Data Science as Political Action: Grounding Data Science in a Politics of Justice

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Abstract
In response to increasing public scrutiny and awareness of the social harms associated with data-driven algorithms, the field of data science has rushed to adopt ethics training and principles. Such efforts, however, are ill-equipped to address broad matters of social justice. Instead of a narrow vision of ethics grounded in vague principles and professional codes of conduct, I argue, the field must embrace politics (by which I mean not simply debates about specific political parties and candidates but more broadly the collective social processes that influence rights, status, and resources across society). Data scientists must recognize themselves as political actors engaged in normative constructions of society and, as befits political practice, evaluate their work according to its downstream impacts on people’s lives.

I justify this notion in two parts: first, by articulating why data scientists must recognize themselves as political actors, and second, by describing how the field can evolve toward a deliberative and rigorous grounding in a politics of social justice.

Part 1 responds to three arguments that are commonly invoked by data scientists when they are challenged to take political positions regarding their work: “I’m just an engineer,” “Our job isn’t to take political stances,” and “We should not let the perfect be the enemy of the good.” In confronting these arguments, I articulate how attempting to remain apolitical is itself a political stance—a fundamentally conservative one (in the sense of maintaining the status quo rather than in relation to any specific political party or movement)—and why the field’s current attempts to promote “social good” dangerously rely on vague and unarticulated political assumptions.

Part 2 proposes a framework for what a politically engaged data science could look like and how to achieve it. Recognizing the challenge of reforming the field of data science in this manner, I conceptualize the process of incorporating politics into data science as following a sequence of four stages: becoming interested in directly addressing social issues, recognizing the politics underlying these issues, redirecting existing methods toward new applications that challenge oppression, and developing practices and methods for working with communities as productive partners in movements for social justice. The path ahead does not require data scientists to abandon their technical expertise, but does require them to expand their notions of what problems to work on and how to engage with social issues.
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Introduction

The field of data science is entering a period of reflection and reevaluation.1 Despite—or, more accurately, because of—its rapid growth in both size and stature in recent years, data science has been beset by controversies regarding its social impacts. Machine learning algorithms that guide important decisions in areas such as hiring, healthcare, criminal sentencing, and welfare are often biased, inscrutable, and proprietary (Angwin et al., 2016; Buolamwini and Gebru, 2018; Eubanks, 2018; O'Neil, 2017; Obermeyer et al., 2019; Wexler, 2018). Algorithms that drive social media feeds manipulate people’s emotions (Kramer, Guillory, and Hancock, 2014), spread misinformation (Vosoughi, Roy, and Aral, 2018), and amplify political extremism (Nicas, 2018). Facilitating these and other algorithms are massive datasets, often gained illicitly or without meaningful consent, that reveal sensitive and intimate information about people (de Montjoye et al., 2015; Kosinski, Stillwell, and Graepel, 2013; Rosenberg, Confessore, and Cadwalladr, 2018; Thompson and Warzel, 2019).

Among data scientists, the primary response to these controversies has been to advocate for a focus on ethics in the field’s training and practice. Universities are increasingly creating new courses that train students to consider the ethical implications of computer science (Fiesler, Garrett, and Beard, 2020; Grosz et al., 2019; Singer, 2018; Wang, 2017); one crowdsourced list includes approximately 250 such classes (Fiesler, 2018). Former U.S. Chief Data Scientist D.J. Patil has argued that data scientists need a code of ethics akin to the Hippocratic Oath (Patil, 2018). The Association for Computing Machinery (ACM), the world's largest educational and scientific computing society, updated its Code of Ethics and Professional Conduct in 2018 for the first time since 1992 (Association for Computing Machinery, 2018). The broad motivation behind these efforts is the assumption that, if only data scientists were more attuned to the ethical implications

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1 Throughout this essay, I use data science to refer not just to what is explicitly branded as “data science,” but more broadly to the application of data-driven artificial intelligence and machine learning to social and political contexts; a data scientist is anyone who works with data and algorithms in these settings. This definition is intended not to mask the distinctions between technical disciplines and professions, but to appropriately account for the full set of related practices that often fall under different labels.
of their work, many harms associated with data science could be avoided (Greene, Hoffmann, and Stark, 2019).

Although emphasizing ethics is an important and commendable step in data science’s development toward becoming more socially responsible, it is an insufficient response to the broad issues of social justice that are implicated by data science. As one review of AI ethics principles concluded, “Shared principles are not enough to guarantee trustworthy or ethical AI” (Mittelstadt, 2019). Ethics (at least as it has been deployed in the context of data science) suffers from several limitations.

First, data science ethics relies on an artificial divide between technology and society. Existing ethics codes tend to follow a logic of technological determinism (Dafoe, 2015; Smith and Marx, 1994), treating technology as an unstoppable force following a predetermined path that requires ethical design in order to avoid negative impacts (Greene, Hoffmann, and Stark, 2019; Metcalf, Moss, and boyd, 2019). This framework leads to technological solutionism, focusing on improving the design of technology as the key to creating ethical technologies (Metcalf, Moss, and boyd, 2019). Similarly, computer science courses approach ethical engineering with an emphasis on individual thoughtfulness, in the hope that technologists thinking about ethics will lead to better social outcomes (Silbey, 2018). In this way, we are presented with digital technology as a natural force that can merely be tinkered with. But technologies are not simple tools that can be designed into

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2 In Black Feminist Thought, Patricia Hill Collins defines a “social justice project” as “an organized, long-term effort to eliminate oppression and empower individuals and groups within a just society.” Oppression, she writes, is “an unjust situation where, systematically and over a long period of time, one group denies another group access to the resources of society” (Collins, 2000). Thus, social justice as a concept is particularly concerned with promoting equity across society’s institutions. Toward these ends, efforts to promote social justice include abolishing discrimination in policing; ending mass incarceration; expanding access to healthcare, shelter, and education; and eliminating policies that enable or exacerbate poverty.

3 It is important to note that dominant applications of ethics to data science represent just a particular instantiation of ethics as an academic discipline. As a result, it is common for ethicists to respond to critiques of ethics with a defense of the field: à la “your critique mischaracterizes ethics.” In this debate, both sides are, within their own terms, correct. Critics, focused on applications and colloquial usage of ethics, rightly point to the limitations of existing approaches. Ethicists, focused on the academic field of ethics, rightly argue that ethics is far richer than described. With this in mind, we must be attentive to the differences between what I would classify in this context as ethics-in-theory and tech-ethics-in-practice. Two responses are necessary. First, defenders of ethics must be careful to characterize their interjections as defenses of ethics-in-theory, not tech-ethics-in-practice; otherwise, defenses of ethics-in-theory may inadvertently serve as undeserved defenses of tech-ethics-in-practice. Conversely, critics of tech ethics must recognize that tech-ethics-in-practice does not represent the full domain of ethics and that ethics-in-theory has much to offer both their own critiques and tech-ethics-in-practice.
having good or bad outcomes. Instead, technological development is contingent on social, economic, and political conditions and on the varying levels of agency that people have to alter the direction of technological development. Efforts to avoid harm cannot be reduced to narrow questions of design. For instance, even if criminal justice risk assessments are designed to perfectly satisfy goals of accuracy and algorithmic fairness, their deployment can nonetheless reinforce injustice by legitimizing unjust practices and hindering more structural criminal justice reforms (Green, 2020).

Second, data science ethics rarely come with any mechanisms to ensure that engineers follow ethical principles or to hold violators accountable (Mittelstadt, 2019). One small experimental study found that presenting software engineers with the ACM Code of Ethics had no effect on behavior (McNamara, Smith, and Murphy-Hill, 2018). This result mirrors studies that have similarly shown the limits of ethics codes to affect behavior in other domains (Brief et al., 1996; Kish-Gephart, Harrison, and Trevino, 2010). Moreover, in a move that has been called “ethics-washing” (Wagner, 2018), tech companies are deploying the language of ethics to resist the enactment of regulation—i.e., precisely to avoid accountability (Metcalf, Moss, and boyd, 2019; Nemitz, 2018; Ochigame, 2019; Wagner, 2018). This is a common effect of ethics within the sciences: in cases such as population genetics, “systems of ethics […] play key roles in eliding fundamental social and political issues,” allowing scientists to proceed with politically charged scientific practices while escaping responsibility under a veneer of being ethical (Reardon, 2011). In other words, not only do data science ethics codes misunderstand the relationship between technology and social change—they are themselves based on an incomplete theory of social change: while ethics codes can help make a group appear ethical, on their own they do little to ensure a culture of ethical behavior (Wood and Rimmer, 2003). In this sense, engineers treat ethics codes and technology through similar perspectives of determinism, taking for granted that each artifact will spur a particular social outcome rather than recognizing the complexities of integrating these tools into social contexts.

Finally, data science ethics lack an explicit normative underpinning, instead defaulting to vague normative principles and to conventional business ethics and logics
Today’s high-level ethics principles “hide deep political and normative disagreement” (Mittelstadt, 2019). From a historical perspective, this should not be particularly surprising: simply put, advancing social justice is not the function that professional ethics serves. Instead, the primary role of ethics codes is to define what it means to be a “professional” within any given field; these codes, especially in computing, rarely make explicit claims about specific normative principles or obligations to society, instead offering broad recommendations that, for example, computer scientists “be ever aware of the[ir] social, economic, cultural, and political impacts” and “contribute to society and human well-being” (Stark and Hoffmann, 2019). As a result, write digital media and information scholars Luke Stark and Anna Lauren Hoffmann, data scientists should “take ‘ethics’ as a starting point, not as an end. Codes of ethics increasingly serve to demarcate data culture as a domain of experts, and conversations around professional ethics in data science and related fields such as ML/AI are a necessary but absolutely insufficient condition for [promoting] progressive, just and equitable social outcomes” (Stark and Hoffmann, 2019).

While ethics provides useful frameworks to help data scientists reflect on their practice and the impacts of their work, these approaches have not resolved the normative questions of what impacts are desirable and how to negotiate between conflicting perspectives (nor the question of how to leverage technology toward these ends). For these normative matters there is no simple nor intrinsically correct answer—only decisions that can be reached through deliberation and debate. As philosopher John Rawls writes, “The ‘real task’ of justifying a conception of justice is not primarily an epistemological problem [that requires] the search for moral truth interpreted as fixed by a prior and independent order of objects and relations,” but rather to “search for reasonable grounds for reaching agreement rooted in our conception of ourselves and in our relation to society” (Rawls, 1980).

For this task described by Rawls, ethics codes must cede to a related form of social evaluation: politics. In the absence of universal moral principles, data scientists must engage in the process of negotiating between competing perspectives, goals, and values.
By developing tools that inform or make important social and political decisions—who receives a job offer, what news people see, where police patrol—data scientists increasingly shape social outcomes around the world. These decisions and responsibilities cannot be managed through to a narrow professional ethics that lacks normative weight and supposes that, with some reflection and a commitment to best practices, data scientists will make the “right” decisions that lead to “good” technology.

Just as many data scientists have begun to recognize that data and technology are not neutral, data scientists must similarly recognize that data science itself is not neutral—that they, as practitioners, are not neutral actors. Instead, data science is a form of political action. Data scientists must recognize themselves as political actors engaged in normative constructions of society and, as befits political work, evaluate their efforts according to the downstream impacts on people’s lives.

To be clear, by politics and political, I do not refer directly to partisan or electoral debates about specific parties and candidates. Instead, I invoke these terms in a broader sense transcends activity directly pertaining to the government, its laws, and its representatives. Two aspects of politics are paramount. First, politics is everywhere in the social world. As defined by politics professor Adrian Leftwich, “politics is at the heart of all collective social activity, formal and informal, public and private, in all human groups, institutions and societies” (Leftwich, 1984). Second, politics has a broad reach. Political scientist Harold Lasswell describes politics as “who gets what, when, how” (Lasswell, 1936). The “what” here could mean many things: money, goods, status, influence, respect, rights, and so on. Understood in these terms, politics comprises anything that affects or makes claims about the who, what, when, and how in social groups, both small and large.

As architects of decision-making systems, data scientists are political actors in that they play an increasingly powerful role in defining such distributions across a wide array of social contexts. By structuring how institutions conceive of problems and make decisions, data scientists are some of today’s most powerful (and obscured) political actors. For scientists possess “a source of fresh power that escapes the routine and easy definition of a stated political power” (Latour, 1983). In other words, the world cannot be so easily divided up into science on the one hand and traditional politics on the other—
instead, “the scientific workplace functions as a key site for the production of social and political order” (Jasanoff, 2003). As such, “technological dramas” represent “a specifically technological form of political discourse” (Pfaffenberger, 1992).

This essay will justify and develop the notion of data science as political action. My argument raises two questions: 1) Why must data scientists recognize themselves as political actors? and 2) How can data scientists ground their practice in a politics of social justice? The two parts of this essay will take up these questions in turn.

If we are to understand data science as political action, then it is imperative to develop a political theory of data science. The starting point for such a theory is science, technology, and society (STS), which has been described as “the political philosophy of our time” (Pfaffenberger, 1992). I will also engage with fields such as critical algorithm studies and philosophy of technology, which have for decades studied the interactions between technology and society, as well as with other fields such as law, sociology, and critical race theory, which more broadly study social and political systems.

The field of data science needs a new approach that does not confine itself to a superficial technical neutrality. This approach does not require that every data scientist share a singular political vision—that would be wildly unrealistic. In fact, it is precisely because the field (and world) hosts a diversity of normative perspectives that we must surface political debates and recognize the role they play in shaping data science practice. Nor is this argument meant to suggest that articulating one’s political commitments is a simple task. Normative ideals can be complex and conflicting, and one’s own principles can develop and evolve over many years. Data scientists need not have precise answers about every political question, but must nonetheless act in light of their principles and grapple with the uncertainty that surrounds these ideals.

This is the necessary path forward. My intention is not to stop data science in its tracks or to critique individual practitioners, but to articulate a new direction that the field must forge if it is to wield its power responsibly and promote a more equal and just society.
Part 1: Why must data scientists recognize themselves as political actors?

The first part of this essay will attempt to answer this question in the form of a dialogue with a well-intentioned skeptic. In particular, I will respond to three canonical arguments that are invoked by data scientists when they are challenged to take political stances regarding their work. These arguments have been expressed in a variety of public and private settings and will be familiar to anyone who has engaged in discussions about the social impacts of data science.

These are by no means the only arguments proffered in this larger debate, nor are they meant to represent any sort of “official” or unified position among data scientists. In practice, computer scientists are “diverse and ambivalent characters” (Seaver, 2017) who engage in “nuanced, contextualized, and reflexive practices” (Neff et al., 2017) as they “continuously straddle the competing demands of formal abstraction and empirical contingency” (Passi and Jackson, 2017). Some computer science subfields (such as CSCW (Bowker et al., 1997)) have long histories of engaging with sociotechnical practices and normative implications, while others (such as FAccT, formerly FAT*) are actively developing such approaches. Nonetheless, in my experience, the three positions considered here are the most common and compelling arguments made against a politically oriented data science. Any promotion of a more politically engaged data science must contend with them.

Argument 1: “I’m just an engineer.”

This statement represents a common attitude among engineers. Although engineers develop new tools, the thinking goes, their work does not determine how a tool will be used. This denial of being a political actor relies on simplistic notions of technologies as objects that lack any inherent normative character and that can simply be used in good or bad ways. By this logic, engineers bear no responsibility for the impacts of their creations.
It is common for computer scientists to argue that the impacts of technology are unknowable. As one computer scientist who faced criticism for developing facial recognition software argued in defense of his work, “Anything can be used for good. Anything can be used for bad” (Vincent, 2018). Similarly, during the 2019 NeurIPS Joint Workshop on AI for Social Good, in which two panelists highlighted the harmful impacts of AI on communities of color, several computer scientists in the audience countered that it is impossible to know what the impacts of research will be or to prevent others from misusing products (Adjodah, 2019).

By articulating their limited role as neutral researchers, data scientists provide themselves with an excuse to abdicate responsibility for the social and political impacts of their work. When a paper that used neural networks to classify crimes as gang-related was challenged for its potentially harmful effects on minority communities, a senior author on the paper deflected responsibility by arguing, “It’s basic research” (Hutson, 2018).

Although this is a common fallacy that guides much thinking about digital technologies, many scholars have articulated the ways in which technology embeds politics and shapes social outcomes. As political theorist Langdon Winner describes, “technological innovations are similar to legislative acts or political foundings that establish a framework for public order that will endure over many generations. For that reason, the same careful attention one would give to the rules, roles, and relationships of politics must also be given to such things as the building of highways, the creation of television networks, and the tailoring of seemingly insignificant features on new machines. The issues that divide or unite people in society are settled not only in the institutions and practices of politics proper, but also, and less obviously, in tangible arrangements of steel and concrete, wires and semiconductors, nuts and bolts” (Winner, 1986).

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4 In a similar manner, Mark Zuckerberg has repeatedly attempted to evade accountability for Facebook’s mishaps by professing that he neither intended nor foresaw the negative consequences of the company’s decisions (Tufekci, 2018).
In other words, even though technology does not conform to conventional notions of politics, it often shapes society in much the same way as laws, elections, and judicial opinions.

There are many examples of engineers developing and deploying technologies that, by structuring behavior and shifting power, shape aspects of society. As one example, Winner famously (and controversially (Joerges, 1999; Woolgar and Cooper, 1999)) points to how Robert Moses designed the bridges over the parkways on Long Island, New York with low overpasses. Moses did this not for technical purposes such as ensuring structural stability, but to prevent buses (which predominantly carried lower-class and non-white urban residents) from navigating these parkways and accessing the parks to which they led (Winner, 1986).

This was not the first time that engineers generated social changes through the design of traffic technologies. As historian Peter Norton describes in Fighting Traffic, when automobiles were introduced onto city streets in the 1920s, they created chaos and conflict in the existing social order. Many cities turned to traffic engineers as “disinterested experts” whose scientific methods could provide a neutral and optimal solution. But the solution that these engineers devised was laden with unexamined assumptions and values, namely, that “[traffic] efficiency worked for the benefit of all.” As traffic engineers changed the timings of traffic signals to enable cars to flow freely, their so-called solution “helped to redefine streets as motor thoroughfares where pedestrians did not belong.” These actions by traffic engineers helped shape the next several decades of automobile-focused urban development in U.S. cities (Norton, 2011).

Although these particular outcomes could be chalked up to unthoughtful design, any decisions that Moses or the traffic engineers made would have had some such impact: determining how to design bridges and time streetlights requires judgments about what outcomes and whose interests to prioritize. Whatever they and the public may have believed, traffic engineers were never “just” engineers optimizing society “for the benefit of all”—instead, they were engaged in the process, via formulas and construction, of defining which street uses should be supported and which should be constrained. Moses
and the traffic engineers may not have decreed by law that streets were for cars, but their technological intervention assured this outcome by other means.

Data scientists today risk repeating this pattern of designing tools with inherently political characters yet largely overlooking their own agency and responsibility. By imagining an artificially limited role for themselves, engineers create an environment of scientific development that requires few moral or political responsibilities. But this conception of engineering has always been a mirage. Developing any technology contributes to the particular “social contract implied by building that [technological] system in a particular form” (Winner, 1986).5

Of course, we must also resist placing too much responsibility on engineers. The point is not that, if only they recognized their social impacts, engineers could themselves solve social issues—technology is just one tool among many to address complex social problems (Green, 2019). Nor should we desire that engineers be granted more responsibility to determine technology’s role in society. As STS scholar Sheila Jasanoff argues, “The very meaning of democracy […] increasingly hinges on negotiating the limits of the expert’s power in relation to that of the publics served by technology” (Jasanoff, 2006). Having unelected and unaccountable technical experts make core decisions about governance away from the public eye imperils essential notions of how a democratic society ought to function.

Yet the design and implementation of technology does rely, at some level, on trained practitioners. It is therefore necessary to put the role of a data scientist in context: not “just” an engineer, but an engineer nonetheless. Data scientists ought to be held accountable for their research, yet should not be expected to solve problems on their own nor be fully responsible for how their tools are deployed. So, what responsibilities should data scientists bear? How must data scientists reconceptualize their scientific and societal roles? These questions will animate the rest of our discussion.

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5 Facial recognition software represents just one example of a technology that establishes “a framework for public order” (Winner, 1986) inextricably linked with unjust and oppressive structures of social control. Due to its ability to pervasively identify and track people without their knowledge or consent, facial recognition has been described as “the plutonium of AI” (Stark, 2019) and called “the most uniquely dangerous surveillance mechanism ever invented” (Hartzog and Selinger, 2018).
Argument 2: “Our job isn’t to take political stances.”

Data scientists who make statements of this sort likely accept the response to Argument 1 but feel hamstrung, unsure how to appropriately act as more than just an engineer. “Sure, I’m developing tools that impact people’s lives,” they may acknowledge, before asking, “But isn’t the best thing to just be as neutral as possible?” Indeed, recent ethnographic work has found that data science projects emerge with “explicit normative considerations [rarely] in mind” (Passi and Barocas, 2019).

Although it is understandable how data scientists come to this position, their desire for neutrality suffers from two important failings. First, neutrality is an unachievable goal, as it is impossible to engage in science or politics without being influenced by one’s background, values, and interests. Second, striving to be neutral is not itself a politically neutral position—it is a fundamentally conservative one.⁶

An ethos of objectivity has long been prevalent among scientists. Since the nineteenth century, objectivity has evolved into a set of widespread ethical and normative scientific practices. Conducting good science—and being a good scientist—meant suppressing one’s own perspective so it would not contaminate the interpretations of observations (Daston and Galison, 2007).

Yet this conception of science was always rife with contradictions and oversights: the practice of science, even when conducted under the model of objectivity, requires active theorizing to develop questions, hypotheses, protocols, and objectives. Knowledge is shaped and bounded by the social contexts that generated it. This insight forms the backbone of standpoint theory, which articulates that “nothing in science can be protected from cultural influence—not its methods, its research technologies, its conceptions of nature’s fundamental ordering principles, its other concepts, metaphors, models, narrative structures, or even formal languages” (Harding, 1998). Although scientific standards of objectivity account for certain kinds of individual subjectivity, they are too narrowly construed: “methods for maximizing objectivism have no way of detecting values,

⁶ I use conservative here in the sense of maintaining the status quo rather than in relation to any specific political party or movement.
interests, discursive resources, and ways of organizing the production of knowledge that first constitute scientific problems, and then select central concepts, hypotheses to be tested, and research designs” (Harding, 1998).

These processes make the supposedly objective scientific “gaze from nowhere” nothing more than “an illusion” (Haraway, 1988). Every aspect of science, broadly conceived, is imbued with the characteristics and interests of those who produce it. This does not invalidate every scientific finding as arbitrary, but points to science’s contingency and reliance on its practitioners—all research and engineering are developed within particular institutions and cultures and with particular problems and purposes in mind. While a society in the desert may deeply study water’s evaporative properties (and know little about ice), for example, a society in the tundra may focus on the varied ways in which water can freeze into ice (and know little about evaporation). Even if the scientists within these cultures abide by the rules of scientific objectivity, they nonetheless operate in a context indelibly marked by local interests.

Just as it is impossible to conduct science in any truly neutral way, there similarly is no such thing as a neutral (or apolitical) approach to politics. As philosopher Roberto Unger writes, political neutrality is an “illusory and ultimately idolatrous goal” because “no set of practices and institutions can be neutral among conceptions of the good” (Unger, 1987).

Even if it were possible to be neutral and apolitical, however, such a stance would be undesirable. For neutrality does not mean value-free—it means acquiescence to dominant social and political values, freezing the status quo in place. Neutrality may appear to be apolitical, but that is only because hegemonic power manifests pervasively without appearing explicitly political. Anything that challenges the status quo—which efforts to promote social justice must by definition do—will therefore be seen as political. But efforts for reform are no more political than efforts to resist reform or even the choice simply to not act, both of which preserve existing systems.

Although surely not the intent of every scientist or engineer who strives for neutrality, broad cultural conceptions of science as neutral entrench the perspectives of dominant social groups, who are the only ones entitled to legitimate claims of neutrality.
For example, many scholars have noted that neutrality is defined by a masculine perspective that exists in opposition to a feminine one, making it impossible for women to be seen as objective or for neutral positions to consider female standpoints (Harding, 1998; Keller, 1985; Lloyd, 1993; MacKinnon, 1982). The voices of Black women are particularly subjugated as partisan and anecdotal (Collins, 2000). Because of these perceptions, when people from marginalized groups critique scientific findings, they are cast off as irrational, political, and representing a particular perspective—a “special-interest group” (Haraway, 1988). The practices and cultures of science and the perspectives of the dominant groups that uphold it, on the other hand, are rarely considered to suffer from the same maladies.

Data science exists on this political landscape. Whether articulated by their developers or not, machine learning systems already embed political stances. Overlooking this reality merely allows these political judgments to pass without scrutiny, in turn granting data science systems with more credence and legitimacy than they deserve.

Predictive policing systems offer a particularly pointed example of how striving to remain neutral entrenches and legitimizes existing political conditions. The issue is not simply that the training data behind predictive policing algorithms is biased due to a history of overenforcement in minority neighborhoods—our very definitions of crime are the product of racist and classist historical processes. Dating back to the eras of slavery and reconstruction, cultural associations of Black men with criminality have justified extensive police forces with broad powers (Butler, 2017). The War on Drugs, often identified as a primary cause of mass incarceration, emerged out of an explicit agenda by the Nixon administration to target people of color (Alexander, 2012). As Nixon’s special counsel John Ehrlichman explained years later, “We knew we couldn’t make it illegal to be either against the war or black. But by getting the public to associate the hippies with marijuana and blacks with heroin, and then criminalizing both heavily, we could disrupt those communities. We could arrest their leaders, raid their homes, break up their meetings, and vilify them night after night on the evening news. Did we know we were lying about the
drugs? Of course we did” (Baum, 2016). Meanwhile, crimes like wage theft— which steal far more value than all other kinds of theft (such as burglaries) combined, but are carried out by business owners against low-income workers (Meixell and Eisenbrey, 2014)—are systemically underenforced by police and therefore do not even register as relevant to conversations about predictive policing.

Moreover, predictive policing rests on a model of policing that is itself unjust. Predictive policing software could exist only in a society that deploys vast punitive resources to prevent social disorder following “broken windows” tactics (just as, for instance, methods for studying election polls could exist only in a society with democratic elections). Policing has always been far from neutral: “the basic nature of the law and the police, since its earliest origins, is to be a tool for managing inequality and maintaining the status quo” (Vitale, 2017). The discriminatory issues with policing are not flaws of training or methods or “bad apple” officers, in other words, but are endemic to policing itself (Butler, 2017; Vitale, 2017).

Against this backdrop, the very act of choosing to develop predictive policing algorithms is not at all neutral. Accepting common definitions of crime and how to address it does not allow data scientists to remove themselves from politics—it merely allows them to seem removed from politics, when in fact they are upholding the politics that have led to our current social conditions.

Although predictive policing represents a notably salient example of how data science cannot be neutral, the same could be said of all data science. Biased data is certainly one piece of the story, but so are existing social and political conditions, definitions and classifications of social problems, and the set of institutions that respond to those problems. None of these factors can be removed from politics and said to be neutral. And while data scientists are of course not responsible for creating these aspects of society, they are responsible for choosing how to interact with them. Neutrality in the face of injustice only reinforces that injustice (Green, 2020). When engaged with aspects of the

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7 When employers deny their employees of wages or benefits to which they are legally entitled (e.g., not paying employees for overtime work).
world steeped in history and politics, in other words, it is impossible for data scientists to not take political stances.

Argument 3: “We should not let the perfect be the enemy of the good.”

Following the responses to Arguments 1 and 2, the engineers who make this statement acknowledge that their creations will unavoidably have social impacts and that neutrality is not possible. Yet still holding out against a thorough political engagement, they fall back on a seemingly pragmatic position: while not perfect, these tools improve society in incremental but important ways; we should therefore support their development rather than argue about what a perfect solution might be.

Despite being the most sophisticated of the three arguments, this position suffers from several underdeveloped principles. First, data science lacks robust theories and discourse regarding what “perfect” and “good” actually entail. As a result, the field typically adopts a superficial approach to politics that involves making vague (almost tautological) claims about what social conditions are desirable. Second, this argument fails to articulate how to evaluate or navigate the relationship between the perfect and the good. Efforts to promote social good thus tend to take for granted that technology-centric incremental reform is an appropriate strategy for social progress. Yet, considered from a perspective of substantive equality and anti-oppression, it is not clear that these efforts to do good are, in fact, consistently doing good.

Across the broad world of data science, from academic institutes to conferences to companies to volunteer organizations, “social good” (or just “good”) has become a term du jour. Numerous universities across the United States and Europe have hosted the Data Science for Social Good Summer Fellowship. Several major computer science conferences have hosted AI for Social Good workshops, and in 2014 the theme of the entire ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD) was “Data Mining for Social Good.” Since 2014, the company Bloomberg has hosted an

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8 [http://www.dssgfellowship.org](http://www.dssgfellowship.org)
9 [https://aiforsocialgood.github.io/](https://aiforsocialgood.github.io/)
10 [https://www.kdd.org/kdd2014/](https://www.kdd.org/kdd2014/)
annual Data for Good Exchange.\textsuperscript{11} The non-profit Delta Analytics strives to promote “Data-driven solutions for social good.”\textsuperscript{12}

While this energy to do good among the data science community is both commendable and exciting, the field has not developed (nor even much debated) any working definitions of the term “social good” to guide its efforts. Instead, the field seems to operate on a “know it when you see it” approach, relying on rough proxies such as crime=bad, poverty=bad, and so on. The term’s lack of precision prompted one of Delta Analytics’ founders to write that “‘data for good’ has become an arbitrary term to the detriment of the goals of the movement” (Hooker, 2018). The notable exception is Mechanism Design for Social Good (MD4SG), which articulates a clear research agenda “to improve access to opportunity, especially for communities of individuals for whom opportunities have historically been limited” (Abebe and Goldner, 2018).

In fact, the term “social good” lacks a thorough definition even beyond the realm of data science. It is not defined in dictionaries like Merriam-Webster, the Oxford English Dictionary, and Dictionary.com, nor does it have a page on Wikipedia, where searching for “social good” automatically redirects to the page for “common good”—a term similarly undefined in data science parlance (Berendt, 2018). To find a definition one must look to the financial education website Investopedia, which defines social good as “something that benefits the largest number of people in the largest possible way, such as clean air, clean water, healthcare and literacy,” and describes it as a way for companies to focus on more than just profits, in the vein of corporate social responsibility (Investopedia, 2018). There is, of course, a deep literature spanning philosophy, STS, and other fields that consider the nature and meaning of what is “good”—yet this literature rarely speaks in terms of “social good” nor is it typically referenced within data science efforts to promote “social good.”

This lack of grounding leads to “data for good” projects spanning a wide range of political characters. For example, some work under this umbrella is explicitly developed to enhance police accountability and promote non-punitive alternatives to incarceration (Bauman et al., 2018; Carton et al., 2016), while other work uses data to predict and

\textsuperscript{11} \url{https://www.bloomberg.com/company/d4gx/}
\textsuperscript{12} \url{http://www.deltanalytics.org}
classify crimes to aid police investigations (Center for Technology Society & Policy, 2018; Seo et al., 2018). That such politically disparate and conflicting work could be part of the same movement should prompt a reconsideration of the core terms and principles. When the movement encompasses everything, it stands for nothing.

The point is not that there exists a single optimal definition of “social good,” nor that every data scientist should agree on one set of principles. There is a multiplicity of perspectives that must be openly acknowledged to surface debates about what “good” actually entails. Currently, however, the field lacks the language and perspective to sufficiently evaluate and debate differing visions of what is “good.” By framing their notions of good in such vague and undefined terms, data scientists get to have their cake and eat it too: they can receive praise and publications based on broad claims about solving social challenges while avoiding substantive engagement with social and political impacts.

USC’s Center for Artificial Intelligence in Society (CAIS) is emblematic of how data science projects labeled as promoting “social good” can cause harm by wading into hotly contested political territory with a regressive perspective. One of the group’s projects involved deploying game theory and machine learning to predict and prevent behavior from “adversarial groups.” Although CAIS motivated the project by discussing “extremist organizations such as ISIS and Jabhat al-Nusra,” it quickly slipped into focusing on “criminal street gangs” (USC Center for Artificial Intelligence in Society, 2018). In fact, the project’s only publication involved a controversial paper classifying gang crimes in Los Angeles (Hutson, 2018; Seo et al., 2018). This conflation of terrorists and gang members echoes the language of “superpredators” used in the 1990s to justify harsh policing and sentencing practices (Vitale, 2018) and is part of a long lineage of military ideas and practices being transferred to local police departments for use in poor and minority neighborhoods (Atkinson, 2016). Moreover, the paper took for granted the legitimacy of the Los Angeles Police Department’s gang data—a notoriously biased type of data (Felton, 2018) from a police department that has a long history of abusing minorities in the name of gang suppression (Vitale, 2017).

Whether or not the data scientists behind this and similar projects recognize it, their decisions about what problems to work on, what data to use, and what solutions to propose
involve normative stances that affect the distribution of power, status, and rights across society. They are, in other words, engaging in political activity. And although these efforts are intended to promote “social good,” that does not guarantee that everyone will consider them to be beneficial. Despite their label, projects like CAIS’ gang classification paper are many people’s version—most notably, the communities subject to gang-preventive police tactics—of a distinct and severe “bad” (Stop LAPD Spying Coalition, 2018).

Most dangerously, while data science’s vague framing of social good appears to result from a failure to recognize that such claims could be contested rather than from an explicit attempt to stifle debate, this approach nonetheless allows those already in power to present their normative judgments about what is “good” as neutral facts that are difficult to challenge. As discussed with regard to Argument 2, neutrality is an impossible goal and attempts to be neutral tend to reinforce the status quo. Thus, if the field does not openly reflect on the assumptions and values that underlie essential aspects of data science—such as identifying research questions, proposing solutions, and defining “good”—the assumptions and values of dominant groups will tend to win out. Projects that purport to enhance social good without a reflexive\(^\text{13}\) engagement with social and political context are likely to reproduce the exact forms of social oppression that many working towards “social good” seek to dismantle.

It is clear that the field’s notion of “social good” is poorly defined and far from universally shared. Indeed, after previously acknowledging that their technologies have social impacts, data scientists may now further backtrack and concede that some may disagree with their definitions of “good.” But, they may say, “Isn’t some solution, however imperfect, better than nothing?” The natural corollary of “we should not let the perfect be the enemy of the good” is that “we should not delay solutions over concerns of optimal” outcomes (Sylvester and Raff, 2018).

At this point the second main failure of Argument 3 becomes clear: it tells us nothing about the relationship between the perfect and the good. Although efforts to

\(^{13}\) Reflexivity refers to the practice of treating one's own scientific inquiry as a subject of analysis (Bloor, 1991).
promote “social good” can be productive,\(^{14}\) data science has thus far not developed any rigorous methodology for considering the relationship between algorithmic interventions and social impacts. The field takes for granted that, even though data science cannot provide perfect solutions to social problems, it can nonetheless contribute to “good” by contributing incremental reforms that improve many aspects of society. The argument appears to be that we all agree that crime, poverty, and discrimination are problems, so we should applaud any attempts to alleviate those issues and not waste time and energy debating the ideal solution (let alone whether that solution should involve digital technologies). Meanwhile, the argument treats “the perfect” as an unrealistic utopia that, on account of its impossibility of being realized, is not worth articulating or debating.

Pursuing social good without considering the long-term impacts can lead to great harm, however: what may seem good in a narrow sense can be actively harmful from a broader perspective. Understood in these terms, the dichotomy between the idealized perfect and the incremental good is a false one: it is only through debating and refining our imagined conditions of the perfect society—an essential component of politics—that we can conceive of and evaluate potential incremental goods. Because there is a multiplicity of imagined perfects, which in turn suggest an even larger multiplicity of incremental goods, any incremental good must be evaluated based on what type of society it promotes in both the short and long term.

Evaluating these incremental goods and long-term perfects is therefore the essential task, for not all incremental reforms are made equal or push society down the same path. As social philosopher André Gorz proposes, we must distinguish between “reformist reforms” and “non-reformist reforms” (Gorz, 1967). “A reformist reform,” explains Gorz, “is one which subordinates its objectives to the criteria of rationality and practicability of a given system and policy.” A non-reformist reform, on the other hand, “is conceived not in terms of what is possible within the framework of a given system and administration, but in view of what should be made possible in terms of human needs and demands.”

\(^{14}\) See e.g., the set of projects completed by the Data Science for Social Good Fellowship: http://www.dssgfellowship.org/projects/.
These two types of reform may appear similar from the outside, as they are both types of incremental reform, but they are conceived through quite distinct processes: reformist reformers start from within existing systems and look for ways to improve them; in contrast, non-reformist reformers start from beyond existing systems, focusing on what social conditions are desirable, and then look for ways to promote those outcomes. Because of the distinct ways that these two types of reforms are conceived, the pursuit of one versus the other can lead to widely divergent social and political outcomes.

The solutions proposed by data scientists are almost entirely reformist reforms. The standard logic of data science—grounded in accuracy and efficiency—tends to require accepting and working within the parameters of existing systems to promote the achievement of their goals. Data science interventions are therefore typically proposed to improve the performance of a system rather than to substantively alter it. And while these types of reforms certainly have value under the right conditions, such an ethos of reformist reforms is unequipped to identify and pursue the larger changes that are necessary across many social and political institutions (this approach may even serve to entrench and legitimize the status quo). From the standpoint of existing systems, it is impossible to imagine alternative ways of structuring society—when reform is conceived in this way, “only the most narrow parameters of change are possible and allowable” (Lorde, 1984).

In this sense, the field’s current strategy of pursuing a reformist, incremental good resembles a greedy algorithm: at every point in time, the strategy is to make immediate improvements in the local vicinity of the status quo. But although a greedy strategy can be useful for simple problems, it is unreliable in complex search spaces: we may quickly find a local maximum, but will never reach a further-afield terrain of far better solutions. Data scientists would never accept a greedy algorithm for complex optimization problems, and similarly should not accept a reformist strategy for complex political problems—where “the optimum solution demands ‘structural reforms’ which modify the relationship of forces, the redistribution of functions and powers, [and] new centers of democratic decision making” (Gorz, 1967).15

15 In many contexts, of course, it is not possible to achieve perfect solutions through optimization techniques. But even in these settings, data scientists approach the problem with rigor, developing and characterizing
The U.S. criminal justice system, a domain where data scientists are increasingly striving to do good, exemplifies the limits of a reformist mindset. The problem is that most data science efforts to contribute “good” are grounded in the existing logics and discourses of the criminal justice system. Even if they lead to incremental improvements, such reforms tend to legitimize the criminal justice system’s structural racial violence (Green, 2020). As political scientist Naomi Murakawa explains, “Administrative tinkering does not confront the damning features of the American carceral state, its scale and its racial concentration […] Without a normatively grounded understanding of racial violence, liberal reforms will do the administrative shuffle” (Murakawa, 2014).

Because criminal justice reform can be “superficial and deceptive” (Karakatsanis, 2019), it is particularly important to couch reform efforts within a broader vision of long-term, non-reformist change. This is the emphasis articulated by the movement for prison abolition (Davis, 2003; McLeod, 2015). Recognizing the violence inherent to confining people in cages and to controlling people’s lives through the threat or enactment of force, prison abolition aims to create a world without prisons. Notably, with this goal in mind, prison abolitionists object to reforms that “render criminal law administration more humane, but fail to substitute alternative institutions or approaches to realize social order maintenance goals” (McLeod, 2013). It is not enough that reforms produce superficial improvements to the criminal justice system; instead, only reforms that reduce or replace carceral responses to social disorder are pursued.

Pretrial risk assessments exemplify how data scientists’ reformist reforms can make it harder to achieve structural social change. In response to the injustices of cash bail—which requires criminal defendants to pay money to be released from custody until their trial—groups including data scientists (Corbett-Davies, Goel, and González-Bailón, 2017), criminal defense organizations (Gideon’s Promise et al., 2017), U.S. senators (Harris and Paul, 2017), and state legislatures (New Jersey Courts, 2017) have proposed replacing money bail with risk assessments that determine who should be detained until trial based approximation algorithms. The same logic applies in political contexts, where the optimal solution is rarely achievable (if even definable): it is necessary to fully characterize the problem space and to evaluate how robustly and effectively different approaches can lead to desired outcomes.
on each defendant’s predicted likelihood to be rearrested before trial or fail to appear for trial. Yet such calls for an algorithmic reform overlook the ways in which seemingly “good” (and “fair”) criminal justice algorithms can reinforce carceral injustice, whether through legitimizing unjust policies and logics (Green, 2019, 2020), distorting deliberative processes (Green, 2018), biased uses by practitioners (Albright, 2019; Cowgill, 2018; Green and Chen, 2019), shifting control of governance toward unaccountable private actors (Brauneis and Goodman, 2018; Joh, 2017; Wexler, 2018), or allowing public officials to claim credit for embracing reform even as they ignore or squash more substantive change (Karakatsanis, 2019).

Meanwhile, an entirely separate incremental reform—an abolitionist, non-reformist, and non-technological one—is possible: ending cash bail and pretrial detention. Such a change would be one small step toward abolishing practices that contribute to mass incarceration. And it is not unattainable: recent surveys have found that 71% of voters in New York State support ending pretrial jail for misdemeanors and non-violent felonies (FWD.us, 2018) and 46% of voters nationwide support ending cash bail, compared to 24% opposed (Data for Progress, 2018).

Although adopting pretrial risk assessments and abolishing pretrial detention appear to respond to the same problem, they derive from conflicting visions of the “perfect.” One envisions a just world as one that includes pretrial detention, believing that the current issue with pretrial detention is not that the practice is itself bad, merely that it is determined today along a bad criterion; accordingly, we should remedy the means by which people are selected for pretrial detention. Meanwhile, the other envisions a just world as one without pretrial detention; accordingly, we should abolish the practice altogether. Thus we see that the debate about risk assessments has little to do with technical matters such as fairness and accuracy or pragmatic considerations about the perfect versus the good, and instead hinges on political questions about how the criminal justice system should be structured. It is only be articulating our imagined perfects that we can even recognize the underlying tension between these two incremental reforms, let alone properly debate which one to choose.
By following such logic, many criminal justice reform advocates have recognized the false promise of risk assessments: in July 2018, a coalition of more than 100 advocacy groups signed a shared statement of civil rights concerns, writing, “We believe that jurisdictions should work to end secured money bail and decarcerate most accused people pretrial, without the use of ‘risk assessment’ instruments” (The Leadership Conference Education Fund, 2018). And in February 2020, the Pretrial Justice Institute, a pretrial reform organization that had long championed pretrial risk assessments, declared, “We now see that pretrial risk assessment tools […] can no longer be a part of our solution for building equitable pretrial justice systems” (Pretrial Justice Institute, 2020).

The point is not that data science is incapable of improving society, only that data science must be evaluated against alternative reforms as just one of many options rather than evaluated merely against the status quo as the only possible reform. There should not a starting presumption that machine learning (or any other type of reform) provides an appropriate solution for every problem. Proposing any type of reform is inherently political because it relies on assumptions about what can or should be altered and the relative desirability of different changes; data science reforms tend to (implicitly if not explicitly) accept the core structures and logics of existing systems, assuming that the appropriate reform is to optimize operations given these parameters. There may be situations in which this assumption is correct, but it should not be made or accepted lightly, without thorough interrogation and deliberation.

Striving to stay out of politics is sociotechnically, epistemically, and politically misguided. Although common, this position overlooks technology’s social impacts and privileges the status quo. The field of data science will be unable to meaningfully advance social justice without accepting itself as political. The question that remains is how it can do so.

Part 2: How can data scientists ground their practice in politics?
The first part of this essay argued that data scientists must recognize themselves as political actors. Yet several questions remain: What would a data science that is explicitly
grounded in a politics of social justice look like? How might the field evolve toward this end?

While it is difficult to provide a precise account, we must imagine this future as the first step toward attaining it. After all, my intent is not to halt the development of data science tools or discourage data scientists from working on social problems—it is to highlight a new direction that the field must forge if it is to thoughtfully and responsibly contribute to a more democratic and just future. The path ahead does not require us to abandon our technical expertise. But it does entail expanding our notions of what problems to work on and how to engage with society. This process may involve an uncomfortable period of change, where our conceptions of many aspects of data science evolve. But I am confident that in the process, exciting new areas for research and practice will emerge, producing a field that is equipped to play an important role in promoting equity and social justice.

I conceptualize the process of incorporating politics into data science as following four stages, with reforms at both the individual and institutional/cultural levels. Stage 1 (Interest) involves data scientists becoming interested in working directly on addressing social issues. In Stage 2 (Reflection), the data scientists involved in that work come to recognize the politics that underlie these issues and their attempts to address them. This leads to Stage 3 (Applications), in which data scientists direct the methods at their disposal toward new problems. Finally, Stage 4 (Practice) involves the long-term project of developing new methods and structures that orient data science around a politics of social justice.

I discuss each stage in more detail below. While not every person or project will follow this precise trajectory, it presents for data scientists a possible path to incorporating

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16 It could be argued that the order of Stages 1 and 2 should be reversed: that data scientists should reflect first, then act to address social issues. This would be the most responsible and socially beneficial approach and is the practice that data scientists should follow over the long term (as described above, data science projects that involve insufficient reflection can lead to significant social harm). In my experience, however, data scientists’ paths toward engaging with politics tend to begin with an interest in addressing social challenges, which then leads to more thorough reflection on the political nature of this work (it is possible that this trend has shifted in recent years, as the zeitgeist within data science has evolved from applications to ethical implications). In any case, and in either order, interest and reflection represent important steps toward a more politically-engaged data science.
politics into their practice. In fact, many data scientists already are following some version of these stages toward a politically informed data science.

An essential component of successfully following this path is to prioritize achieving social and political outcomes over deploying technology. This requires an attitude of agnosticism: “approaching algorithms instrumentally, recognizing them as just one type of intervention, one that cannot provide the solution to every problem” (Green and Viljoen, 2020). This technologically-agnostic approach of focusing on social impacts—with technology as a means (just one of many) rather than as an end in itself—enables the critical evaluations of algorithmic work that facilitates progression from Stage 1 to Stages 2, 3, and 4. Without this emphasis on social impacts, it becomes easy to remain stuck at Stage 1 (or to progress to the following the stages in a merely superficial manner). That is one reason why such a path is particularly difficult to pursue within computer science, with its emphasis on formalization (Green and Viljoen, 2020): abstracting a social or political problem into one that is tractable within algorithmic thinking streamlines engagement for data scientists but obfuscates and deemphasizes social impacts.

Recognizing data science as a form of political action will empower and enlighten data scientists with a better framework to improve society through their work. As a form of political action, data science can no longer be separated from broader analyses of social structures, policies, and alternative reforms, treating those elements as fixed or irrelevant. Instead, the field must ground its efforts in debating what impacts are desirable and how to promote those outcomes—thus prompting rigorous evaluations of the issues at hand and openness to the possibility of non-technological alternatives. Such deliberation needs to occur not just among data scientists, but also with scholars from other fields, policymakers, communities of people affected by data science systems, and more. A political orientation will not only free data scientists to motivate their work without needing to rely on notions that can pass as neutral, but will also help them achieve social change through an approach that moves beyond good intentions and focuses rigorously on downstream impacts.
Stage 1: Interest

The first step toward infusing a deliberate politics into data science is for data scientists to orient their work around addressing social issues. Such efforts are already well underway, from “data for good” programs to civic technology groups to the growing numbers of data scientists working in governments and non-profits.

Nonetheless, relative to the interest around such work, there is a dearth of opportunities (across academia, industry, government, and other organizations) for data scientists to apply their skills to an articulated vision of social benefit. Many academic departments and conferences tend not to consider such work to be valid research (unless it first and foremost provides a “technical” contribution), companies can find more profit elsewhere, and governments and non-profits have only a few such positions for employees. Thus, many data scientists who want to do socially impactful work often settle for more traditional research or jobs.

In order to drive interest and training in using data science to address social issues, data science education programs should incorporate such work into their curricula. For example, data science classes that involve problem sets and final projects could incorporate data about society (municipal open data is a valuable resource for this) and allow students to work on social challenges. Resources like job boards and university career services can make it easier for data scientists to find fulfilling roles related to social impact.

In the longer term, data science should work towards a model of “public interest technology” (an idea derived from public interest law) that provides roles, training, and a broader culture of support for data scientists to work directly on improving society through both direct technical work and informing technology policy. This could include jobs where technologists spend several years working in or with government and advocacy groups (along the lines of the United States Digital Service and the Ford Foundation Technology Fellowship) and clinics (again following a model from legal education) where students are supervised as they work directly with “clients” such as activists and government agencies (along the lines of the Data Science for Social Good Summer Fellowship). As part of their

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17 See e.g., a list of job boards and other resources that I have compiled: https://www.benzevgreen.com/jobs/.
training, these programs should emphasize that the driving goal is to positively impact society rather than to deploy technology; the more that students are able to work directly with governments, communities, and service providers (rather than on abstract technology problems), the more thoroughly they will learn this lesson and advance to Stage 2.

**Stage 2: Reflection**

As they increasingly work on data science for social good projects, data scientists will (to the extent that they maintain an open-minded and critical approach grounded in impact rather than technology) come into contact with the political nature of both the issues at hand and their own efforts to address these issues. Whether or not data scientists had an articulated vision of “social good” when they entered Stage 1, the realities of working with real people, data, and institutions will hopefully highlight the inevitably political nature of this work (and the notions of “good” that drive it), requiring data scientists to interrogate their efforts and make normative judgments.

We have seen this process play out most clearly in questions related to algorithmic bias and fairness. Where just a few years ago it was common to hear claims that data represents “facts” and that algorithms are “objective” (Jouvenal, 2016; Smith, 2015), today it is widely acknowledged within data science that data contains biases and that algorithms can discriminate; in addition to the annual ACM Conference on Fairness, Accountability, and Transparency (FAccT, formerly FAT*), there have been numerous workshops dedicated to these issues at major computer science conferences.\(^\text{18}\) Moreover, there is also an emerging literature that articulates the limitations and politics of the approaches to studying and promoting algorithmic fairness (Green, 2020; Green and Viljoen, 2020; Hoffmann, 2019; Selbst et al., 2019).

Over time, data scientists must expand this critical and reflexive lens to increasingly interrogate how all aspects of their work—most of which they have tended to take for granted as mere “technical” definitions and objectives—connect to political processes. For example, to return to our earlier discussion of predictive policing, it is not

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\(^{18}\) See e.g., the list of FAccT Network events: [https://facetconference.org/network/](https://facetconference.org/network/).
sufficient to develop algorithms just with a recognition that crime data is biased—it is necessary to also orient the practice of data science around the recognition that our definitions of crime, the set of institutions that are tasked with responding to it, and the interventions that those institutions provide are all the result of historical political processes laden with discrimination.

Reflection of this sort is propelled by approaching research with an open mind and honoring the expertise of other disciplines, policymakers, and affected communities. Basic fluency in areas such as STS and critical algorithm studies should be required of all data scientists—it should be seen as equally essential to the practice of data science as knowledge of databases and statistics.

Stage 3: Applications
In the short term, the insights provided in Stage 2 need not shake the fundamental structures and practices of data science. Instead, they will empower data scientists to identify how existing methods can be applied to address injustice and shift social and political power. These insights will also help data scientists recognize situations in which non-technological reforms are more desirable than technological ones (Baumer and Silberman, 2011; Green, 2019).

Several frameworks can guide data scientists in these efforts. For example, André Gorz’s schema of reformist and non-reformist reforms provides a way to evaluate interventions based the political path they move us down rather than based on a false dichotomy between incremental and radical reform. Gorz highlights the need for non-reformist reforms and argues that “structural reform always requires the creation of new centers of democratic power” (Gorz, 1967).

The notion of “critical design” from designers Anthony Dunne and Fiona Raby similarly articulates the need to incorporate a critical mindset into the design process and to avoid creating technologies that merely perpetuate current social and political conditions. Dunne and Raby explain, “Design can be described as falling into two very broad categories: affirmative design and critical design. The former reinforces how things are
now, it conforms to cultural, social, technical and economic expectation. Most design falls into this category. The latter rejects how things are now as being the only possibility, it provides a critique of the prevailing situation through designs that embody alternative social, cultural, technical or economic values” (Dunne and Raby, 2001). While this dichotomy does not perfectly capture the complexity of real-world design (Bardzell and Bardzell, 2013), it provides a framework that data scientists can employ to imagine new applications for their work that critique and seek to alter the status quo rather than accept and uphold it.

A related framework, which has its roots in social work, is that of “anti-oppressive practice,” whose “driving force [...] is the act of challenging inequalities.” Recognizing that a social worker’s involvement in someone’s life “is not a neutral event” and emphasizing the need to empower those in need and to reduce structural inequalities, anti-oppressive practice demands that social workers practice continual reflexivity to consider how their own identity, values, and power affect their interactions with service users (Burke and Harrison, 1998).

The computer scientists Thomas Smyth and Jill Dimond have incorporated the notion of anti-oppressive practice into what they call “anti-oppressive design,” which they describe as “a guide for how best to expend resources, be it the choice of a research topic, the focus of a new social enterprise, or the selection of clients and projects [...] rather than relying on vague intentions or received wisdom about what constitutes good.” For example, Smyth and Dimond distinguish between social service—which assists the oppressed but does not alter the structures that created their oppression—and social change, noting that the former, although valuable, “is at odds with the definition of anti-oppression.” They also emphasize that technologists must remain cognizant of technology’s limits and acknowledge when nontechnical solutions are more effective than technical ones (Smyth and Dimond, 2014).

At each stage of the research and design process, data scientists should evaluate their efforts according to these frameworks: Would the implementation of this model represent a reformist or non-reformist reform? Is the design of this algorithm affirmative or critical? Would empowering our project partner with this system challenge—or entrench—
oppression and inequality? Such analyses can help data scientists interrogate their notions of “good” to engage in non-reformist, critical, and anti-oppressive data science.

Such an ethos has emerged among recent data science projects related to policing. For example, some researchers developing methods to identify people who are at risk of being involved in crime or violence explicitly articulate an intention to work with community groups and social service providers rather than with law enforcement, recognizing that the latter tend to contribute to structural oppression (Bauman et al., 2018; Frey et al., 2018; Green, Horel, and Papachristos, 2017). By aiding preventative social services rather than punitive police interventions, these efforts help shift our perceptions of what responses to social disorder are possible and desirable, demonstrating a critical and anti-oppressive approach to both defining the problem and selecting project partners.

Complementing work that thoughtfully chooses research partners is work that orients the analytic gaze to look for evidence of discrimination and injustice. Data science projects focused on assessing police behavior provides a salient example. Police quantify (i.e., use data to measure and manage) the public not because the public is inherently quantifiable, but as a tool of authority and power; reversing this lens by quantifying the police shifts perceptions regarding whose behavior is measurable and accountable. One example of this work used machine learning to predict which police officers will be involved in adverse events such as racial profiling or inappropriate use of force (Carton et al., 2016). Others have used new statistical methods and sources of data to find evidence of racial bias in police behavior (Goel, Rao, and Shroff, 2016; Voigt et al., 2017). These projects demonstrate how incorporating a political perspective into data science produces new directions for research and applications rather than a dead end.

Although Stage 3 represents a significant evolution of data science toward politics, it suffers from two notable shortcomings. The first is that it is possible to operate as described here without ever articulating an explicit politics; as such, this stage may do little to provide the field with a broad political ethos. Although not raising a project’s political motivations may enable some projects to pass without scrutiny, it does little to provide language or direction for other data scientists. For every data scientist who recognizes her work as political, there are many more who see data science as neutral or are unsure how to
incorporate political values into their work. The field will never transform if political debates remain shrouded. Moreover, only relatively minor reforms could be successfully promoted in this manner: more significant reforms will be noticed and will advance only if they can be explicitly defended.

The second and more significant issue is that merely directing data science toward new applications remains fundamentally undemocratic: it allows data scientists to shape society without open deliberation or accountability. Notably, the many efforts to promote algorithmic accountability take it for granted that it is algorithms that must be made accountable, never considering whether or how to hold data scientists themselves accountable. In this frame, a cadre of data scientists—no matter their intentions or actions—retain an outsized power to shape institutions and decision-making processes. Even when their actions are grounded in anti-oppressive ideals, the efforts of data scientists can serve coercive functions if they are not grounded in the needs and desires of the communities supposedly being served.

In order to promote long-term structural change and social justice, larger shifts in data science practice are necessary. We must move on to Stage 4.

**Stage 4: Practice**

All designers face an ethical dilemma: if they attempt to remain neutral and focus on direct needs, they risk entrenching the status quo; if they take an advocacy position, on the other hand, they inevitably impose their own values on society. In order to distribute responsibility and authority, designers must therefore incorporate participatory approaches into their practice (Bardzell, 2010).

Data scientists are caught in the same conundrum. As described above, many data scientists are reluctant to take political stances for fear of imposing their values on others. Yet such a desire to stay on the sidelines merely privileges current conditions and thus itself imposes a set of values. Recognizing data science as political action provides a way to navigate this tension: it is acceptable to advocate for particular positions (after all, it is
impossible to avoid supporting any positions), but this advocacy must be grounded within a fundamental respect for and fostering of democratic deliberation.

Such a focus on participation reframes the current lack of diversity in data science (West, Whittaker, and Crawford, 2019) not just as a failure of education and inclusion, but as a form of democratic exclusion. Given that data science is a form of political action and that this action is significantly influenced by practitioners’ perceptions of problems and ways to address them, then excluding certain demographics from the design and development of algorithms excludes these people also from a form of politics.

Such exclusion has significant consequences on the production and impacts of data science: it is hard to imagine, for example, that predictive policing and facial recognition would so commonly be developed for law enforcement purposes if more data scientists came from poor and minority backgrounds. Notably, one of the only facial recognition companies to explicitly reject working with law enforcement is one founded and led by a Black man: in a 2018 article, Kairos founder Brian Brackeen centers his Blackness as an important component in this decision, writing, “As the black chief executive of a software company developing facial recognition services, I have a personal connection to the technology, both culturally and socially” (Brackeen, 2018). Brackeen’s perspective highlights the value of groups such as Black in AI, LatinX in AI, Queer in AI, and Women in Machine Learning, all of which work to increase the presence of underrepresented groups in the field of artificial intelligence.

Researchers must also develop procedures for incorporating a multitude of public voices into the design and deployment of algorithms. When engineers privilege their own perspectives and fail to consider the multiplicity of needs and values across society, they tend to contribute to erasing and subjugating those who are already marginalized (Birhane, 2019; Costanza-Chock, 2018; Harrington, Erete, and Piper, 2019; Hoffmann, 2018; Srinivasan, 2017). To avoid participating in these oppressive (even if inadvertent) acts, data scientists must center affected communities in their work.

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19 https://blackinai.github.io/
20 http://www.latinxinai.org/
21 https://sites.google.com/view/queer-in-ai/
22 https://wimlworkshop.org
A central component of developing such a practice is for data scientists to shift from “solving” over-simplified social problems toward addressing social challenges in their full complexity (Green, 2019). Achieving changes along these lines requires developing new epistemologies, methodologies, and cultures for data science. And while the path ahead remains somewhat speculative, several broad directions are clear.

Data scientists must abandon their desire for a removed objectivity in favor of participation and deliberation among diverse perspectives. Donna Haraway argues for a new approach centered on “situated knowledges”: she articulates the need “for a doctrine and practice of objectivity that privileges contestation [and] deconstruction,” one that recognizes that every claim emerges from the perspective of a particular person or group of people (Haraway, 1988). Following this logic, the “neutral” data scientist who attempts to minimize position-taking (yet makes decisions that shape society) must be replaced by a data science of situated values—a “participatory counterculture of data science” (McQuillan, 2017).

Complementing this participatory approach is for data science to focus more directly on “designing with” rather than “designing for” affected communities and social movements. One approach toward this end is to follow the principle of “Nothing About Us Without Us,” which has been invoked in numerous social movements (in particular, among disability rights activists in the 1990s) to signify that no policies should be developed without direct participation from the people most directly affected by those policies. This ethos has important resonance with regard to artificial intelligence (Whittaker et al., 2019). The Design Justice Network articulates a powerful enactment of these values, with its commitments to “center the voices of those who are directly impacted” and to “look for what is already working at the community level” (Design Justice, 2018).

This type of approach, which can benefit from an emphasis on relational ethics (Birhane and Cummins, 2019), represents a notable departure from traditional data science practice and values—efficiency and convenience—toward democracy and empowerment. A great deal of work in recent years has exemplified this approach (Asad, 2019; Costanza-Chock et al., 2018; Dickinson et al., 2019; Maharawal and McElroy, 2018; Matias and Mou, 2018; Meng and DiSalvo, 2018; Scheiber and Conger, 2019). Mechanisms for
participatory design and decision making—such as charrettes, participatory budgeting, and co-production—present further models of designing with communities. Any such efforts should entail not just the design of an algorithm, but also broader questions such as whether an algorithm should be developed in the first place and toward what ends it should (if developed) be used.

The field must also develop concrete mechanisms to not only prioritize the people who will be most directly affected by algorithms but also to hold data scientists (and others) accountable to those groups. To these ends, some cities have formed civic bodies and enacted ordinances that create community oversight and control over municipal data, algorithms, and surveillance technology (Green, 2019). People’s councils, modeled on Athenian democracy as well as twentieth century worker committees, could provide another mechanism for empowering groups of people to hold data scientists democratically accountable (McQuillan, 2018). Enacting any such mechanisms of accountability will require new partnerships that include civil society groups and government officials in addition to data scientists.

Adapting data science to these practices will require new methods. Although it is a challenging endeavor, incorporating political considerations into data science methodology can spur innovation: the field need look no further than the plethora of methods that have been developed in just the last several years for creating fair and interpretable models. Broadly speaking, data science must move toward a “critical technical practice” that rejects “the false precision of [mathematical] formalism” to engage with the political world in its full complexity and ambiguity (Agre, 1997). For example, the field must develop methods that transcend the individualistic focus of most machine learning models and instead assess structural and institutional conditions of oppression and inequality. It is also necessary to create practices for incorporating diverse perspectives and values into algorithm development. Recent work that used formerly gang-involved young people from Chicago to provide context about the meaning of tweets represents one example along these lines (Frey et al., 2018).

The field will also need to change its internal structures to incentivize thoughtful discussion of the normative and political claims that underlie the development and
deployment of algorithms. This change requires, first and foremost, expanding conceptions of what merits the gold star of research: a “novel contribution.” To embrace justice and tackle the most pressing social issues related to algorithms, data science must take a holistic approach to research that looks for more than simply technical contributions: solving real problems for real people often requires thoughtfully adapting technology to serve well-articulated needs; silver bullet sophisticated technologies look impressive but tend to produce ineffective or even perverse outcomes (Green, 2019). This process of blending technical and nontechnical methods is often far more challenging than solving the primarily computational problems typically valued by technical disciplines. The field must also create space for critique and reflection by welcoming contributions that advance our understanding of data science even when they do not lead to an immediate improvement in technical systems (Agre, 1997). New workshops, conferences, and journals will be essential mechanisms for fostering these ends.

More broadly, data scientists must adopt a reflexive political standpoint that grounds their efforts in rigorous evaluations of downstream social and political consequences. Just as critical legal scholars have recognized that legal reforms are indeterminate and need to be evaluated according to their material effects (what they do) rather than their ideological ones (what they say) (Tushnet, 1993), so data scientists must come to recognize that algorithms are indeterminate and need to be evaluated based on how they actually impact society. In other words, what ultimately matters is not the text of a law or the code of an algorithm, but whether that law or algorithm actually promotes social justice when introduced into complex sociopolitical environments.

As one example of a reform that emphasizes impacts as a central concern, in 2018 the ACM Future of Computing Academy proposed that peer reviewers should consider the potential negative implications of submitted work and that conducting “anti-social research” should factor negatively into promotion and tenure cases (Hecht et al., 2018). Just two years later, the Neural Information Processing Systems Conference (NeurIPS)—one of the world’s top AI conferences—announced that every paper at the 2020 conference must include a “broader impact” section that discusses the positive and negative social consequences of the research (Neural Information Processing Systems Conference, 2020).
Another proposal calls for ethics pen-testing, adapting the notion of “penetration testing” from security to test the ethical implications of artificial intelligence (Berendt, 2019).

Data scientists cannot be expected to perfectly predict the impacts of their work—the entanglements between technology and society are far too complex—but, through collaborations with people from other fields and milieus, well-grounded analyses are possible. Just as data scientists would demand rigor in claims that one algorithm is superior to another, they should also demand rigor in claims that a particular technology will have any particular impacts.

Toward this end, one necessary direction for future research is to develop interdisciplinary frameworks that will help data scientists consider the downstream impacts of their interventions. This requires a “porous” approach to developing and evaluating algorithms that accounts for the indeterminacy in the application of these systems (Green and Viljoen, 2020). One initial step along these lines is to study algorithms within a sociotechnical context, for example by analyzing how pretrial risk assessments actually influence the decisions of judges in addition to evaluating whether the predictive models themselves make accurate and fair predictions (Green and Chen, 2019; Stevenson, 2018).

Such reforms both depend on and will facilitate necessary changes in norms about what it means to be a data scientist. Given that work driven by normative goals is often considered inferior to work driven by technical ones, it is unfortunately common for students today to be discouraged from pursuing research that is motivated directly by social or political objectives. Yet this trend points to an encouraging evolution in the field: students today are generally more attuned than current faculty to data science’s social and political ramifications and many are eager to incorporate considerations of social justice into their work.

Absent broader social and political changes that contribute to a more just society, however, we can only speculate about the attributes of a data science that is committed to a political vision of social justice. For as historian Elizabeth Fee notes, “we can expect a sexist society to develop a sexist science; equally, we can expect a feminist society to develop a feminist science” (Fee, 1983). Similarly, we can expect a militarized society of surveillance capitalism to produce a militarized and invasive data science (Pein, 2018;
Zuboff, 2015). Individual engineers can achieve only so much in the face of these structural conditions: at AT&T, when two data scientists refused to work on a project due to ethical concerns, the company allowed them to recuse themselves but simply had other employees complete the project in their stead (Simonite, 2018).

These challenges speak to the need for changes in data science to occur alongside broader structural reforms that create the conditions for more just impacts of technology—and for data scientists to work in support of these reforms. Recent protests and organizing among tech workers against their companies’ partnerships with the United States Departments of Defense and Homeland Security and handling of sexual harassment hint at how building solidarity and power among workers can shift the development of data science toward social justice. Rather than perceiving themselves as “just an engineer,” these technologists recognize their position within larger sociotechnical systems, perceive the connection between their work and its social ramifications, and hold themselves (and their companies) accountable for these impacts. Building on this movement, thousands of computer science students from more than a dozen U.S. universities have pledged that they will not work for Palantir due to its partnerships with Immigration and Customs Enforcement (ICE) (Mijente, 2019).

Data scientists alone cannot be held responsible for promoting social and political progress. They are one set of actors among many; just because data science is a form of political action does not mean that it is the only (or most important) form. The task of data science is not to eradicate social challenges on their own, but to act as thoughtful and productive partners in broad coalitions and social movements striving for a just society.

**Conclusion**

Like all forms of modeling, data science relies on defining the bounds of what is variable and what is fixed, what is of interest and what is immaterial, in order to analyze and make statements about the world. Such cordonning has allowed data science to realize remarkable accomplishments and amass prestige. Yet as data science is increasingly embedded within social and political contexts, the field has come up against the contradictions set within its
models: by design, data science lacks the language and methods to fully recognize and evaluate its impacts on society, even as it is increasingly oriented around social impacts. As with other fields such as cryptography (Rogaway, 2015), data science’s formalist and technical mode of reasoning obscures from those on the inside the political realities that are apparent to those on the outside.

When major questions of structure, policy, and values are settled, ethics may be an appropriate framework to ensure the social beneficence of data science. But it is first necessary to answer these questions and continually reevaluate those answers; this process forms the heart of politics. By focusing on ethics without strong normative or deliberative principles—effectively ignoring or taking for granted that the major political questions are settled—data science solidifies existing structures and narrows our perspective about the possibility and desirability of broader social change. This is a political stance, and a fundamentally conservative one.

The field of data science must abandon its self-conception of being neutral to recognize how, despite not being engaged in what is typically seen as political activity, data science logics, methods, and technologies shape society. Restructuring the values and practices of data science around a political vision of social justice will be neither easy nor immediate, but it is necessary. Not so much for the field’s survival—data science will surely continue to grow in size and stature over the coming years—but for it to truly advance rather than subvert social justice. Only by deliberating about the political goals and strategies motivating data science and developing new methods and norms can data scientists thoughtfully and rigorously contribute to improving society. Given the political stakes of algorithms, it is not enough to have good intentions—data scientists must ground their efforts in clear political commitments and rigorous evaluations of the consequences.

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