BJHS Themes (2023), **8**, 35–49
doi:10.1017/bjt.2023.3

RESEARCH ARTICLE

Artificial intelligence and the conjectural sciences

Luke Stark

Faculty of Information and Media Studies, Western University, London, Canada
Email: cstark23@uwo.ca

Abstract

Drawing on prior work in the history and philosophy of statistics, I argue that in many cases analyses powered by artificial-intelligence (AI) techniques such as machine learning (ML) are fundamentally 'conjectural': reliant on *ex post facto* abductive logics often misinterpreted in contemporary machine-learning systems as reliably reproducible truth. Here I relate what Carlo Ginzburg calls 'the conjectural sciences' as a historical category to their contemporary instantiation in machine learning and the practice of 'automated conjecture'. I observe how the automation of physiognomic and phrenological concepts are exemplary of the ways in which discredited conjectural pseudosciences are being revived by today's AI research. Finally, I argue that the conceptual distinction between 'conjectural' and 'empirical' science can help support contemporary efforts to regulate the design and use of AI systems by providing conceptual and historical justification for the non-development of certain classes of systems intended to automate inference.

> How often is imagination the mother of truth?[1]

Contemporary artificial-intelligence (AI) technologies are purportedly set to transform the practice of both the natural and human sciences. According to some commentators, today's machine-learning (ML) techniques have the potential to foster a 'revolution' in scientific discovery.[2] AI systems grounded in deep learning, such as generative adversarial networks (GANs), offer the prospect of extrapolating results from scientific data without underlying models or a set of explicit theoretical assumptions guiding their analysis.[3] Even if these technologies do not represent a sea change in the epistemological foundations of Western scientific inquiry, deep-learning models are still potentially useful instruments for practitioners, differing in degree but not in kind from the usual scientific practice of extrapolating hypotheses from repeated cycles of empirical observations and testing.

1 Arthur Conan Doyle, *The Valley of Fear*, Project Gutenberg (eBook #3289) (1 June 2002), at www.gutenberg.org/cache/epub/3289/pg3289-images.html (accessed 9 June 2023).

2 Jessica Montgomery, *The AI Revolution in Scientific Research*, London: The Royal Society/Alan Turing Institute, 2019.

3 Dan Falk, 'How artificial intelligence is changing science', *Quanta Magazine*, 11 March 2019, at www.quantamagazine.org/how-artificial-intelligence-is-changing-science-20190311/# (accessed 21 May 2021). GANS produce synthetic data with the same characteristics as a training set, 'pitting the computer against itself' in working towards greater predictive accuracy.

The enthusiasm for ML-supported pattern detection in large scientific data sets has extended from astrophysics and biochemistry to applied psychology, clinical medicine and computational social science: all fields which today 'aspire to understand the workings of nature, people, and society' using ML techniques.[4] Yet the current enthusiasm for such analyses across science and industry has inadvertently demonstrated an uncomfortable fact. In the rush to apply ML to the broadest range of problems possible, its developers have inadvertently shone a spotlight on an epistemological fissure whose history long pre-dates the development of these technologies, but which is fundamental to their application: the distinction between what the Italian historian Carlo Ginzburg terms 'empirical' and 'conjectural' science.[5]

Drawing on scholarship in the history and philosophy of science and in science and technology studies (STS) on the history of statistics and probability, I argue that in many cases today's ML-driven analyses are fundamentally 'conjectural' ones. As defined by Ginzburg, 'conjectural science' draws conclusions reliant on *ex post facto* interpretation: abductive insights, often misinterpreted in contemporary work around AI as reliably reproducible truths.[6] Such automated conjecture has become rife. All scientific practice entails some amount of conjecture, but the application of such techniques to social and behavioral analysis has highlighted, not created, a long-standing problem.[7] Individual human actions cannot be reliably aggregated into general and repeatable empirical rules. Conjectural science cannot support certain classes of claims regarding the regularity of past human action, nor the predictability of future human activity – yet ML's proponents continue to make such claims regardless.

Here I relate the conjectural sciences as a historical category to their contemporary instantiation in machine-learning research and practice. First, I summarize the definition of 'conjectural science' itself, typified by a particular way of constructing knowledge about human beings through an 'interpretative method based on taking marginal and irrelevant details as revealing clues'.[8] Drawing on historical examples, I map Ginzburg's categorization of this conjectural paradigm onto the design and deployment of contemporary AI systems, and the development of what I term 'automated conjecture'. Finally, I document how conjectural AI is rampant in both commercial and institutional applications today, and the dangers of its unconsidered deployment.

Alongside this descriptive analysis, I also make a normative claim: that scholarship from the history of probability and statistics can support contemporary efforts to regulate the design and use of AI systems, particularly those applications through which automated conjecture perpetuates and extends societal injustices. Restricting the use of automated conjecture across AI's areas of application would significantly decrease the societal harms caused by these technologies. If the inferences being automated and scaled in AI systems are faulty, then no amount of technical or regulatory buttressing can ever set them aright.

'Conjectural' science: tracks in the snow

A conjecture is a conclusion made based on incomplete information, a form of abductive reasoning. Abduction is generally understood as an appeal to explanation based on non-

4 Montgomery, op. cit. (2), p. 1.

5 Carlo Ginzburg, 'Morelli, Freud and Sherlock Holmes: clues and scientific method', *History Workshop Journal* (1980) 1, pp. 5–36.

6 Ginzburg, op. cit. (5).

7 Igor Douven, 'Abduction', in E.N. Zalta (ed.) *The Stanford Encyclopedia of Philosophy* (2021), at https://plato.stanford.edu/archives/sum2021/entries/abduction (accessed 4 June 2022).

8 Ginzburg, op. cit. (5), p. 11.

necessary inferences, those 'beginning with data or, more specifically, with surprising or anomalous phenomena'.[9] Abduction, in other words, helps us tell stories about the world.[10] Abductive reasoning permits 'the leap from apparently insignificant facts, which could be observed, to a complex reality which directly at least could not'.[11] Our interpretation of clues about the past enables not just retrospective diagnosis, but also the construction of coherent narratives about the present and future in our daily lives.

Conjecture plays a role in supporting the other major categories of inference: inductive and deductive. Inductive inferences are generally understood as descriptive appeals to statistical frequency while deductive inferences entail some necessary effects from a particular cause. Abduction is central to the generation of inductive and deductive hypotheses: the philosopher Charles Sanders Peirce defined abduction as inference 'which depends on our hope, sooner or later, to guess at the conditions under which a given kind of phenomenon will present itself'.[12] This hope of guessing is central to abduction's other definition, that of 'inference to the best explanation': in its most common usage, abductive inference serves to justify the how and why of events through the most plausible possible narrative.[13] Such conclusions based on incomplete information are the definition of conjecture.

The Italian historian Carlo Ginzburg takes the ubiquity of conjecture in human life as the starting point for an analysis published in Italian in 1979, which appeared in English translation in 1980 as 'Morelli, Freud and Sherlock Holmes: clues and scientific method'.[14] Ginzburg's work characteristically concerns particular micro-historical case studies, and the essay synthesized a number of such cases to develop a broader theory about the origins and trajectories of two distinct epistemological models, and by extension two kinds of 'science': what Ginzburg terms 'conjectural' science and 'empirical' science. For Ginzburg conjectural science is typified by a particular abductive way of constructing knowledge about human beings through 'symptomatology' or 'the discipline which permits diagnosis … on the basis of superficial symptoms or signs, often irrelevant to the eye of the layman'.[15] Such symptoms are understood by the conjectural scientist as being outside conscious human control, in the realm of habit. They purportedly betray the truth about an individual even if and as she seeks to conceal it.[16] In the history of disciplines ranging from art history to archaeology, and from medicine to astronomy (at least in its early form), 'tiny details provide[d] the key to a deeper reality, inaccessible by other methods'.[17] Much as in historical scholarship, which Ginzburg also identifies as a conjectural science, these details, though potentially telling, are contingent – they fail to repeat reliably or with regularity, requiring *phronesis*, or practical applied judgement on the part of the conjectural scientist to assess the parameters of any given individual case.[18]

9 Jutta Schickore, 'Scientific discovery', in Zalta, op. cit. (7), at https://plato.stanford.edu/archives/sum2019/entries/scientific-discovery (accessed 23 July 2022).

10 Douven, op. cit. (7).

11 Ginzburg, op. cit. (5), p. 13.

12 Charles Sanders Peirce, *The Collected Papers of Charles Sanders Peirce*, vol. 7: *Science and Philosophy* (ed. A.W. Burks), Cambridge, MA: Harvard University Press, 1958, p. 248.

13 Douven, op. cit. (7).

14 Ginzburg, op. cit. (5). As observed in the introduction (p. 1) to the piece by its translator, British historian and activist Anna Davin, Ginzburg's article 'ranges across societies and periods in a way which is extraordinary – even shocking – to the English reader' of historical scholarship.

15 Ginzburg, op. cit. (5), p. 12.

16 Clemens Apprich, Wendy Hui Kyong Chun, Florian Cramer and Hito Steyerl, *Pattern Discrimination*, Minneapolis: University of Minnesota Press/Meson Press, 2018.

17 Ginzburg, op. cit. (5), p. 11.

18 Bent Flyvbjerg, Todd Landman and Sanford Schram, 'Important next steps in phronetic social science', in B. Flyvbjerg, Todd Landman and Sanford Schram (eds.), *Real Social Science: Applied Phronesis*, Cambridge: Cambridge University Press, 2012, pp. 285–97.

Exemplars of conjectural 'scientists' are figures like the nineteenth-century art historian Giovanni Morelli. Morelli's method determined the provenance of paintings by identifying distinctive aspects of the painted figure – 'earlobes, fingernails, shapes of fingers and toes' – using those details to conjecture the name of the master who had created it.[19] Sigmund Freud, too, can be understood as a conjectural scientist. Psychoanalysis, he wrote, aimed to 'divine secret and concealed things from despised or unnoticed features, from the rubbish-heap, as it were, of our observations'.[20] The inadvertent slips and morbid symptoms of the psychoanalyst's patients allowed the conjecture of a broader narrative about the analytic subject's psychic condition. In these cases, what constituted the 'best' explanation involves the application of phronetic judgement to particular cases in order to map out how each case differs from or aligns with past evidence and general categorial knowledge.

'Empirical' science: falling repeatedly from a great height

Ginzburg contrasts the conjectural paradigm with what he terms 'empirical' scientific inference. For him, 'empirical' science is exemplified by a figure like Galileo Galilei, whose physical experiments (such as dropping weights from tall buildings in his native Pisa) were conducted solely with reference to 'figures, numbers, and movements'.[21] Regularity and repeatability are the hallmarks of such 'empirical science'. Conjectural inference allows only partial or proxy measurements and makes deductive hypotheses impossible, while the formulation of deductive hypotheses entails sacrificing 'understanding of the individual element to achieve a more or less rigorous and more or less mathematical standard of generalisation'.[22] Yet 'empirical' is a misleading label, to the extent that abductive conjecture also grounds narrative in observable phenomena. What Ginzburg terms 'empirical' science is more precisely characterized by a movement from inductive or statistical to deductive inference: through repeated measurements of the properties of physical objects, Galileo could formulate deductive hypotheses which he could then test and confirm.

The practice of science is, of course, vastly richer and much less schematic than Ginzburg's distinction between the conjectural and the empirical suggests. While the Galilean scientist was in theory 'professionally deaf to sounds and forbidden to taste or smell', in practice material and social contingency is intrinsic to the scientific method. Scientists cannot operate without making abductive conjectures.[23] Yet as Henry M. Cowles observes, 'The scientific method does not exist. But the "scientific method" does'. As an ideal, 'empirical' science represented a desirable regularity both of process and of results, an instrumental series of mental steps leading to useful and reproducible knowledge.[24] The commonality of this idealization for scientific practice can, of course, not be understated. Scientists sought to apply the 'extrasensory eye of mathematics' to the study of human phenomena from as early as the late seventeenth century, and it is well known that, by the nineteenth century, statistical methods, particularly the language and outputs of probability theory, offered a way to treat inductive inference as regular and repeatable in practice.[25] Yet the literature noting how difficult it is to truly 'tame'

19 Ginzburg, op. cit. (5), p. 7.

20 Ginzburg, op. cit. (5), p. 10.

21 Ginzburg, op. cit. (5), p. 16.

22 Ginzburg, op. cit. (5), p. 19.

23 Ginzburg, op. cit. (5), p. 16.

24 Henry M. Cowles, *The Scientific Method: An Evolution of Thinking from Darwin to Dewey*, Cambridge, MA: Harvard University Press, 2020, pp. 1, 8.

25 On mathematics see Ginzburg, op. cit. (5), p. 20. Ian Hacking observes that, by the nineteenth century, 'it became possible to see that the world might be regular and yet not subject to universal laws of nature'. See Ian

chance is capacious. As Theodora Dryer observes, probabilities cannot be constructed in a vacuum. Instead, 'elaborate mathematical and social infrastructures are needed to sustain the probabilistic worldview' to 'express limited information in terms of likelihoods'.[26]

Philosophers of science such as Karl Popper have described the inevitable 'theory-ladenness of observation', and critical approaches to the history and philosophy of scientific disciplines, including artificial intelligence, have consistently argued that all scientific knowledge is contingent and situated.[27] Nonetheless, scientists' deliberate bracketing of subjective experience and the embrace of 'mechanical objectivity' as a component of an idealized 'scientific method' have supported and extended 'empirical' science's claims as a source of neutral, fact-based claims about the world.[28] Conjectural analysis could be characterized either by the move from inductive to abductive inference, or by abductive inference alone.[29] In such cases, any 'inference to the best explanation' is highly contingent on an inherently unstable definition of the word 'best'. Statistical probabilities will not be sufficiently explanatory in every case and will often fail to capture what is interesting or relevant. Scholars in conjectural disciplines have therefore faced, as Ginzburg puts it, an 'awkward dilemma': should they attempt to 'achieve significant results from a scientifically weak position, or should they put themselves in a strong scientific position but get meager results?'[30]

When 'Morelli, Freud and Sherlock Holmes: clues and scientific method' was published in the late 1970s, the status of quantitative method in the study of the social world and debate regarding the extent to which social phenomena followed empirically regular patterns were already so venerable as to be almost cliché.[31] Ginzburg's idealizations thus served a purpose. Though admittedly oversimplified, the shorthand distinction between the 'conjectural' and 'empirical' sciences was intended to clarify how and when each of these frameworks failed epistemologically, and to draw attention to conjectural method as an inescapable reality in both the history of science and certain realms of contemporary practice.[32] Each epistemological regime possessed what the other lacked, and neither could be done without.[33]

M. Hacking, *The Taming of Chance*, Cambridge: Cambridge University Press, 1990; and Hacking, *The Emergence of Probability*, 2nd edn, Cambridge: Cambridge University Press, 2006. On statistics see Theodore M. Porter, *Trust in Numbers: The Pursuit of Objectivity in Science and Public Life*, Princeton, NJ: Princeton University Press, 1996; Theodora J. Dryer, 'Algorithms under the reign of probability', *IEEE Annals of the History of Computing*, 2018, pp. 93–6; Sarah Igo, *The Averaged American: Surveys, Citizens, and the Making of a Mass Public*, Cambridge, MA: Harvard University Press, 2007.

26 Dryer, op. cit. (25), p. 93.

27 For critical approaches see, for instance, Karen Barad, 'TransMaterialities: trans*/matter/realities and queer political imaginings', *GLQ: A Journal of Lesbian and Gay Studies* (2015) 2–3, pp. 387–422; Lily Hu, 'Race, policing, and the limits of social science', *Boston Review*, 6 May 2021, at https://bostonreview.net/articles/race-policing-and-the-limits-of-social-science (accessed 10 May 2021). On AI see, for instance, Lucy Suchman, *Human–Machine Reconfigurations: Plans and Situated Actions*, Cambridge, Cambridge University Press, 2006; Anna Lauren Hoffmann, 'When fairness fails: data, algorithms, and the limits of antidiscrimination discourse', *Information, Communication, and Society* (2019) 7, pp. 900–15.

28 On theory-ladenness see Benjamin Chin-Yee and Ross Upshur, 'Three problems with big data and artificial intelligence in medicine', *Perspectives in Biology and Medicine* (2019) 2, pp. 237–56, 240. On objectivity see Porter, op. cit. (25); Lorraine Daston and Peter Galison, 'The image of objectivity', *Representations* (1992) 40, pp. 81–128; Steven Shapin, 'The sciences of subjectivity', *Social Studies of Science* (2012) 2, pp. 170–84.

29 Ginzburg, op. cit. (5), p. 15.

30 Ginzburg, op. cit. (5), p. 28.

31 Thomas P. Wilson, 'Qualitative "versus" quantitative methods in social research', *Bulletin of Sociological Methodology* (1986) 10(1), pp. 25–51; Donald T. Campbell, 'Methods for the experimenting society', *Evaluation Practice* (1991) 3, pp. 223–60.

32 Hacking, *The Emergence of Probability*, op. cit. (25).

33 A full account of the debates regarding using qualitative and quantitative methods in tandem in the human social sciences is well beyond the scope of this paper. See Lee Sechrest and Souraya Sidani, 'Quantitative and

https://doi.org/10.1017/bjt.2023.3 Published online by Cambridge University Press

Conjectural science and artificial intelligence

Why elevate the simplifying distinction between conjectural and empirical knowledge? Consider the recent proliferation of 'artificial-intelligence' technologies, which rely on large quantities of data about human activities to make predictions about past results and future outcomes. In the last decade, computing power and the amounts of digital data about various aspects of the social world available to researchers in industry and academia have greatly increased. This quantitative change has led some computer scientists to claim that the distinctions between inductive correlation and deductive causation have disappeared entirely. The hopes expressed in a 2009 commentary by several prominent computer scientists and psychologists are representative of this view.[34] The appeal of AI-driven statistical analyses, paired with very large data sets to be analysed, is purportedly that the inferences drawn about data about individuals can be understood as reliable and repeatable through sheer quantity alone.

While it may seem paradoxical to claim that contemporary ML methods are fundamentally abductive, historians have shown that making inferences towards the 'best' and most useful explanation was central to the development of machine learning as a field over several decades. The question of how humans produce 'situated knowledge' irreducible to a set of regular or repeatable variables was a perennial problem for statisticians. In the 1950s, John W. Tukey cautioned against overreliance on inductive inference divorced from the material realities of the phenomena being studied.[35] And in his well-known 2001 article 'Statistical modelling: the two cultures', the statistician Leo Breiman advocated for a new focus on what he termed 'algorithmic modeling', or finding functions predictive of natural processes.[36] By definition, such natural processes were black-boxed, their workings not only unknown but not required to be known by the statistician. If the predictive model roughly matched observed results, then such abductive inference was good enough.[37] Jones traces the recent history of this instrumentalist turn in statistics to advances in computer-based pattern recognition made in commercial and military laboratories in the 1960s.[38] Mendon-Plasek likewise points to tightly related developments in the nascent field of machine learning in the 1950s, including an emphasis on determining contextual significance as a fundamental element of pattern recognition. 'Researchers seeking to make pattern recognition into a reputable field of inquiry', Mendon-Plasek writes, 'saw their object of study as the mechanical identification of significance and the reproduction of human judgment'.[39] This process of developing mechanisms for automated conjecture underpins the contemporary development of machine learning.

---

qualitative methods: is there an alternative?', *Evaluation and Program Planning* (1995) 1, pp. 77–87; Derek Beach, 'Multi-method research in the social sciences: a review of recent frameworks and a way forward', *Government and Opposition* (2020) 55(1), pp. 163–82.

34 David Lazer *et al*., 'Computational social science', *Science* (2009) 5915, pp. 721–3. For a more recent restatement of this ambition, see Iyad Rahwan *et al*., 'Machine behaviour', *Nature* (2019) 568, pp. 477–86.

35 Alexander A. Campolo, '"Thinking, judging, noticing, feeling": John W. Tukey against the mechanization of inferential knowledge', *Know: A Journal on the Formation of Knowledge* (2022) 5, pp. 83–111.

36 Leo Breiman, 'Statistical modeling: the two cultures (with comments and a rejoinder by the author)', *Statistical Science* (2001) 3, pp. 199–231.

37 Matthew L. Jones, 'How we became instrumentalists (again)', *Historical Studies in the Natural Sciences* (2018) 5, pp. 673–84, 683.

38 Jones, op. cit. (37), p. 677.

39 Aaron Mendon-Plasek, 'Mechanized significance and machine learning: why it became thinkable and preferable to teach machines to judge the world', in M. Castelle and J. Roberge (eds.), *The Cultural Life of Machine Learning: An Incursion into Critical AI Studies*, Cham: Springer International Publishing, 2020, pp. 1–48, pp. 32–3.

The abductive quality of AI inference stems from the various contingencies of these systems' models, ground-truth data, use cases and applications.[40] In fact, recent scholarship argues implicitly that ML systems cannot be anything other than abductive: the contingent biases of a given data set invariably provide the grist for any algorithmic model trained on that data, and any subsequent ML-driven prediction on other data 'in the wild'.[41] Louise Amoore observes that such logic entails 'the process of modelling a society becoming a political end in itself'.[42] The shibboleth that data alone can both substitute for and supplant theoretical models typifies the field. Technology journalist and *Wired* magazine editor-in-chief Chris Anderson declared in a 2008 issue that the analysis of large data sets with AI-driven inference would mean 'a world in which massive amounts of data and applied mathematics replace every other tool that might be brought to bear', making the scientific method 'obsolete'.[43] Increased computing power and large volumes of data about human activities have made such analyses both practical and attractive. In theory, the more data you provide to an ML model, the more it will settle on the 'best' outcome by finding the 'true' story being told in the data itself.

Here is where Ginzburg's cautions regarding the appropriate uses of conjectural science become newly relevant. Passing off conjectural science as 'empirical' has a particular epistemological valence: it reifies and naturalizes the flattening of human experience into discrete, instrumental and manipulable variables.[44] Behavioral and social sciences grounded in inductive analysis are particularly susceptible to exhibiting these weaknesses. To the extent that fields concerned primarily with individual differences, especially human differences, have tried to ground themselves in rules and laws, 'the more impossible it became to construct a body of rigorously scientific knowledge'.[45] Aggregated statistical probability does not guarantee that observations true for most cases will apply with certainty to any particular individual.[46] This error, known as the ecological fallacy, is a case of moving implicitly from induction to abduction: an assumption that what is probabilistically likely in a range of cases will occur in any one case.

Of faces and horse teeth

Public and scholarly scepticism of 'the end of theory' has advanced considerably since Anderson's triumphant 2008 declaration of 'the end of theory'. Much of this criticism has tracked to the longer debates around the utility and appropriateness of quantitative versus qualitative methods noted above.[47] Here, I advance a different critique: that by their own admission, ML-based predictive systems, particularly when applied to data about humans and the social world, are conjectural science raised to its most acute form. Far from being a triumph of 'deductive' science over individualizing

40 Anja Bechmannh and Geoffrey C. Bowker, 'Unsupervised by any other name: hidden layers of knowledge production in artificial intelligence on social media', *Big Data + Society* (2019) 1, pp. 1–11.

41 Florian Jaton, 'We get the algorithms of our ground truths: designing referential databases in digital image processing', *Social Studies of Science* (2017) 6, pp. 811–40; Jaton, 'Assessing biases, relaxing moralism: on ground-truthing practices in machine learning design and application', *Big Data + Society* (2021) 1, pp. 1–15.

42 Louise Amoore, 'Machine learning political orders', *Review of International Studies* (2022) 49(1), p. 9.

43 Chris Anderson, 'The end of theory: the data deluge makes the scientific method obsolete', *Wired*, 23 June 2008, at www.wired.com/science/discoveries/magazine/16-07/pb_theory (accessed 2 May 2021).

44 Michel Foucault, *Lectures on the Will to Know*, 1st Picador pbk edn (ed. D. Defert, François Ewald, Alessandro Fontana and Arnold I. Davidson), New York: Picador, 2014; Cowles, op. cit. (24), p. 18.

45 Ginzburg, op. cit. (5), p. 19.

46 Steven Piantadosi, David P. Byar and Sylvan B. Green, 'The ecological fallacy', *American Journal of Epidemiology* (1988) 5, pp. 893–904.

47 Bernhard Rieder, 'Scrutinizing an algorithmic technique: the Bayes classifier as interested reading of reality', *Information, Communication & Society* (2017) 1, pp. 100–17.

https://doi.org/10.1017/bjt.2023.3 Published online by Cambridge University Press

conjecture, ML systems are conjectural science automated on an enormous scale. As Jones observes, 'the promise of the data sciences … ostensibly comes from overcoming older theory-laden categorizations to characterize individuals in their specificity, all in order to predict their behavior'.[48] The dream of AI-driven analysis of human social activity and behaviour is to make what have always been, at bottom, a set of contingent, past-focused activities into domains wherein observations are regular, testable and, perhaps most radically, repeatable – 'sciences of the particular', or at least ones presentable as such to funders and the public at large.

In explicating how conjectural epistemology has been automated by ML technologies, I emphasize the fundamental error of deploying such conjectural automated decision-making systems in practice. The so-called 'gayface' study, held up since its publication by critics as a prime example of an AI-driven analysis both inaccurate and unethical, is an indexical case study of contemporary AI as conjectural science that illustrates the stakes of such error.[49] Indeed, the title of Blaise Agüera y Arcas, Margaret Mitchell and Alexander Todorov's thorough critique of the 'gayface' piece and other similar analyses – 'Physiognomy's new clothes' – makes the connection to conjectural science explicit.[50] As Ginzburg observes, pseudosciences like phrenology and physiognomy are quintessentially conjectural: practices of extrapolating about human character 'involving analysis of particular cases, constructed only through traces, symptoms, [and] hints' visible on the exterior of the body.[51]

The authors of the 'gayface' study, Yilun Wang and Michael Kosinski, admit at the outset of their paper that physiognomic conjectures are precisely what they wish to automate. Wang and Kosinksi begin by averring that physiognomy is 'a mix of superstition and racism disguised as science', and that because of its inextricable imbrication with 'scientific' racism, 'studying or even discussing the links between facial features and character became taboo, leading to a widespread presumption that no such links exist'. Yet in the following sentences, the authors let conjecture (alongside bigotry) in through the back door: 'there are many demonstrated mechanisms', they write, 'that imply the opposite'.[52] Citing a variety of past work in social psychology (some of which is only tangentially related to their argument), the authors ground their analysis in the claim that the 'existence of such links between facial appearance and character is supported by the fact that people can accurately judge others' character, psychological states, and demographic traits from their faces'. This claim is itself abductive: further, it comes with a critical caveat: 'Such judgments are not very accurate but are common and spontaneous'.[53] The authors go on to suggest that if individuals can make such determinations accurately on occasion, an automated model with access to large amounts of data will be able to make accurate inferences even more frequently.

The distinction between 'common and spontaneous' judgement and large-scale causal analysis is one Ginzburg observes in the history of conjectural disciplines, in a passage worth citing at length:

48 Jones, op. cit. (37), p. 684.

49 Yilun Wang and Michal Kosinski, 'Deep neural networks are more accurate than humans at detecting sexual orientation from facial images', *Journal of Personality and Social Psychology* (2018) 2, pp. 246–57.

50 Blaise Agüera y Arcas, Margaret Mitchell and Alexander Todorov, 'Physiognomy's new clothes', *Medium*, 7 May 2017, at https://medium.com/@blaisea/physiognomys-new-clothes-f2d4b59fdd6a; Blaise Agüera y Arcas, Alexander Todorov and Margaret Mitchell, 'Do algorithms reveal sexual orientation or just expose our stereotypes?' *Medium*, 11 January 2018, at https://medium.com/@blaisea/do-algorithms-reveal-sexual-orientation-or-just-expose-our-stereotypes-d998fafdf477.

51 Ginzburg, op. cit. (5), p. 14.

52 Wang and Kosinski, op. cit. (49), p. 246.

53 Wang and Kosinski, op. cit. (49), p. 247.

> The ability to tell an unhealthy horse from the state of its hooves, a storm coming up from a shift in the wind, or unfriendly intentions from the shadow in someone's expression, would certainly not be learnt from treatises on the care of horses, or on weather, or on psychology … A fine common thread connected them: they were all born of experience, of the concrete and individual. That concrete quality was both the strength of this kind of knowledge, and its limit – it could not make use of the powerful and terrible tool of abstraction.[54]

By abstraction, here Ginzburg means the process of using inductive evidence to abductively claim necessary causal certainty. The effects of abstraction when applied to such data are 'rigid' and 'schematic': as Ginzburg observes, 'One need only think of the gulf separating … treatises of physiognomy (judging character or mood from the appearance) from its perceptive and flexible practice by a lover or a horse-dealer or a card-player'.[55] The point is that the 'common and spontaneous' – and often inaccurate – judgements made by individuals cannot be aggregated into general and repeatable empirical rules without losing any analytic utility they might have held.

And yet such an aggregation is precisely what Wang and Kosinski claim AI systems can accomplish successfully. Those authors suggest that ML systems, in this case deep neural networks, offer 'an opportunity to identify links between characteristics and facial features that might be missed or misinterpreted by the human brain'.[56] Bracketing its other flaws, the study presents its analysis as overcoming the epistemological gap between conjectural and empirical modes of reasoning, even if the authors do not fully recognize that such a gap exists. Yet bridging this gap is conceptually impossible – a failure evident to contemporary critics of nineteenth-century physiognomy and phrenology, if not to some of today's AI practitioners.

Divination and apophenic conjecture

Conjecture as a form of abductive reasoning also explains machine learning's emphasis on the language of prediction.[57] Machine-learning methods leverage induction to present abduction as deduction.[58] These technologies produce a sense of certainty by appealing simultaneously both to inductive probabilities and to a user's subjective perception of likelihood. Such conjectures can then be applied to the future. Indeed, the practice of divination itself is grounded in a conjectural logic. The relationship in divination between clues and narrative is the reverse of that in a conjectural field such as history: instead of developing the best possible explanation out of incomplete material from the past, the soothsayer or sage draws on both signs and present conventions to extrapolate a narrative about what is to come. Yet both conjecture and divination 'require minute examination of the real, however trivial, to uncover the traces of events which the observer cannot directly experience'.[59] And recent philosophical work on human prospection, or mental representation of possible futures as a component of human psychological

54 Ginzburg, op. cit. (5), p. 21.

55 Ginzburg, op. cit. (5), p. 22.

56 Wang and Kosinski, op. cit. (49), p. 247.

57 Juan C. Perdomo, Tijana Zrnic, Celestine Mendler-Dünner and Moritz Hardt, 'Performative prediction', *ArXiv* (2020) abs/2002.06673, n.p.

58 Other recent work noting the centrality of abductive logic in AI systems includes Luciana Parisi, *Contagious Architecture: Computation, Aesthetics, and Space*, Cambridge, MA: MIT Press, 2013; Louise Amoore and Rita Raley, 'Securing with algorithms: knowledge, decision, sovereignty', *Security Dialogue* (2017) 1, pp. 3–10; Amoore, op. cit. (42).

59 Ginzburg, op. cit. (5), p. 13.

https://doi.org/10.1017/bjt.2023.3 Published online by Cambridge University Press

activity, points to the centrality of conjectural narrativization in the subjective navigation of the world in time.[60] Conjecture is reliant on narrative, and inverse prediction problems often require narration. As Katz observes, 'figures produced by masters of scientific storytelling are so tightly controlled to match the narrative that the reader is left with little to ponder or interpret'.[61] Contemporary automated conjecture thus performs a double dance: abductive claims become deductive ones, and a contingent narrative about the past becomes a necessary one about the future.

At the conclusion of 'Morelli, Freud and Sherlock Holmes', Ginzburg suggests that conjecture can be a useful tool for penetrating the complexity of contemporary life. 'The existence of a deep connection which explains superficial phenomena can be confirmed' he suggests, 'when it is acknowledged that direct knowledge of such a connection is impossible'. Reality is opaque, but the 'elastic rigour' of conjecture can lead the judicious analyst to identifying 'certain points – clues, signs – which allow us to decipher it'.[62] In this context, Ginzburg is again perhaps thinking of the craft of the historian and those of other disciplines in the humanities and qualitative social sciences.

Yet the perverse genius of much recent work using ML to analyse human beings and their social worlds (including the Wang and Kosinski paper) has been to recast conjecture, or the drawing of abductive conclusions with incomplete information, into inductive predictions with such a high probability that they should be understood practically as reliable causal inference.[63] It is worth noting the specific motivation Wang and Kosinski provide for their work in the 'gayface' study. The authors claim that 'the low accuracy of humans when judging character from others' faces does not necessarily mean that relevant cues are not prominently displayed', but that 'people may lack the ability to detect or interpret them'.[64] Their solution is the de facto automation of conjecture. In Wang and Kosinski's vision, *ex post facto* observations of contingent behavior imperceptible to humans can be aggregated into regular and repeatable natural laws; incomplete information on the part of the human gives license for machines to understand partial conjectures as whole facts about both the past and the future.

The epistemological similarities between the ideal cases of conjecture and divination, prediction and extrapolation, make such elisions unsurprising. Narayanan and Salganik observe that the term 'prediction' is often applied to machine-driven conjecture about both the past and the future: limits to ML prediction of future events are often around 'measuring input/output states accurately and collecting sufficiently many training examples [both of which] are highly dependent on the nature of the system'.[65] These authors list several other potential limits to the 'predictive' power of automated analyses, both prospective and retrospective. One such limit, these authors suggest, stems from their claim that 'since [statistical] noise tends to accumulate in the forward direction, inverse prediction problems tend to be easier than forward problems'.[66] The authors define such 'inverse prediction' problems as ones in which, 'Given the output of the data-generating process, the task is to predict the input' – in other words, conjectures as Ginzburg defines them: 'When causes cannot be repeated, there is no alternative but to infer them from

60 Martin E.P. Seligman, Peter Railton, Roy F. Baumeister and Chandra Sripada, 'Navigating into the future or driven by the past', *Perspectives on Psychological Science* (2013) 2, pp. 119–41.

61 Yarden Katz, 'Against storytelling of scientific results', *Nature Methods* (2013) 11, p. 1045.

62 Ginzburg, op. cit. (5), p. 27.

63 Jones, op. cit. (37).

64 Wang and Kosinski, op. cit. (49), p. 247.

65 Arvind Narayanan and Matt Salganik, 'Limits to prediction: pre-read' (2020), at www.cs.princeton.edu/~arvindn/teaching/limits-to-prediction-pre-read.pdf, p. 2

66 Narayanan and Salganik, op. cit. (65), p. 4.

their effects'.[67] This is the Holmesian trick of sketching the biography and situation of a woman from the ink stains on her fingers and the dust on her skirts.

Ginzburg points to conjecture as 'a basic model for explanation or divination which could be oriented towards past or present or future, depending on the form of knowledge called upon'.[68] Recall, though, the rigidity and schematizing quality of the effects of abstraction when applied to human data. Even highly bounded inverse prediction problems such as object recognition – of abnormalities in medical images, for instance – struggle at scale. Artificial-intelligence techniques are lauded as proving the irrelevance of the purportedly humanistic focus on individualities, contingencies and contexts, when in fact they are entirely and often unreflexively dedicated to extrapolating from just these contingencies. Though such analysis aspires to the epistemological norms of 'empirical' science, machine learning does not support reproducible science as commonly understood in these cases. Such conjectures produce abductive insights misinterpreted as widely applicable objective truths.[69]

Automated conjecture is arguably underpinned by the affordances of the digital network itself. M.R. Sauter argues that 'the internet is an apophenic machine': a technical apparatus whose hyperlinked structure invites its users to see patterns and relationships between things even if those connections are faint or nonexistent.[70] As Sauter and other scholars of conspiracy such as Kathleen Stewart note, apophenia is not intrinsically irrational, and Ginzburg's genealogy of conjectural epistemology helps illustrate why: in some contexts, *ex post facto* inference of narrative has served humans well. Yet this 'overabundance of meaning-making' also supports conspiratorial conjectures of all sorts.[71]

Digital apophenia's conspiratorialism is the mirror image of conjectural automation via ML systems. There is, of course, a difference: conclusions produced by the former mode of thinking are unfalsifiable, while inferential predictions made by machine-learning models are meant to be updated with the collection of more and better empirical data. Yet in the context of human social activities, the latter data analysis hits the same insuperable epistemological barrier as that faced by the conspiracist: whatever regularity and repeatability exist at the level of the population can neither be assumed to hold at the level of the individual, nor continue to persist as social conditions change. Regularity is often an artefact of the data collection and datafication processes themselves, not necessarily of the underlying human behaviours at hand.[72]

In practice, automated conjecturing systems, or what Sun-ha Hong terms 'technologies of speculation', are apophenic machines: alarming chimeras of conjectural epistemology and computational technique. As Hong observes, 'imperfect algorithms, messy data, and unprovable predictions are constantly intersected with aspirational visions, human judgment, and a liberal dose of black-boxing'.[73] In many AI-driven analyses of data about humans, we find the worst of both epistemological worlds. At best, attempts to generalize conjectures duplicate well-known observations obtained through qualitative

67 Ginzburg, op. cit. (5), p. 23.

68 Ginzburg, op. cit. (5), p. 14.

69 To be fair to such research, conceptual confusions between empirical and conjectural sciences long predate digital computers.

70 M.R. Sauter, 'The apophenic machine', *Real Life*, 15 May 2017, at https://reallifemag.com/the-apophenic-machine (accessed 3 July 2021).

71 Sauter, op. cit. (70).

72 Hacking, *The Taming of Chance*, op. cit. (25); Donald A. MacKenzie, *Mechanizing Proof*, Cambridge, MA: MIT Press, 2001.

73 Sun-ha Hong, *Technologies of Speculation: The Limits of Knowledge in a Data-Driven Society*, New York: NYU Press, 2020, p. 3

means; at worst, they perpetuate stereotype and bigotry under the veneer of apparently deductive quantitative evidence articulated publicly as a form of objectivity.

The social limits of automated conjecture

The automation of conjectural inference is not morally neutral. Stereotyping has always been one of the dangerous outcomes of conjectural science: phrenology, physiognomy and 'scientific' racism are in part the results of conjecturing misapplied as causation. 'Knowledge based on making individualising distinctions', Ginzburg observes, 'is always anthropocentric, ethnocentric, and liable to other specific bias'.[74] Even in vernacular situations in daily life, we are warned not to judge a book by its cover: ethical conjectural research requires a high degree of reflexivity on the part of practitioners, and an attentiveness to the contingencies of power asymmetries and historical context.[75] In many cases, particular researchers may not be in the position, for whatever reason, to appropriately make such inferences at all.

Such reflexivity and caution have often been lacking in the computational sciences. 'Despite a wealth of evidence directly discrediting … racist pseudoscience', Birhane and Guest observe, AI research implicitly reliant on the conceptual underpinnings of bogus conjectural fields like physiognomy has helped discredited ideas – such as 'the eugenic belief that human races have a biologically based hierarchy in order to support racist claims of racial inferiority or superiority' – to return to mainstream discourse.[76] Wendy Chun's recent exploration of the concept of 'homophily', or the claim that 'birds of a feather [do and should] flock together', is instructive in this regard.[77] Posited as a contingent social phenomenon by post-Second World War social scientists, the idea of homophily has been transformed into a truism that justifies the reification of discriminatory and exclusionary inferential judgements by both humans and machines.

Automated conjecture, for reasons which should by now be clear, is a conceptually bankrupt method in the context of most human sciences. For all their attempts to 'wrangle, tame, and reduce the fog of uncertainty', AI/ML practitioners cannot fully guarantee future results from past performance: exposing the conjectural roots of machine learning suggests that any rigorous study of human behaviour, psychology or other complex social states is unamenable to the abductive analysis performed by ML systems.[78] Even the elements of fields like medicine most amenable to a causal epistemological paradigm – diagnosis of physiological pathologies – are shot through with conjectures.[79] Though technologists continue to promise to make conjectures regular for all practical purposes, Ginzburg's typology suggests that machine learning is, at bottom, epistemologically limited by the logic of inference itself.

74 Ginzburg, op. cit. (5), p. 20.

75 On reflexivity see Linda Finlay, 'Negotiating the swamp: the opportunity and challenge of reflexivity in research practice', *Qualitative Research* (2002) 2, pp. 209–30; on power see Pratyusha Kalluri, 'Don't ask if AI is good or fair, ask how it shifts power', *Nature* (2020) 583, p. 169.

76 Abeba Birhane and Olivia Guest, 'Towards decolonizing computational sciences', *arXiv* (2020), at https://arxiv.org/pdf/2009.14258.pdf, pp. 1–10, 2.

77 Apprich *et al*., op. cit. (16); Wendy Hui Kyong Chun, *Discriminating Data: Correlation, Neighborhoods, and the New Politics of Recognition*, Cambridge, MA: MIT Press, 2022. As computer scientist Abeba Birhane wryly observes, 'You won't believe how much of machine prediction of human behaviour is just stereotyping'. See https://twitter.com/Abebab/status/1344278978618658818 (accessed 6 May 2021).

78 Dryer, op. cit. (25), p. 94.

79 Joseph Agassi and Nathaniel Laor, 'The computer as a diagnostic tool in medicine', *Technology in Society* (1984) 6(3), pp. 235–9; Chin-Yee and Upshur, op. cit. (28).

https://doi.org/10.1017/bjt.2023.3 Published online by Cambridge University Press

To their credit, many AI/ML practitioners would not deny how partial, contextual and indeterminate the results of their analyses can be.[80] Yet the exigent appeal of contemporary automated conjecture – abduction dressed up in quantitative guise – is powerful and totalizing, drawn from a longer-standing charisma around statistical evidence that distinguishes political modernity and its colonial and capitalist mechanisms of exploitation.[81] What William Deringer terms 'political calculation', or the mobilization of different sets of quantitative evidence in the clash of opposing policy agendas, is now a routine part of political debate.[82] The power of such arguments comes from their marriage of inductive and abductive inference, figures supporting a narrative. Unfortunately, careful observations regarding edge cases and uncertainty are often lost in the public reception and mobilization of automated conjecture. Machine-learning technologies serve to obscure the work that abduction performs, with politically reactionary actors frequently presenting speculations about the complex causes of human activity as natural necessities deduced from large amounts of data.

Machine-learning systems, moreover, often launder the normative assumptions of their creators behind sets of opaque, black-box processes.[83] This opacity has the effect of absolving humans from the need to account for or rectify error. As Sarah Hamid notes, law enforcement officials often celebrate the failure of automated conjecture systems deployed in morally questionable contexts such as policing because it suggests that these technologies are being deployed 'scientifically'.[84] By appealing to both the charisma of quantitative evidence and the myth of the 'scientific method', proponents of these technologies can position situational failure as a necessary step in an assumed teleology that will see correlative conjecture merge more and more seamlessly with prediction.[85] The fact that AI systems do not and likely will not ever have the capacities to develop such phronetic judgement is rarely discussed.[86]

Perhaps most insidiously of all, such automated systems push their subjects to conform, in myriad ways, to the categories of conjecture through which individuals are analysed. Ian Hacking terms this phenomenon 'the looping effect of humankinds': 'to create new ways of classifying people is also to change how we can think of ourselves … which in turn creates a looping effect, because people of the kind behave different and so are different'.[87] Statistical aggregations of humans in the abstract have often produced contradictory stories for the individuals described by them, and thus caught up in them. On the one hand, recognizing the self as part of a larger group, such as LGBTQ people via the Kinsey report, has helped fuel political emancipation.[88] Yet such aggregations, and

80 Jones, op. cit. (37).

81 Luke Stark, 'Desanctifying the charisma of numbers', *Journal of Cultural Economy* (2018) 1, pp. 83–9; Morgan G. Ames, *The Charisma Machine: The Life, Death, and Legacy of One Laptop per Child*, Cambridge, MA: MIT Press, 2019.

82 William Deringer, *Calculated Values: Finance, Politics, and the Quantitative Age*, Cambridge, MA: Harvard University Press, 2018.

83 Danielle Keats Citron, 'Technological due process', *Washington University Law Review* (2008) 85(6), pp. 1249–1313; Frank Pasquale, *The Black Box Society*, Cambridge, MA: Harvard University Press, 2015; Elizabeth R. Petrick, 'Building the black box: cyberneticians and complex systems', *Science, Technology, & Human Values* (2020) 4, pp. 575–95.

84 'Community defense: Sarah T. Hamid on abolishing carceral technologies', *Logic*, 31 August 2020, at https://logicmag.io/care/community-defense-sarah-t-hamid-on-abolishing-carceral-technologies (accessed 20 July 2021).

85 Chun, op. cit. (77); Amoore, op. cit. (42), p. 12.

86 Brian Cantwell Smith, *The Promise of Artificial Intelligence: Reckoning and Judgment*, Cambridge, MA: MIT Press, 2019; Mazviita Chirimuuta, 'Rules, judgement and mechanisation', presented at the Philosophy, Psychology, and Informatics Group, University of Edinburgh, 3 November 2021.

87 Quoted in Cowles, op. cit. (24), p. 15.

88 Igo, op. cit. (25).

the visibility to the state that comes with them, are not always salutary.[89] Such legibility has enabled the worst atrocities of the last centuries, from the horrors of American race science, to the compulsory sterilization of Indigenous women by the Canadian government, to mass incarceration, to Nazi eugenics and the Holocaust. Conjecture claimed as a science has often been wielded as a terrible instrument of power. As Ginzburg puts it, the 'increasingly clear tendency for state power to impose a close-meshed net of control on society [comes via] attributing identity through characteristics which were trivial and beyond conscious control'.[90] We are thus often driven to evade, subvert and contest the institutionalized conjectures under which we are pinned by institutional analysis.[91] Who is permitted the space to conjecture without social accountability, and to put those conjectures into forms that can classify and define others, is central to the contemporary analysis of power as our activities are increasingly hemmed in by the conjectures made by digital machines.

Conclusion

Sherlock Holmes, created by the nineteenth-century author and physician Sir Arthur Conan Doyle, is the quintessential conjectural scientist. Holmes is famous for divining the circumstance and even character of individuals through inference, and Conan Doyle could ensure that the fictional detective's conjectures were invariably correct. History is itself also a conjectural science, but it is not fiction, and outside the pages of detective stories, infallible Holmsian conjecture is nonsense. Though historical knowledge can be instructive, it cannot be instrumentalized without risking becoming propaganda or myth. And though even history has at various points aspired to deduce the regularity of quasi-scientific laws in historical development, it has not done so with much success. History's 'lessons' are not pat: historiography (the history of history as a discipline) suggests that curiosity, reflection and being as alert to the present as to the past are necessary but not sufficient conditions for strong historical work.[92] Such work includes the collective conjecturing of political futures, which always entail normative choices: what narratives to embrace; which values to defend; and how to ensure fairness, accountability and justice within a polity.

Researchers, practitioners, institutional regulators and citizens concerned about automated conjecture may therefore find the conjectural/empirical distinction sketched above a useful and usable heuristic in making design and policy choices around the development and deployment of AI systems. Human activity must be routinized and made as predictable as socially possible for automated conjectural science to work at peak efficiency: AI, as a conjectural science, is about making the world that its promoters want. It is the ubiquity and invasiveness of AI-driven systems that their promoters hope will ensure predictability and profit.[93] Regulation via the epistemological structure of a problem space is therefore one mechanism to address the social impact of rapid advances in the ML methods used for automated decision making. Though the distinction between conjectural and empirical science is an idealized one, assessing ML systems and their use cases for the extent to which they do meet these definitions is a useful exercise. This assessment

89 Jacob Gaboury, 'Becoming NULL: queer relations in the excluded middle', *Women & Performance: A Journal of Feminist Theory* (2018) 2, pp. 143–58.

90 Ginzburg, op. cit. (5), p. 24.

91 Finn Brunton and Helen Nissenbaum, 'Vernacular resistance to data collection and analysis: a political theory of obfuscation', *First Monday* (2011) 5, pp. 1–22.

92 Sarah Maza, *Thinking about History*, Chicago: The University of Chicago Press, 2017.

93 Luke Stark, 'Algorithmic psychometrics and the scalable subject', *Social Studies of Science* (2018) 2, pp. 204–31.

should be grounded both in the forms of inference involved in a particular automated analysis, and in the domain in which the analysis is being performed. For instance, inferences regarding personality, criminality or emotional state can be recognized as fundamentally abductive and conjectural, and thus inappropriate for automation. The broad class of 'physiognomic AI systems' increasingly being promoted in areas such as immigration and border enforcement, policing, online hiring, human-resource management and commercial advertising would all be categorically banned under such a policy.[94] Given the shaky epistemological foundations and social toxicity of much automated conjecture about human activities and behaviour, such use cases deserve heightened legal, technical and social scrutiny. Using this proposed standard, the automation of conjectural pseudosciences such as phrenology is self-evidently fruitless alongside morally abominable.

The distinction between conjectural and empirical science also provides a conceptual basis on which to reject certain use cases of ML systems before they are developed in the first place. Sandra Wachter and Brent Mittelstadt have recently proposed that the 'right to reasonable inference' be recognized as a fundamental element of digital regulation.[95] The authors argue both that 'protection should be granted to data based primarily on its usage and impact', and that data controllers should be forced to 'proactively justify their design choices for high-risk inferential analytics'.[96] The historical and conceptual distinctions sketched out in this piece provide one possible mechanism to adjudicate such justifications, by showing how the inferences made by AI systems are grounded not only in the digital data being collected and analysed, but also in the logics and narratives underpinning these technologies' initial development.

The tension between conjectural and empirical science is long-standing. As Ginzburg observes, empirical epistemology has always foundered when engaging the messy social and subjective aspects of human beings, while conjecture raised to a system produces outcomes that are simultaneously banal, discriminatory and nonsensical.[97] AI systems are attractive to some scientists and technologists because they seem to show a way to paper over these tensions once and for all. In fact, AI should be the technical mechanism that at last illustrates that the chasm is impossible to bridge, and that automated conjecture is antithetical both to strong societies and to strong science.

Acknowledgements. I'm grateful to a number of people who have helped me expand and refine this argument since its original instantiation in early 2019; these include Katharine Dempsey, Sun-ha Hong, Benjamin Chin-Yee, Fernando Diaz, Daniel Susser and participants in a number of workshops and panels, including at the Machine Agencies Research Group at Concordia University, the 2022 Society for the Social Studies of Science annual meeting in Puebla, Mexico, and the 2023 Canadian Communications Association annual meeting in Toronto, Canada. I'm particularly grateful to Marita Sturken, who introduced Ginzburg's 'Morelli, Freud and Sherlock Holmes' to me as a graduate student, and to the organizers of the Mellon Sawyer Seminar on Histories of AI: A Genealogy of Power at the University of Cambridge – Syed Mustafa Ali, Stephanie Dick, Sarah Dillon, Matthew Jones, Jonnie Penn and Richard Staley – who have supported this work and this wonderful volume. Special thanks too to my doctoral advisees Daniel Arauz Nuñez and Pinar Barlas, and to the students in my graduate and undergraduate courses on artificial intelligence, ethics and health: their engagement with the paradoxes of automated conjecture has been inspiring and motivating.

94 Luke Stark and Jevan Hutson, 'Physiognomic artificial intelligence', *Fordham Intellectual Property, Media, and Entertainment Law Journal* (2022) 4, pp. 922–78.

95 Sandra Wachter and Brent Mittelstadt, 'A right to reasonable inference: rethinking data protection law in the age of big data and AI', *Columbia Business Law Review* (2019) 2, pp. 494–620.

96 Wachter and Mittelstadt, op. cit. (95), pp. 616, 618.

97 Ginzburg, op. cit. (5), p. 28.

Cite this article: Stark L (2023). Artificial intelligence and the conjectural sciences. *BJHS Themes* **8**, 35–49. https://doi.org/10.1017/bjt.2023.3