PHILOSOPHY OF COMPUTATIONAL SOCIAL SCIENCE

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ABSTRACT: Computational social science is an emerging field at the intersection of statistics, computer science, and the social sciences. This paper addresses the philosophical foundations of this new field. Kant and Peirce provide an understanding of scientific objectivity as intersubjective validity. Modern mathematics, and especially the mathematics of algorithms and statistics, get their objectivity from the intersubjective validity of formal proof. Algorithms implementing statistical inference, or *scientific algorithms*, are what distinguishes computational social science epistemically from other social sciences. This gives computational social science an objective validity that other social sciences do not have. Objections to the scientific realism of this philosophy from the positions of anti-instrumentalism, postmodern interpretivism, and situated epistemology are considered and either incorporated into this philosophy of computational social science or refuted. Speculative predictions for the field of computational social science are offered in conclusion: computational social science will bring about an end of narrative in the social sciences, contract the field of social scientific knowledge into a narrower, more hierarchical field of expertise, and create a democratic crisis that will only be resolved through universal education in computational statistics.

KEYWORDS: Computational social science; Scientific algorithms; Postmodern interpretivism

Computational social science has been defined as an emerging scientific field at the intersection of statistics, computer science, and the social sciences (Counts et al., 2014; Mason, W. et al., 2014) Many researchers and students today are developing computational social science by synthesizing the practices of these fields with little thought to the intellectual foundations of their work. As the new field becomes more successful, it will be necessary to develop the philosophical theory underlying these practices as a science. This will both guide researchers in the epistemic norms of their own practice and intellectually position computational social science relative to other social sciences. This paper explains these intellectual foundations, addresses several critical objections, and concludes with predictions about the field that extend logically from these arguments.

Section 1, "Scientific Algorithms", outlines a philosophy of computational social science based on the history of philosophy of computation, statistics, and rationality. It also gestures at theoretical and empirical work by social scientists that is consistent with this philosophy despite not being computational.

Section 2, "Responding to Criticism", raises critical objections to the position outlined in Section 1. These objections are drawn from social sciences, such as Science and Technology Studies, that are tangential to computational social science and the fields from which it originates. This section also responds to these criticisms from the perspective of the computational social scientist.

Section 3, "Predictions", draws out the logical consequences of the foundations of computational social science to make several predictions about this new scientific field. These are intended both as theoretical claims subject to intellectual debate and empirical claims about the future of computational social science.

1. SCIENTIFIC ALGORITHMS

Statistics and computer science have a long shared intellectual history that has gone by various names: artificial intelligence, machine learning, data science. There is widespread consensus within the field about the firmness of its mathematical foundations and appropriate application of its methods (Russell et al. 2003).

The social sciences, in contrast, are heterogeneous and fragmented into 'disciplines'. This has been attributed to the difficulty of establishing legitimacy and consistent funding within a university setting, and to the fact that social science researchers are so often researching what interests them based on their personal values (boyd 2016). The social sciences are also fragmented because their political relevance means that its institutional conditions are often influenced by political power, which is both a cause and effect of the lack of credibility in the social sciences relative to the "hard" sciences (such as physics) (Bourdieu 2004).

Computational social science can be seen as an opportunity to extend the rigor and objectivity of computational statistics to the study of social phenomena. It accomplishes this through use of what I will call "scientific algorithms," special algorithms that perform the logical operations that correspond to an ideally rational observer. These algorithms are designed through an ongoing process of collective reasoning that ensures that they represent the impartial consensus of rational investigators, free from the bias of any partial perspective.

History of rational and pragmatic epistemology

The history of scientific epistemology is long. Without doing justice to its full trajectory, two important milestones are noteworthy for the arguments in this paper.

The first is Immanuel Kant's *Critique of Pure Reason* (Kant, I., 1781/2007). This work resolved a tension that existed at the time between two schools of thought about the foundation of knowledge. Locke had proposed that the senses were the foundation of all knowledge. Everything was learned through qualities perceptible to the senses. This seemed a plausible explanation for learning at the time. Contrary to this, Descartes had proposed that the foundation of all knowledge was logical thought. He famously proposed that the first step a philosopher should take is to doubt their senses and question whether the world they perceived was the creation of an evil demon.

Neither of these views proved satisfying and Kant had a profound solution. Rather than treat the project of epistemology to be the discovery of a "God's eye view" of reality that lay beyond all human experience (the *noumenon*), he proposed that philosophy should uncover the reality that was available to human perspective. This has been called the transition from transcendental realism to transcendental idealism (Allison, 2004), because it changed the view of what was "really real" (transcendental) from "real" objects to what was available as an idea.

A consequence of this change in perspective was that Kant could argue philosophically from shared human experience of perception and reasoning. He argued that the foundation of knowledge was *transcendental reason* that discovered the lawful structure of the sensed world and the corresponding logical concepts needed to understand it. He believed this transcendental reason was available to all rational subjects. It therefore gave its conclusions objectivity, not in the sense of being independent from *any* mind and experience, but rather by being independent from the *particularity* of any individual's mind or experience.

A second important milestone in the history of epistemology is the work of logician Charles Peirce, who is largely considered to be the founder of the school of thought known as pragmatism. Peirce's pragmatism emphasized two points. First, knowledge is for action; what makes an idea distinctive is that it has a distinctive effect on the pattern of behavior of one who has it (Peirce, 1878). Second, the scientific enterprise is a social one. Reason is not an individual accomplishment but rather something that reaches its highest potential when it is used to settle disagreements between persons (Peirce, 1877). For classical pragmatism, the truth is defined as the ideal consensus of rational investigators over time.

The most important thing to take away from a study of Kant and Peirce is that the project of science is the project of discovering truths that are robustly intersubjective.

Kant discovered that knowledge can be universal even though it is subjective. What makes subjective knowledge universal for Kant is that it is discovered through universal principles of reason. Peirce acknowledged more individual difference than Kant but restored the idea of universal scientific knowledge by showing how scientific knowledge is developed through the pursuit of agreement between different subjects. We will use this principle of robust intersubjectivity as the standard of knowledge throughout this discussion of philosophy of computational social science.

These old ideas from the 18th and 19th centuries may seem far removed from a philosophy of computational social science. Nevertheless, they are important steps in the history of scientific thought and especially the underlying epistemology of the social sciences. Many students today have never studied Kant or Peirce and so have never thought through these philosophical perspectives.

Algorithms and intersubjectivity

The 20th century saw the transformation of the world through the power of digital computing. What many people don't know is that origins of the digital computer were rooted in a radical transformation in the philosophy of mathematics and logic. Computing technology is based on the logical relationship between the modern algorithm and the modern mathematical proof. What made these new proofs and algorithms so powerful--powerful enough to transform society all over the world--was a new standard of rigor that established greater intersubjective validity in mathematics.

Before the discovery of modern logic, mathematics had proceeded in what today looks like an informal and haphazard way. This process is demonstrated in the most skillful way by Lakatos (1976), who tells the story of a theorem in geometry as a dialogue between students in a classroom that condenses a debate that occurred over several centuries. Over the course of history, the standards of what was considered to be a valid form of mathematical argument were the subject of active debate.

In the early part of the 20th century, a number of discoveries changed the way mathematics was done. For a number of reasons that are beyond the scope of this paper, the mathematical consensus shifted to the view that a proof had to consist in a finite number of mechanically repeatable steps within a formal system of symbols. What made this systematic way of thinking so compelling was how many different mathematical representations could be shown to be reducible or equivalent to each other within a common framework of metalogic.

Whitehead and Russell's *Principia Mathematica* (1910) showed that mathematical proofs about the natural numbers could be reduced to a more basic mathematics, set theory. Alonzo Church would show how this method of formal proof could be used to define the set of computable *functions*, which take input data and return output data. Later it was proven that Church's lambda calculus was equivalent to the mathematical description of the famous Turing Machine, which was the blueprint for Alan Turing's physical computing machine. (Li and Vitanyi, 2008, p.24. Irvine, 2003)

The success of digital computing comes in no small part to these discoveries of the equivalence between computation and mathematical reasoning. An algorithm, in the modern sense, is in many ways logically equivalent to a mathematical proof. What they have in common is how they guarantee that any person or any machine taking the same steps from the same starting point will get the same result.

We can see this as a continuation of the trajectory of science started by Kant and Peirce. Mathematical logic and computer programming jointly took a step forward for science's ability to arrive at robust intersubjective conclusions. It did this by formalizing mathematical proof and then implementing these proofs as algorithms. Algorithms are operations that in principle can be performed both by people and machines, or some combination of them. Regardless of who or what performs these operations, the relationship between the input and output of the algorithm is always mathematically the same. Mechanical algorithms are a way of extending the powers of collective thought. When these algorithms are verifiable and verified by thousands of mathematicians, programmers, and machines, there is no room for bias from partial perspective within its systems.

In some ways formal logic without data is like Descartes trying to reason about the world without using his senses. It cannot be the whole philosophy of science. These computational tools have been combined with the mathematics of inference from data, statistics, to be the powerful foundation of computational science we know today.

Statistics and rationality

Concurrent with the discover of the modern algorithm and its connection with mathematical proof, the 20th century saw great strides in theories of statistics, rationality, and the mind. Mathematicians used formal proof to expand the axioms of probability to develop the laws of statistical inference. Bayesian inference, a method in statistics whereby one updates one's subjective beliefs about the world based on rigorous analysis of new data, has proven especially effective in contemporary machine learning techniques.

It must be noted that Shannon's information theory, which made modern telecommunications possible, was also derived from the axioms of probability. A mathematical synthesis of information theory with theory of computation was accomplished almost simultaneously by Solomonoff, Chaitin, and Kolmogorov in the form of algorithmic information theory. This informs thinking about machine learning algorithms today. (Li and Vitanyi, P. 2008)

An important feature of Bayesian statistics is that according to its method, one is guaranteed to converge on the true understanding of the phenomenon studied as one collects more data about it. Astute statisticians will note the many assumptions that need to be true for this to be the case. Much of contemporary statistics research is devoted to what kinds of inferences can be made with only finite data (as opposed to the theoretically infinite data of asymptotic guarantees). But in practice, our limited understanding of statistical theory has not prevented its wide adoption for its aspirational qualities. Because of its promise of converging knowledge, statistics is a way to approach intersubjectively valid knowledge of the sensory world.

According to the successful computational cognitive science paradigm, all cognition can be modeled as computational information processing. To a large extent the laws of rational thought have been codified in basic statistical and computational theory. (Anderson, 1991; Chater and Oaksford, 1999; Chater and Vitanyi. 2003; Russell et al., 2003; Griffiths, T. et al., 2008; Tenenbaum, J., et al., 2011) Contemporary machine learning and artificial intelligence is mainly just the implementation of these principles in machine systems designed to accomplish an expanding range of tasks.

A philosophically deep point about both statistical theory and theory of computation is that the same mathematical principles that were developed as laws of rational thought are now used as laws of nature governing technology we use every day. Information theory, derived from the axioms of probability theory much like Bayesian reasoning, is essential for the design of telecommunication codes and networking protocols. Complexity theory and theory of computation, originally theories of what was provable by mathematicians, are now used to design computer algorithms. The term "artificial intelligence", which is as old as Turing, captures this correspondence well. We are intelligent; so are our artifacts: because we share a logic.

We may call algorithms that implement statistical inference *scientific algorithms*, and consider computational social science as the application of scientific algorithms to understand social phenomena. The centrality of scientific algorithms in computational social science gives it, more than any other social science to date, the potential for the discovery of objective truth. This objectivity is won through the reproducibility of its results: through formal proof in the case of its logical foundations, and as calculations algorithmically performed in the case of substantive empirical research. The scientific use of scientific algorithms affords the social sciences with a new horizon.

2. CRITICAL OBJECTIONS

The philosophy of computational social science described above is a form of scientific realism: it takes the discoveries made by scientific consensus to be real, or more real than the contents of the perspectives of those who are not participating in the scientific social process. For many good reasons, the social sciences have for decades harbored many philosophical objections to this kind of realism. Among these are critiques of scientific instrumentalism, postmodern interpretivism, and standpoint epistemology.

While each of these positions has played an important political role in the history of the social sciences, they are each inconsistent with the philosophical foundations of computational statistics. Therefore, from the perspective of computational social science, they are incorrect. This section will summarize three classes of critical objection to the foundations of computational social science, and respond to each. In each case, there is something to be learned from the objection. These lessons learned should be considered as much part of the philosophy of computational social science as the veracity of scientific algorithms.

Critiques of instrumentalism

One important critique of science and technology that surfaced in the 20th century alongside the discovery of modern computation is the accusation that it may be excessively instrumental. "Instrumental" here means that it enables scientists and technologists to improve the means to reach their goals without informing what those goals should be in the first place. For example, Heidegger (1954) famously argued in a poetic style that technology that is first used to treat nature as a resource to be extracted and controlled will one day be used to treat humanity as a controlled resource.

Horkheimer (1947) levelled a similar objection specifically to what he saw as a disastrous synthesis of formalized reason and pragmatism. He argued that formalizing reason would lead to people forgetting how to reason naturally for themselves, and that pragmatism, because it is indifferent to its ends, leads people to forget to reason about what is truly moral. His book-length argument was one of many condemnations of capitalism that contributed to the influential Frankfurt School of criticism. In this broadly Marxist framework, technology is a form of capital that operates according to its own logic. If left unchecked, it will enslave, not liberate, humanity.

This is a fearsome criticism to computational statistics and especially its applications to the social sciences. There are two responses from the perspective of the philosophy of computational social science.

The first is that this concern about the instrumentalism of science is the product of a specific historical context: post-war Germany, in a world where the advance of nuclear physics was giving many causes for concern about the unchecked progress of science (Carson, 2010). These concerns were about the power unleashed by the physical sciences. It would be misplaced to bring the same concerns to the exact sciences of computational theory and statistics.

The second response is that nothing about computational social science precludes it from being a study of ends as well as a study of means. Indeed, a mathematized ethics that has the same robust intersubjectivity as a mathematical proof would be the most wonderful discovery one could hope for from computational social science. It can overcome this objection by explicitly taking moral and ethical values as an object of study within its scientific field.

Postmodern interpretivism

A second class of objections to scientific realism can be characterized as *postmodern interpretivist* objections. These objections come from schools of thought that originate in the humanities and can be thought of as an extension of the methodological assumptions of the humanities into the sciences. By considering all phenomena to be like texts to be interpreted, these objectors argue that the special authority of scientists is undeserved because after all theirs is just another interpretation.

It is difficult to maintain this objection in light of the specific history of mathematics and computation. Once one understands just how intersubjective verifiability is the condition of a scientific algorithm, the claim that scientific algorithms result in interpretations that are as valid as any other interpretation stops being credible. But perhaps because this history of computation and the philosophical progress it depends on is not widely known, the postmodern critique is alive and well in even recent scholarship.

Much of the success of the postmodern critique of science can be attributed to Bruno Latour, who is influential in Science and Technology Studies today. For example, here is how he is used in a widely cited article, "Critical Questions for Big Data: Provocations for a Cultural, Technological, and Scholarly Phenomenon" by boyd and Crawford (2012):

'Numbers, numbers, numbers,' writes Latour (2010). 'Sociology has been obsessed by the goal of becoming a quantitative science.' Sociology has never reached this goal, in Latour's view, because of where it draws the line between what is and is not quantifiable knowledge in the social domain.

Big Data offers the humanistic disciplines a new way to claim the status of quantitative science and objective method. It makes many more social spaces quantifiable. In reality, working with Big Data is still subjective, and what it quantifies does not necessarily have a closer claim on objective truth – particularly when considering messages from social media sites. But there remains a mistaken belief that qualitative researchers are in the business of interpreting stories and quantitative researchers are in the business of producing facts. In this way, Big Data risks reinscribing established divisions in the long running debates about scientific method and the legitimacy of social science and humanistic inquiry.

Boyd and Crawford anticipate the evolution of Big Data (an industry buzzword referring to the algorithmic analysis of large-scale data, especially social data) into computational social science. As primarily humanistic researchers, they emphasize the element of data analysis that is most available to the humanities: the interpretation of results. In so doing, they downplay the differences between qualitative and quantitative research methods, ignoring how the latter are accumulation of centuries of accumulated technical procedure that is subject at each generation to rigorous scientific scrutiny. That computational social science would reinscribe an understanding of the importance of the scientific method in establishing facts is not a risk, it is a condition of doing computational social science properly. This is not to say that there isn't a role for interpretation in computational social science. It is just not the same as the role it plays in the humanities.

This would be all there is to say on this topic were it not for a pernicious tendency in interpretivist rhetoric to maintain this objection not through logic, but through stylistic ambiguity. This fallacious form of argumentation was once defended as a part of postmodernist scholarship by Lyotard (1984) as "legitimation by paralogy". Bourdieu (2004) characterizes these tactics like so: the critic makes an ambiguous claim that has both a radical interpretation and a banal one. For example, the claim that scientific facts are artificial can be interpreted to mean that they are untrue, or instead that they are the result of a social or cognitive process of creation. Without engaging the long lineage in philosophy of explanation of how we arrive at true conclusions through social and cognitive processes, the critic begins political mobilization based on the insinuation that the facts are fake while having prepared their path of retreat in advance.

By saying facts are artificial in the sense of manufactured, Latour and Woolgar intimate that they are fictitious, not objective, not authentic. The success of this argument results from the 'radicality effect', as Yves Gingras (2000) has put it, generated by the slippage suggested and encouraged by skillful use of ambiguous concepts. The strategy of moving to the limit is one of the privileged devices in pursuit of this effect … but it can lead to positions that are untenable, unsustainable, because they are simply absurd. From this comes a typical strategy, that of advancing a very radical position (of the type: scientific fact is a construction or — slippage — a fabrication, and therefore an artefact, a fiction) before beating a retreat, in the face of criticism, back to banalities, that is, to the more ordinary face of ambiguous notions like 'construction', etc.

Latour would later repudiate his radical position on the grounds that it was irresponsible to undermine the authority of science when those critiques would be used by climate change deniers to advocate for socially damaging policies (Latour, 2004). And on the eve of Big Data, he would be bullish about the role of quantification in sociology, though it would require a different use of statistics than has been traditionally used in the natural sciences (Latour, 2010). Recently developed algorithmic methods for understanding network data prove this point in practice. Late Latour is more or less in agreement with the scientific consensus of computational social science.

Boyd and Crawford have indeed composed their "provocations" effectively, deploying ambiguous language that can be interpreted as a broad claim that quantitative and humanistic qualitative methods are equivalent in their level of subjectivity, but defended as the banality that there are elements of interpretation in Big Data practice. But these provocations should not be confused with proof. They are reminders that though scientific algorithms can make computational social science *more* objective, there will always be the problem of the perspective of the interpreter. This problem is characterized well by the third major objection to scientific realism, standpoint epistemology.

Situated epistemology

A third objection to the scientific realism implied by the offered philosophy of computational social science is the objection that knowledge is *situated*, meaning that knowledge is always dependent on the context in which it is learned and the position of its subject. (Brown,, Collins, and Duguid, 1989) Often the claim that situated knowledge is privileged over a ficticious "God's eye view" is associated with feminist epistemology, which emphasizes how women are differently situated from men and the implications this has for philosophy of science (Haraway 1988; Anderson, 2015).

Computational social science must concede the core of the situated epistemologist's argument as an indisputable fact. Any individual human's knowledge is situated by virtue of the human condition. And their perspective will be partial because their access to data will be (a) finite and (b) biased by their position. This conclusion follows from the mathematical theory of computation and statistics as much as it does from other philosophical or theoretical argument.

Where computational social science must part ways with the situated epistemologist is how it sees science in relation to partial perspective. For the computational social scientist, impartial knowledge is still the scientific ideal. It is achieved collectively and through the historical process of verifying logical argument and collecting and processing more data. Merely human partiality can be overcome, gradually, through the use of scientific algorithms. One might say that the success of computational social science depends on the social construction of an *algorithmic situation* which is capable of knowing about society more fully than other social sciences. This algorithmic situation is collectively and intersubjectively validated in the process of its construction, and continues to be validated afterwards through the practice of computational social science.

Partial perspectives, or the individual understandings of particular subjects, are important as objects of study to the computational social scientist but not valid in their own right. They have validity only to the extent that they are validated in processes of intersubjective verification. This motivates a fascinating research problem in computational social science: the algorithmic collection and representation of composite perspective. Properly representing multiple perspectives, with their differences and similarities, would be both a substantive and logical advance in the logic of the social sciences (Benthall, 2016).

3. PREDICTIONS

The first section of this paper outlined a philosophy of computational social science based on an understanding of the scientific algorithm as convergently valid intersubjective inference. The second section addressed prominent critical objections to this view. This third and final section draws speculative conclusions from the preceding arguments. This philosophy of computational social science suggests that this field will challenge the centrality of narrative in the social sciences. In so doing, it will become a contracting field, deep and abstract like physics, with a narrowing population of experts. This will result in a crisis of democratic governance as political expertise, which will be synonymous with computational social scientific expertise, becomes esoteric and untrusted. The solution to this crisis will be universal education in the principles of computational social science.

End of narrative

One of the pioneers of contemporary quantitative sociology, Miller McPherson, developed a sociological theory that explained many phenomena as the result of relatively simple mechanism: populations are sampled from an underlying multidimensional feature space, or Blau space, and their origin in the space determines their place in the social network. (McPherson, 1983; McPherson and Ranger-Moore, 1991). This work has inspired contemporary computational social scientists (e.g. Kim and Leskovec, 2012)

In a paper surveying this work, McPherson (2004) reflects on "the cost of Blau space"--how sociologists might be dissatisfied with the kind of explanation his theory provides. "We lose a vast amount of local detail," he writes, because social explanation comes from macro-level structure rather than micro-level interactions. "The usual sociologist's reaction to this is to feel somehow dissatisfied with this explanation because it accords too well with common sense."

We give up the stories. The uniqueness of each individual's path through time and Blau space is sacrificed for the generality of reducing that path to a vector of coordinates which characterize position in time, geography, and social structure. The discourse, the negotiated reality, the micro exchanges are all relegated to the spline generator of the homophily principle of Blau space.

Most importantly, we give up the claim to agency. The mechanism that drives movement in Blau space is not very amenable to political, social, or emotional manipulation. The distribution of action across the vast social distances of Blau space reduces the forces of individual human agency to a mere whisper beyond the immediate social environment. Taking in the social world through Blau space mutes even the ponderous tones of organization and institution. For those committed to maintaining the traditional social science view (or those in need of a vibrant story line for MBA students), Blau space will be an uncomfortable venue for dialogue. It remains to be seen whether the benefits will overcome the discomfort.

What McPherson warns for his model of Blau space may well be extended to other manifestations of computational social science as well. Because computational social science uses computational models for explanation not narration, it must at its core "give up the stories". However effective they may be for persuasion, narratives will not capture the formal mechanisms posited by computational social science. They will be window dressing, the thought provoking anecdote of an introduction, not the substance of knowledge.

As McPherson notes, this end of narrative will threaten notions of agency based on narrative. It will also threaten other social scientific disciplines who have prioritized *interestingness* (Healy, 2015) over predictive power. Because of the emphasis on formal and statistical verifiability, computational social science will determine many interesting narratives to be untrue or misleading. Those that it can confirm will likely be disappointing from an academic perspective because they will be a confirmation of "common sense".

Contraction

A consequence of the asymptotic convergence of statistical inference that drives computational social science is that the range of hypotheses open to scientific debate will contract over time. Whereas today the social sciences are broad and shallow, accommodating a wide range of explanatory theses, much of this breadth can be attributed to the "data poor" origins of many social sciences. In some fields a case study providing an interesting illustration is considered enough data to make a claim to knowledge. As the quantity of data available for inference grows, scientific work using smaller data sizes will become increasingly anecdotal, a kind of storytelling.

There are two ways larger data sets can diminish social scientific hypotheses developed using smaller ones. The first is to show that the patterns identified in a weaker hypothesis were not signal, but noise. If a small data set confirms a hypothesis, a large data set may prove the apparent structure of the small data was only due to chance. All hypotheses must stand up to the test against the great null hypothesis that the social phenomena that appear are random manifestations of unformed chaos.

The second way larger data sets can diminish social scientific hypotheses is by showing how they are reducible to laws of nature. This is not so much a contradiction of social science as its evolution, but nevertheless it results in a contraction of the scientific field. For the more social science can be reduced to laws, the more it becomes a narrow but deep field akin to mathematics as opposed to the broad and shallow field of empirical observation. Acquiring social scientific knowledge will be a matter of learning increasingly abstract and complex theory. This will in turn result in a changing social structure of expertise, which will be more hierarchical as the knowledge it conveys deepens.

Democracy and divide

If the above arguments are correct and computational social science, through its commitment to intersubjective verifiability, becomes increasingly abstruse, then the emergence of this scientific field will have strange political consequences. The available of social data available for processing expands with the ubiquity of computing and telecommunications. Data scientists at commercial organizations and in government use this data for social control, and computational social science will be instrumental to these efforts. In the near future it is unlikely that all citizens will be equipped with the tools of computational social science. This creates an uncomfortable differential in social power that among other problems threatens the idea that citizens are knowledgeable enough to reflect on how they are to be democratically governed.

While questions of the role of experts in democracy are not new, the fact is that many fields that once claimed social scientific expertise are being displaced by computational social science. Research has already shown that the subtle art of political prediction, a core competency for those involved in policy and governance, is better performed by simple statistical inference than by alleged "experts" (Tetlock, 2005) A sober analyst would conclude that computational social science is destined to be the foundational science of future law.

In the meantime, it faces deep distrust from critics. Pasquale (2015) has noted that many machine learning algorithms are so complex that they are difficult for lawyers to understand, and has concluded that something so complex should not be allowed to exist. This argument ignores how it is mathematically infeasible to solve a complex problem in a simple way. (Burrell, 2016) Metcalf and Crawford (2016) have noted that data science (another term for computational statistics) can draw many interesting conclusions from public data, and argue that in order for data science to be trusted as a science, it needs to regulate itself according to an enriched standard of human subjects research ethics. This argument ignores how computational statistics is simply an extension to an individual's capacity for rational thought and inference. To deny the data scientist the ability to study public data will one day be seen as akin as denying a person the right to see and think.

While there may well be important lawful regulations of the application of computational social science, they need to be designed with a full understanding of the potential of the field. They also need to be designed in such a way that they do not deny future generations access to the very knowledge that will enable them to govern themselves. Rather than restricting computational social science to highly trained experts, we should be looking for ways to make it a part of universal education like literacy.

Just as literacy made modern democracy possible, so too will computational social science make a new kind of enlightened self-governance possible. This will require a tumultuous change in the nature of expertise and education. Until this is accomplished, the biggest challenges for computational social science are not going to be scientific ones. They will be political.

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REFERENCES

John Anderson. 1991. Is human cognition adaptive? Behavioral and Brain Sciences 14: 471– 517.

Anderson, Elizabeth, "Feminist Epistemology and Philosophy of Science", The Stanford Encyclopedia of Philosophy (Fall 2015 Edition), Edward N. Zalta (ed.), URL = <http://plato.stanford.edu/archives/fall2015/entries/feminism-epistemology/>.

Badiou, A., 2008. Conditions,trans. Steven Corcoran. New York: Continuum.

Bamman, D. (2016), "Interpretability in Human-Centered Data Science," CSCW Workshop on Human-Centered Data Science

Beniger, J. (2009). The control revolution: Technological and economic origins of the information society. Harvard University Press.

Benthall, Sebastian. (2016) The Human is the Data Science. Workshop on Developing a Research Agenda for Human-Centered Data Science. Computer Supported Cooperative Work 2016

Bourdieu, P.. 2004. Science of Science and Reflexivity. Translated by Richard Nice. The University of Chicago Press.

boyd, d. (2016). Why Social Science Risks Irrelevance. The Chronicle of Higher Education. Retrieved July 27, 2016, from http://chronicle.com/article/Why-Social-Science-Risks/237192

boyd d and Crawford K (2012) Critical questions for big data. Information, Communication & Society 15(5): 662–679.

Brown, J.S., Collins, A. and Duguid, P., 1989. Situated cognition and the culture of learning. Educational researcher, 18(1), pp.32-42.

Burrell, J. (2016). How the machine 'thinks': Understanding opacity in machine learning algorithms. Big Data & Society, 3(1), 2053951715622512.

Carson, C., 2010. Science as instrumental reason: Heidegger, Habermas, Heisenberg. Continental Philosophy Review, 42(4), pp.483-509.

Chater, N., Oaksford, M. (1999) Ten years of the rational analysis of cognition. Trends in cognitive sciences 3 (2): 57–65. 10.1016/s1364- 6613(98)01273-x.

Chater, N., Vitanyi. P. (2003) Simplicity: a unifying principle in cognitive science? Trends in Cognitive Sciences, Volume 7, Issue 1, January 2003, Pages 19-22, ISSN 1364-6613, http://dx.doi.org/10.1016/S1364-6613(02)00005- 0.

Counts, S., De Choudhury, M., Diesner, J., Gilbert, E., Gonzalez, M., Keegan, B., Naaman, M. and Wallach, H., 2014, February. Computational social science: CSCW in the social media era. In Proceedings of the companion publication of the 17th ACM conference on Computer supported cooperative work & social computing (pp. 105-108). ACM.

Dwork, C., Hardt, M., Pitassi, T., Reingold, O. and Zemel, R. (2012) Fairness through awareness. In Proceedings of the 3rd Innovations in Theoretical Computer Science Conference (ITCS '12). ACM, New York, NY, USA, 214-226. http://dx.doi.org/10.1145/2090236.2090255

Fisher, Ronald A. 1971/1935. The Design of Experiments (9th ed.). Macmillan.

Gleick, J. 2011. The Information. Pantheon Books. New York.

Griffiths, T., Kemp, C., and Tenenbaum, J. (2008) Bayesian models of cognition. In Ron Sun (ed.), Cambridge Handbook of Computational Cognitive Modeling. Cambridge University Press.

Haraway, D., 1988. Situated knowledges: The science question in feminism and the privilege of partial perspective. Feminist studies, 14(3), pp.575-599.

Healy, K., 2015. Fuck nuance. In meetings of the American Sociological Association.

Heidegger, M., 1954. The question concerning technology. Technology and values: Essential readings, pp.99-113.

Hollan, J., Hutchins, E. and Kirsh, D., 2000. Distributed cognition: toward a new foundation for human-computer interaction research. ACM Transactions on Computer-Human Interaction (TOCHI), 7(2), pp.174-196.

Horkheimer, M., 1947/1974. Eclipse of Reason. 1947. New York: Continuum.

Irvine, A. 2003. "Philosophy of logic", in Shanker, S. (ed.), Philosophy of science, logic and mathematics in the twentieth century (Vol. 9). Psychology Press.

Kant, I., 1781/2007. Critique of Pure Reason, translated, edited, and with an Introduction by M. Weigelt, based on the translation by M. Müller.

Kim, J., 2011. Philosophy of mind. ReadHowYouWant. Com.

Kim, M. and Leskovec, J., 2012. Multiplicative attribute graph model of real-world networks. Internet Mathematics, 8(1-2), pp.113-160.

King, G., 2014. Restructuring the Social Sciences: Reflections from Harvard's Institute for Quantitative Social Science. PS: Political Science & Politics,47(01), pp.165-172.

Lakatos, I., 1976. Proofs and refutations: The logic of mathematical discovery (edited by J. Worrall & E. Zahar).

Latour, B., 2004. Why has critique run out of steam? From matters of fact to matters of concern. Critical inquiry, 30(2), pp.225-248.

Latour, B. (2009) 'Tarde's idea of quantification', in The Social after Gabriel Tarde: Debates and Assessments, ed. M. Candea, Routledge, London, pp. 145–162

Lazer, D., Pentland, A.S., Adamic, L., Aral, S., Barabasi, A.L., Brewer, D., Christakis, N., Contractor, N., Fowler, J., Gutmann, M. and Jebara, T., 2009. Life in the network: the coming age of computational social science. Science (New York, NY), 323(5915), p.721.

Lessig, L. (2009) Code: And other laws of cyberspace. ReadHowYouWant.com

Li, M. and Vitanyi, P. 2008. An introduction to Kolmogorov Complexity and its Applications (3rd Edition). Springer.

Lyotard, J.F., 1984. The postmodern condition: A report on knowledge (Vol. 10). U of Minnesota Press.

Marr, D. 1982. Vision. San Francisco, CA: W. H. Freeman.

Mason, W., Vaughan, J.W. and Wallach, H., 2014. Computational social science and social computing. Machine Learning, 95(3), p.257.

McPherson, M., 2004. A Blau space primer: prolegomenon to an ecology of affiliation. Industrial and Corporate Change, 13(1), pp.263-280.M.

McPherson (1983) An ecology of affiliation. American Sociological Review, 48(4):519–532.

McPherson, M. J. and J. R. Ranger-Moore. (1991) Evolution on a dancing landscape: Organizations and networks in dynamic blau space. Social Forces, 70(1):19–42.

Metcalf, J., & Crawford, K. (2016). Where are Human Subjects in Big Data Research? The Emerging Ethics Divide. The Emerging Ethics Divide (May 14, 2016). Big Data and Society, Spring.

Pasquale, F. (2015). The black box society: The secret algorithms that control money and information. Harvard University Press.

Peirce, C.S., 1877. The fixation of belief.

Peirce, C.S., 1878. How to make our ideas clear.

Putnam, H., 1967. Psychological predicates. Art, mind, and religion, 1, pp.37-48.

Russell, S. J., Norvig, P., Canny, J. F., Malik, J. M., & Edwards, D. D. (2003).Artificial intelligence: a modern approach (Vol. 2). Upper Saddle River: Prentice hall.

Sipser, M. 1996. Introduction to the Theory of Computation. Course Technology.

Shackel, Nicholas (2005). The Vacuity of Postmodernist Methodology. Metaphilosophy 36 (3):295-320.

Slezak, P., 1989. Scientific discovery by computer as empirical refutation of the strong programme. Social Studies of Science, 19(4), pp.563-600.

Tenenbaum, J., Kemp, C., Griffiths, T., and Goodman, N. (2011) How to Grow a Mind: Statistics, Structure, and Abstraction. Science 331 (6022), 1279-1285

Tetlock, P. (2005). Expert political judgment: How good is it? How can we know?. Princeton University Press.

Wallach, H., 2016. Computational Social Science: Toward a Collaborative Future. Computational Social Science: Discovery and Prediction}.