leonelli and Marcel Boumans comparatively describe how clustering is achieved by algorithms in business cycle data in economics and in biological taxonomy. Clustering does emerge from older data practices, specific to each discipline. While in the example from the field of economics, timeframes and circles had to be defined and spotted, in the case from the field of biology, knowing types and recognizing shapes is crucial. The epistemological necessity of clustering in the respective research is described by the authors as a process of tidying and ordering, a procedure which opens the data up for the subsequent analysis but bears all the mark of a decisive step. The authors refer to Mary Douglas’ conceptual framework of cleanliness and dirt as powerful remnants of

social order (Boumans and Lenoelli 2020; Arabie et al. 1996; Brunton 1996; Brunton and Kutz 2019). Thus not only phenotyping, fieldwork, photography and timespans, but also the clusters of information identified by automated ‘thinking’. These clusters perform the same social work as categories, which have long been discussed as having a direct bearing on the biological or on the social order. The most creative part of data driven research, the abductive inference of machines, is thus identified as a social technology.

When it comes to data about the social, the orders of nation, class and race already structure available data. This could be elucidated and sustained with many findings from the history of social data, but especially from colonial statistics, which lends historical perspective to the discussion of data colonialism (Couldry and Mejias 2019; Thatcher et al. 2016; Tarnoff 2018; Kavita 2004; Tahu and Taylor 2016; Rainie 2017). All data collected in these contexts are pre-structured by social orders. Statistical classification in British India is said to have stabilized and perpetuated the caste system, and legal categories in other colonies lead to the construction of the group “indigenous” (Cohn 1987; Malègue 2018; Curtis 2001; Raj 2013). The general performative impact of statistical categories is a topic, (Hacking 1985; Bouk 2017; Serra 2018) which becomes of direct importance for citizens, since most statistical categories were employed and built by state statistics, and clustering is used in all kinds of administrative purposes and elections. Both classification and automated clustering in the social sciences do not start with neutral data, all sets are haunted by existing social structure (Myers West et al. 2019). While the statistical methods, which are enhanced by AI, are often perceived as empirical and neutral truths, the recent history of data has proven the performative effect of statistical classification and clustering on societies, colonial societies in particular.

From this perspective of new exclusions and an emerging landscape of colonialism, there are of course more complications than just deliberate or automated forms of classification. There are infrastructural problems, which concern access to calculative power and curated databases, which help to reproduce old asymmetries of global inclusion and exclusion (Dommann and Stadler 2020). Some of the training sets used in AI research on a daily basis, bear the mark of colonial extraction: Famous samples, such as the Pima dataset on diabetes, were proven to be taken involuntarily from indigenous populations, such as the database of dreams or the faulty DNA testing used in the classification of US American populations (Radin 2017; Lemov 2009; TallBear 2013). Indigenous groups frequently became the subject of high resolution studies (cf. UN Indigenous Peoples Council on Biocolonialism), which did pioneer data collection of certain interior dimensions of bodies, ranging from global blood-samples to the comprehensive test sets sampled in Micronesia, where an attempt was made to “collect traces of subjectivity itself, to make an archive of the inner contents of the mind” (Lemov 2009). Data are becoming more intimate, just as machines are (Angerer 2020; Lemov 2017).

Classification and clustering are both scientific practices, which transform due to the new AI technologies. While automated thinking has a long history of raising concerns, not all reactions were negative. Early cybernetics was fascinated by outsourced thinking, self-organizing order and decision making. Causation was ideally delegated to more flexible, dynamic and decentralized structures, eerily parallel to what Hayek described

as the market (Hayek 1945). The automatization of thinking is part and parcel of the history of computers and became an issue, for example in the 1961 conference at Karlsruhe “Denkautomaten” and other instances (Dick 2011; Galison 1997; Bullock 2008; MacKenzie 1995; Anderson 1998). These discussions of automated thinking resonate with the end of theory and the delegation of abduction to colonial machines. Recently, however, there has been criticism of the fundamental dichotomy of human versus machine thinking that come from a classical materialist tradition of thinking with tools, not from new materialism per se (Barad 2007; Barad 2010). Minds, methods and tools are imagined in close collaboration and co-dependence, not in logics of replacement and loss of intellectual sovereignty.

In this vein, David Chalmer’s thesis that GPT-3 is the first algorithm capable of passing as automated thinking is scrutinized by Dutch and British Marxist media theory, namely Olya Kadina, Bas de Boer and James Steinhoff. What is unique to their approach is an economic and materialist reading of the very process of abstraction, which is conceived of as “form-determination”. The principle of emancipating information from things is still one of the most central means of production for advanced capitalism and all the imbalances sustained by real abstraction (*Realabstraktion*) (Elkins 2020; Floridi 2020). With data, money, metric systems, ratings, which become necessary to maintain capitalism, this language of pure functionalism is described as reified theory, as one side of the coin. The authors choose another perspective, where these separations do not occur or at least do not reign supreme. The resulting perspective is reminiscent of Ludmilla Hymans intriguing study of Russian epistemology and psychology of instruments. She characterizes them as a procedural, practical and “instrumental attitude to the world”. The dichotomy of subject and tool is not maintained rigidly but is resolved in favor of a more flexible coexistence with the biosphere, and its many tools and social structures, which are always, and with necessity, rewriting the way we think. It was a brand of Marxist psychology developed by Lev Vygotsky, Alexander Luria, and Alexei Nikolaevich Wassily Leontiev in the 1930s (Hyman 2009). Regarding computers Leontiev wrote:

What functions do we relegate to the computer? All of the executive, operational part, which it does better than us anyway, because we think slowly (as in some eternal slumber). The machine also errs, but less frequently than us. It arms us, but the crucial thing is that as it arms us, it frees our thinking, and our thinking improves and thus creates new operations. And this process will continue to happen. They will only get smarter, these computers. And because they will always be progressing, we will also be getting smarter on this account. And we will creatively define new cognitive problems and find new cognitive solutions. There will be development. Do you think that this development is new? That it was discovered in the era of computers? No. It has always existed, yet before this computer technology it existed on a lower level than what we are capable of now. (Hyman 2009, 23; Leontiev 1975, 345f)

Leontiev's optimistic remarks may be easily reconciled with a progressive version of historiography. Nevertheless, the more contemporary example from the field of particle physics, as described above, also testifies to the fact that computers support and enhance "human" thinking instead of replacing it.

Conclusion: Outlines of a Research Field

A closer investigation of current AI-driven research projects shows that the alleged end of theory is only logical from a point of view, which privileges abstract categories of older philosophy of science over ethnographic or historical investigations of data practices. Since we side with contemporary scientific practices, data and theory become inseparable in any search for evidence. Thus, theoretical thinking does not end and cannot be threatened by enhanced empirical infrastructures. Theory is rather challenged by the new tools provided by AI technology. This is not to say that there is no palpable shift in many disciplines towards data-driven research, or a self-confinement to research on topics about which big data is readily available. Particularly, we have pointed at unsupervised learning as a novelty, which Rob Kitchin even credited with the creativity of abductive potential. Any delegation of exploration to machines in this sensitive field of classificatory order raises mixed feelings, since the history of classification in statistics has shown the colonial impact of categories like ethnicity, gender, heavy worker, untouchable etc. Thus, unsupervised learning and clustering dynamics merit full attention. Any investigation into the ways in which AI changes science should depart from a thorough analysis of the scientific practices of each discipline using AI-based methods, and it should include the laboratories, tools, helping hands, software, theories, and research paradigms, applied contexts a particular research project is geared towards.

In the future, research on research related to AI will perhaps increasingly involve *using machine learning to study machine learning* (or using artificial neural networks to study artificial neural networks, as our research design intends). A relevant hypothesis of such an account is that only AI-based methods might be able keep up with and criticize the kind of results other AI systems produce. And if this were true, one would have every reason to believe that at some point in the future only or essentially 'intelligent' machines can further optimize 'intelligent machines'. In the case of Alpha Go Zero, we have already been able to observe that the optimization of machine learning systems results from interaction with other machine learning systems as well as with itself. This is why it is important to shed light on how AI systems might learn from each other or how they might be capable of studying themselves in the first place. However, the use of AI for current academic research consists only to a small extent in working on problems that push AI's performance to its limits. Accordingly, it seems important to us to explore the ordinary use of ANNs and other AI approaches, following the hypothesis that many scholars first strive to deploy standard AI methods before moving on to bigger challenges.

The effects of AI, especially ANNs, on research methods are manifold and need more comparative studies across the disciplines. By all means, theory will not become obsolete,

as the case of particle physics shows: Data without concepts will remain noise. There is a rising concern that the flipside of the end of theory, the idea of data-driven science, confines research to a very narrow field, which lends itself to data processing. In addition to that data about the social, especially when researching social sciences, cannot be considered raw material in any sense. The data are structured by all pervasive notions of social order implicit in these data, one might say concepts, if not theory.

Further investigation is needed to determine the long-term impact of machine learning and other approaches of AI on scientific methodology. The use of proprietary algorithms in many AI systems raises concerns, among other things, about transparency and reproducibility in research. Additionally, the reliance on large datasets, often generated through simulations, can introduce ambiguity in the relationship between data and empirical phenomena. While AI undoubtedly enables new forms of analysis and knowledge discovery, it also necessitates careful consideration of how these technologies reshape the processes of data acquisition, interpretation, and validation. The integration of AI into scientific practice is prompting shifts at various levels, from the structure of computational architectures to the role of theory and human input in the research process. These shifts require further study to fully understand their implications for the future of scientific inquiry.

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