

Data science of the social: How the practice is responding to ethical crisis and spreading across sectors

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**Abstract**

Data science of the social: How the practice is responding to ethical crisis and spreading across sectors

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This dissertation is based on three years of ethnographic fieldwork within the Data Science Environment at the University of Washington. Employing a practice-based approach, it focuses on two processes involved in "data science of the social" that are core issues for my community of study: addressing the ethical crisis that is facing the field, and advancing data-intensive capacities across social sectors and problem spaces.

In the chapters devoted to ethics, I argue that ethical sense-making in data science of the social is a form of vernacular theorizing informed by implicit understandings of sociomateriality. Recognizing data science practitioners as vernacular theorists puts academic theories of sociomateriality into conversation with practice, and allows for cross-pollination among scholars of science and technology studies, critical data scholars, and data scientists. Given pressing ethical concerns and challenges accompanying data-intensive technologies, such dialogue is both

generative and necessary. The vernacular theorizing of data science practitioners yields four distinct approaches to ethics in data science of the social: data science as ethical convention, data science as ethical interrogation, data science as ethical innovation, and data science as ethical participation. I explore the conditions and processes that support two of these approaches—data science as ethical convention and data science as ethical innovation—by telling the stories of two projects from the “Data Science for Social Good” program at the University of Washington.

The latter chapters of this dissertation explore how data-intensive practices and technologies are spreading to new social sectors and problem spaces. Data science practitioners are often concerned with “scaling” their work by making it replicable in new contexts. This manner of expanding the reach and scope of data science is quite distinct from the type of “scaling” explored in many studies of spatially and temporally distributed scientific work, which frequently focus on the role of information infrastructures and knowledge infrastructures in enabling large-scale scientific collaborations. But the understanding of infrastructure developed in that body of work does not sufficiently capture or explain approaches to scaling in data science of the social. Therefore, I develop the concept of exostructure as a companion to infrastructure and a key mechanism enabling scaling in data science of the social. Exostructures are made up of the components of temporary, project-based collaborations intended to spawn replication or further investment in information and knowledge infrastructures. I argue that the portable, transient, iterative, and customized nature of exostructure lends itself to processes with transformative implications for the relationships among sectors and institutions participating in their development. In particular, through exostructural arrangements, the university is playing emergent roles in the data-based knowledge society by mediating between business and government, mitigating risks for other sectors, and providing a source of intellectual labor.

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## CHAPTER 1 INTRODUCTION

### PREAMBLE

When I began my field work for this dissertation in 2014, data science had already been dubbed “the sexiest job of the 21st century” (Davenport & Patil, 2012). But in spite of (or perhaps because of) such triumphalist prognoses, when I would ask people to define data science in interviews, their responses often were accompanied by some kind of caveat that down-played its significance: data science is just a fad that will eventually fade away, it’s just statistics on a fancy computer, it’s just science but with more data. However, over the course of nearly four years that I have been embedded as an ethnographer with the eScience Institute at the University of Washington, it’s become clear that academic data science is not simply more of the same, and it is not going to evaporate. Instead, data science methods are becoming ever more broadly adopted and deeply entrenched in the academy, with new data science curricula being added to university rosters at a steady clip, including both undergraduate curricula (Tate, 2017) and graduate degree programs (Institute for Advanced Analytics, 2018).

Importantly, though, academic data science is neither envisioned nor instantiated as a new disciplinary silo. In my time at eScience, I have observed projects conducted under the banner of data science that cover a dizzying range of questions about the world, from a medical student attempting to crack the DNA sequence in chromosomal centromeres, to an economist modeling airline mergers and acquisitions, to an engineer trying to detect earthquake damage with audio recordings, to a psychologist studying sleep patterns and academic performance. The discourse around data science rarely even makes reference to “disciplines,” far more often employing the term “domain.” For example, data scientists often riff off of Drew Conway’s Data Science Venn Diagram (Conway, 2010) when talking about “domain knowledge” as a necessary

companion to programming skills and math skills in the triumvirate of requisite data science expertise. Speaking of domains provides a way of accounting for particular subject matter knowledge while sidestepping the complicated intellectual lineages, bureaucratic delineations, and resource territoriality of academic “disciplines.” Rather than data science being thought of as an interdisciplinary or cross-disciplinary academic field, then, it is portrayed more so as domain-agnostic, applicable to any manner of question or problem and extending not just across academic disciplines, but beyond the walls of academia and the confines of scholarly research.

This is the conceit that lies at the heart of my research. In the time I’ve been embedded at the University of Washington’s eScience Institute, the organization’s mission of “advancing data-intensive discovery across all fields” has come to mean not just promoting data science within the academy, but also partnering with government agencies, businesses, and non-profit organizations to apply data science to real-world problems across social sectors. This is happening on several different overlapping fronts, including an annual Data Science for Social Good summer program, participation in national initiatives that promote city-university collaborations such as the MetroLab Network and NSF Big Data Hubs, and a nascent regional partnership called the Cascadia Urban Analytics Corridor. All of these efforts are aimed at harnessing what I call “data science of the social” for the betterment of society.

Data science of the social is, quite simply, data science that puts questions about the social world at the center of attention. It encompasses data about people, and data that directly impacts people’s lives. It may involve data collected as residual traces of online activity; data picked up by sensors collecting ambient information from the places where people live, work, and play; data informing decisions in powerful social institutions like banks and law enforcement agencies; data used to curate the content we see and hear on digital platforms; data that feeds and

“teaches” autonomous technologies used by humans; and much, much more. In other words, data science of the social encompasses the many ways that data is increasingly integrated into the technologies that mediate of many aspects of social life.

And it currently is having a crisis of conscience. This is amply evidenced by a recent string of high profile scandals in the news: Facebook data being used by political campaigns to manipulate the American electorate (Confessore, 2018), self-driving cars running over pedestrians (Griggs & Wakabayashi, 2018), and predictive models in the criminal justice system discriminating against black defendants (Angwin, Larson, Mattu, & Kirchner, 2016), to name just a few. Such events have highlighted concerns over issues of privacy, fairness and accountability in data-intensive technologies, prompting data science practitioners, critics, and regulators to reckon with the profound ethical concerns implicated in data science of the social.

My ethnographic fieldwork was conducted, then, at the height of enthusiasm for the promise of data science, when its reach was expanding dramatically under concerted efforts to bring its methods to bear upon social problems. But simultaneously, the ethical perils inherent in data science of the social were becoming impossible to ignore. These tandem developments seed the overarching questions at the core of my study: How is data science scaling its reach across social sectors and problem spaces? And how are practitioners responding to the ethical crisis currently facing data science of the social?

## RELATED WORKS

These questions speak to a burgeoning area of scholarship that is sometimes referred to as critical data studies (e.g. Iliadis & Russo, 2016; Kitchin & Lauriault, 2014), an emergent cross-disciplinary field that interrogates the social implications of data science, big data, algorithms, artificial intelligence, and other data-intensive approaches and technologies. Important

contributions to this nascent field come from communication (e.g. Gillespie, 2013; Lauriault, 2018), geography (e.g. Dalton, 2018; Kitchin, 2014), law (e.g. Pasquale, 2011; Selbst, 2017), information studies (e.g. Barocas, 2014; e.g. Nissenbaum, 2010), and computer science (e.g. Gross & Acquisti, 2005; Sweeney, 2013). Here, I will outline a number of major themes that have been discussed within the critical data studies literature to date, and articulate my own contributions to this body of knowledge. In brief, I bring a practice-based, organizational lens to bear on the study of data-intensive phenomena.

Personal details about where we live, how educated we are, and what we consume can determine which advertisements we see, how much we pay for goods, and what services are offered to us. Algorithms decide what news, potential romantic partners, jobs, entertainment, and products we are likely to be interested in. Public servants make decisions with the assistance of algorithms that predict where crime will occur, when infrastructure will break, and which restaurants will have sanitation problems. Automated data-driven systems dynamically change the timing of traffic lights, pilot vehicles without human input, and control the heating and cooling of buildings. Our phones, self-tracking devices, and in-home digital assistants constantly monitor our location and behavior and make suggestions about how much we should exercise, when we should go to sleep, and what items we need to stock up on.

In other words, data-intensive approaches and technologies now mediate nearly all aspects of life in computationally advanced societies. Critical data studies has taken up the task of problematizing this phenomenon in a growing body of scholarship that can be roughly clustered into seven thematic areas of concern: demonstrating that data is not raw, objective, or neutral, but socially constructed; uncovering the bias, discrimination, and injustice that can result from the mediation of data-intensive technologies; critiquing the complexities of opacity and

accountability in algorithmic systems; exploring the implications of data-based mediation for political economy and publics; calling attention to issues of privacy and security; and surfacing concerns over emergent forms of governance and citizenship associated with data-intensive technological mediation. In what follows, I provide a selective review of contemporary scholarship that cogently speaks to these themes.

### **Social construction of data**

The big data era was ushered in during the mid-naughts to much fanfare, generated in large part by the exuberant and overly confident rhetoric characteristic of Silicon Valley-based techno-utopian culture. High-profile provocations—declaring the death of theory-driven inquiry, the irrelevance of systematic sampling in a world full of complete data sets, and the promise of perfect prediction—sometimes overshadowed more tempered contemporaneous efforts to integrate new data-intensive technologies and approaches into rigorous scientific research (Kitchin, 2014a).

The triumphalist rhetoric of the technology industry has been met with fierce criticism from academic scholars of science and technology studies, who set about to dispense with mythical notions of data being inherently objective or raw. For example, Lisa Gitelman's (2013) edited volume, *"Raw Data" Is an Oxymoron*, is an attempt to uncover the many layers of work, judgment, and interpretation underneath the polished veneer of data. First and foremost, we must acknowledge that data are not collected, but produced through epistemic acts of grouping and labeling phenomena that otherwise have no natural boundaries or shared existence (Bowker & Star, 2000). As such, "different data sets harbor the interpretive structures of their own imagining" (Gitelman & Jackson, 2013, p. 3) and "classifications function, for good and ill, to underpin the social order" (p. 9). Data are further interpreted as they are "cleaned," a process

that is “as much art as science” (Borgman, 2015, p. 27), involving subjective judgment about what data is good, what data counts, and how data should be transformed in order to ensure they are adequately homologous. Even the act of framing what questions to ask and choosing techniques from among an ever-expanding suite of analytic methods involves subjective judgment that is informed by a data analyst’s identity and situated perspective (boyd & Crawford, 2012). Yet another layer of interpretation is added when data are visualized, a constructed and representational framing that circumscribes what can be asked and known with data (Kitchin, Maalsen, & McArdle, 2016). And the only phase of analysis in which subjectivity is ordinarily explicitly recognized—the phase we call “interpretation”—may include even deeper layers subconscious judgment than we readily acknowledge (boyd & Crawford, 2012).

Importantly, the subjectivity that is baked into data is not an individual phenomenon, but a social one. Data are inextricable from the assemblages in which they are embedded, “amalgams of systems of thought, forms of knowledge, finance, political economies, governmentalities and legalities, materialities and infrastructures, practices, organisations and institutions, subjectivities and communities, places, and marketplaces” (Kitchin, 2014b). Such a perspective underscores how important it is for analysts to investigate and understand the contextual complexities of data collected for one reason and repurposed for another, a phenomenon that is one of the hallmarks of big data and data science. As Eszter Hargittai (2015) has shown, when such care is not taken, big data analysis lends itself to misinterpretation. For example, she discusses a study of Facebook activity purporting to show that weak ties did not help people find jobs, without considering that the real finding might simply be that Facebook is not the preferred platform for interacting with one’s network of weak ties.

Not only do we need to more carefully consider the context in which data is produced, we also need to attend more closely to the multiple and overlapping contexts in which sense-making around data occurs. Sumartojo et al. (2016) “argue against treating data as a given, fixed or already-known aspect of the world” so that we may recognize it as a “rich and emergent aspect of human experience that constitutes part of how we continue to make sense of the world” (p. 39). In their study of health and wellness data generated through self-tracking practices, Brittany Fiore-Gartland and Gina Neff (2015) explore a range of data valences—or expectations for what data mean and what data can do—that diverged across groups of healthcare professionals, patients, technology designers, and advocates. Contradictions in valences indicate that if data is to be useful in a way that even remotely lives up to the hype around the potential of data-intensive epistemologies, we need to understand “the ways that data valences may be contested at the boundaries of institutions and communities” (Fiore-Gartland & Neff, 2015, p. 1480), and develop approaches for translating those varied values and expectations.

### **Bias and discrimination in data-intensive technologies**

Following from the critique that data are neither raw nor neutral, a major concern in critical data studies is the propensity for data-intensive, computational systems to codify and reinforce existing social prejudices and biases. Many algorithmic systems, in particular, “learn” from inputs of social data generated by humans that already reflect our subjective judgment. In these ways, our pre-existing biases and values get baked into an algorithm’s recipe, reflecting back to us our stereotypes and inequities (Burrell, 2016; Jackson, 2013). Safiya Umoja Noble (2018), for example, has demonstrated how search algorithms, in adapting to the behaviors of users, end up learning to return sexualized content when conducting searches for images of women of color, such as “black girls,” or “Asian girls.” Mike Ananny (2011) has written about

how, after he downloaded a dating app that caters to gay men, the recommender system for his phone's app store displayed "Sex Offender Search" in a list of related and relevant options. Latanya Sweeney (2013) has shown similar dynamics at work in algorithms that display ads for internet browsers. When a user searches for an individual's name, it is common for that action to generate advertisements for companies that perform background checks by accessing public records, and sometimes, these advertisements suggest the possibility that an arrest record exists for the individual being sought. Sweeney found statistically significant evidence that more often, "ads suggesting arrest tend to appear with names associated with blacks, and neutral ads or no ads appear with names associated with whites," regardless of whether or not there was an arrest record associated with the names (Sweeney, 2013, p. 4). Such investigations show how insidious associations made by algorithmic systems reinforce negative stereotypes that have long persisted in society. But as Gillespie (2013) points out, such empirical demonstrations don't necessarily lend themselves to easy answers: "To accuse an algorithm of bias implies that there exists an unbiased judgment of relevance available, to which the tool is failing to hew. Since no such measure is available, disputes over algorithmic evaluations have no solid ground to fall back on" (p. 175). Indeed, research has shown that evaluating algorithmic outputs for fairness depends on one's definition of what fairness is, and that ensuring fairness according to one criterion often means permitting unfairness according to another (Chouldechova, 2017).

### **Opacity and accountability in algorithmic systems**

A concern commonly voiced over data-intensive computational technologies is that their opacity makes it difficult to assign accountability. One form of opacity is related to the fact that many people lack the awareness, technical literacy or experience to comprehend data-intensive, computational technologies, what Eszter Hargittai (2002) has referred to as a "second-level

digital divide.” Recent developments and scandals in the news have likely made more people aware of the algorithmic mediation of digital content, but when Eslami et al. (2015) studied people’s perceptions of their Facebook newsfeeds in 2015, well over half of users surveyed didn’t know that an algorithm determined what they saw (p. 153). Such widespread lack of understanding about the basic workings of algorithmic systems—let alone an ability to write and read code (Burrell, 2016)—makes it difficult to hold the proprietors of algorithms and big data accountable.

Another kind of algorithmic opacity is secrecy—intentional concealment on the part of an algorithm owner for self-serving interests, such as protecting market shares or shielding themselves from liability (Pasquale, 2015). Critical data scholars, activists, and regulators have promoted a range of tactics for combating such opacity, from reverse engineering algorithmic logics (King, Pan, & Roberts, 2014), to auditing algorithmic outputs for certain metrics of fairness (Sandvig, Hamilton, Karahalios, & Langbort, 2014), to requiring algorithm owners to provide intelligible explanations for their technologies (Selbst & Barocas, 2018). Such tactics are currently being advanced and contested in ongoing legal battles. Computer science professors from Northeastern University are challenging federal intellectual property rules that prevent auditing of websites when such activity contravenes their terms of service (ACLU, 2018). And in Europe, regulators are sorting out how to implement the stipulation contained in the recently passed General Data Protection Regulations (GDPR) that data subjects have the right to “meaningful information about the logic involved, as well as the significance and the envisaged consequences” of algorithmic decision making and profiling (Selbst & Barocas, forthcoming).

But such approaches may not work for all types of algorithmic opacity, including what Selbst and Barocas (forthcoming) call “inscrutability.” This kind of opacity is specific to

machine learning and artificial intelligence, and "stems from the mismatch between mathematical optimization in high-dimensionality characteristic of machine learning and the demands of human-scale reasoning and styles of semantic interpretation" (Burrell, 2016, p. 2). Burrell's (2016) observation that even "insider" programmers have to grapple with a form of opacity is reminiscent of Evgeny Morosov's (2011) quip that Google's algorithmic systems are "so complex that no Google engineer fully understands them." Burrell (2016) sees no feasible way to eliminate this inherent form of opacity, but suggests some measures we can take to mitigate negative repercussions stemming from it. One option is to essentially build a model of the model, a simplified, pared down approximation of a more complicated machine learning model that allows humans to get a better sense of what is happening under the hood.

A final type of opacity is what Selbst and Barocas (forthcoming) call "non-intuitiveness," which comes into play when the logic of an algorithm can be explained, and yet defies human sensibilities. "The problem in such cases is not a lack of transparency, technical expertise, or inscrutability, but an inability to weave a sensible story to account for the statistical relationships in the model. While people might readily understand the statistical relationship that serves as the basis for decision-making, that relationship may defy intuitive expectations about the relevance of certain criteria to the decision at hand" (Selbst & Barocas, forthcoming). Such relationships are often (rightly) dismissed as spurious correlations that don't imply a causal relationship (Vigen, 2015), but it is also possible that in some cases machines have uncovered true relationships that humans do not yet understand (Selbst & Barocas, forthcoming). To avoid such situations, machine learning researchers can limit the model to only considering a limited range of vetted features with theoretically informed causal relationships, but this also diminishes the inductive power for which machine learning methods are prized.

As we have seen, a prominent response to the deleterious social consequences of algorithmic mediation has been to focus on transparency as a remedy; if we simply understand what algorithms are doing and how they are doing it, we can hold them accountable to society's nobler values and ethical standards. But transparency may not be a panacea. As decision-making becomes distributed across a sociotechnical infrastructure, and increasingly automated (or at least mediated) by computational technologies, determining who is accountable when things go wrong presents a major challenge. Historically, we have assigned moral responsibility to actors only if the following three criteria apply: a) there is a demonstrable causal connection between their actions and the outcome; b) they had the knowledge and ability to weigh the consequences of their actions; and c) they acted of their own free will (Noorman, 2013). The distributed nature of computational tasks makes criteria a) difficult to determine when computational agents are involved, while criteria b) and c) are typically thought to be exclusive characteristics of human beings. A number of philosophers have suggested that there is a pressing need to revisit and re-envision these human-centric notions of morality. Helen Nissenbaum (1997 in Noorman, 2013) suggests that a start would be to reform the organizational and cultural contexts in which computer-based technologies are embedded: we should not be so quick to let institutions off the hook when many different agents are involved in distributed computational tasks; there should be a reversal of the complacency in accepting bugs as an inevitable part of computer systems; and companies should not be able to assert ownership over software without also assuming liability for it.

### **Political economy and publics in data-mediated societies**

Another strain within critical data studies is concerned with implications of data-intensive technologies for political economy and publics. The growth, adoption, and integration of data-

intensive technologies has been referred to as the “datafication” of society (Mayer-Schönberger & Cukier, 2013; van Dijck, 2014), a transformation in which data has become a kind of currency and resource to be exploited for economic gain and operational efficiency (van Dijck, 2014) in the “data economy” (Vertesi & Dourish, 2011). Data are deeply entwined with asymmetric power distributions that Andrejevic (2014) has called the “big data divide”: a gap between “those who collect, store, and mine large quantities of data, and those whom data collection targets” (p. 1673). This is in no small part attributable to the vast resources that must be leveraged to make big data a reality; after all, it requires the mobilization of expensive computational technologies and highly-trained labor (Donovan, Caplan, Matthews, & Hanson, 2018). Though citizens undoubtedly exercise agency through democratized data practices like citizen science and self-tracking (Neff & Nafus, 2016), they are also enmeshed in a shadowy web of powerful actors who collect, aggregate, sell, and analyze their data, from third party apps to data brokers to law enforcement agencies (Pasquale, 2015).

With recent high profile scandals such as Edward Snowden’s revelations about the National Security Agency’s collection of mobile phone records (BBC News, 2014), and researchers unscrupulously sharing personal data from Facebook with political operatives (Confessore, 2018), it is becoming increasingly obvious that data are a valuable commodity being shared, traded, and dissected. And yet people still have little insight into how that system works, where their data goes, and how it is used (Lupton & Michael, 2017). Frank Pasquale (2015) reveals the layers of technical barriers, legal structures, and obfuscatory practices that render the inner workings of the data economy a black box. Mike Michael and Diane Lupton (2016), meanwhile, argue that the public also has difficulty grasping all the ways data intervene in their lives because of the “involutionary” nature of big data, “in which publics are, in varying

degrees, both the subjects and objects of knowledge, both authors and texts, simultaneously informants, information and informed” (p. 5). This recursive relationship between publics and data-driven technologies is also addressed by Tarleton Gillespie (2013) in his concept of “calculated publics.” These are algorithmically derived groupings of people who get lumped together according to characteristics that would otherwise never join them; for example, when an online store displays what “shoppers like you” have purchased, or an online dating application suggests dates from among one’s “friends of friends.”

Not only do algorithms enable the placement of individuals into previously irrelevant groups, they also enable individuals to be profiled and targeted in unprecedented ways. Zeynab Tufecki (2014) focuses on the way this differentiation is giving rise to “computational politics.” The collection of latent data from digital traces of online behavior, combined with sophisticated algorithmic modeling, means that political campaigns are able to profile individuals with high rates of precision in order to identify likely voters and target them with tailored messages. The 2016 presidential election in the US provided a powerful example of this practice, when foreign operatives allegedly identified susceptible social media users and fed them incendiary “fake news” about wedge issues in order to exploit fissures in the American electorate (Confessore & Wakabayashi, 2017). In today’s interconnected, data-driven world, “citizenship transforms into citizen sensing, embodied through practices undertaken in response to (and communication with) computational environments and technologies” (Gabrys, 2014, p. 34). In such a configuration, citizenship entails being both a data consumer (Powell, 2014) and a data product (Gregg, 2015b).

Of course, digital data-based technologies also open up new opportunities for civic participation (Couldry & Powell, 2014). While acknowledging the risks of data-intensive, computational technologies, Andrew Schrock (2016) argues that “we should be attentive to

moments where meaningful change can occur, even if those changes are fraught with forces of neoliberalism and tinged with technocracy" (p. 583). Writing about the phenomenon that has been referred to as "civic technology" or "civic hacktivism," he highlights the potential for volunteer computer programmers and software engineers to fill gaps in requisite skills that many grassroots and nonprofit organizations lack, helping them take advantage of opportunities presented by newly available data (Schrock, 2016).

Civic hackathons have recently emerged as the poster children of such civic technology movements. At these events, which are "marketed as a new form of community service" (Gregg, 2015a, p. 185), a group of volunteers with programming skills get together for a brief period of time to intensely explore one or more open civic data sets and develop pro-social analyses or applications. According to Gregg (2015a), the civic hackathon "celebrates private solutions to public problems," (p. 186), having gained traction in the wake of the 2008 global financial crisis to "ameliorate the otherwise cataclysmic cuts to government spending on civic services like libraries, public schools and other repositories that enable data sharing in many communities" (p. 188). Anthony Townsend (2013) has noted that the crowdsourcing of civic technology can be viewed as a regressive tactic if it leads governments to disinvest in service provision and abdicate responsibility to voluntary entities: "It presumes a surplus of volunteer time and energy. For the working poor, every second of every day is devoted to basic survival. The withdrawal of any government services would remove a critical base of support for these extremely vulnerable communities" (p. 192).

Moreover, Townsend (2013) notes that hackathons and app contests allow programmers to define the problems and solutions to widespread social problems (p. 202), a situation that Gregg (2015a) feels limits the treatment of social issues to the prototypical computer scientist's

perspective, which she sees as “one that avoids analysis of the macro political conditions inherited in software, hardware and code” (p. 191). Leaving social problems for hackers to solve is especially problematic if those hackers are not representative of society at large. According to Gregg (2015a), “data literacy is now vital for effective citizenship, even while pedagogy and training for such literacy is unequally distributed according to gender, age, geography and race” (p. 188). And Lilly Irani (2015), writing about her own participation in a hackathon in India, reflects on the elite nature of the event: “it became clear that the event could not accommodate those for whom it claimed to care” (p. 818).

### **Data privacy, security, and surveillance**

The ubiquitous and asymmetrical data collection described above has also been thoroughly critiqued for the privacy incursions it entails and enables, a phenomenon van Dijck (2014) has called “dataveillance.” This differs from surveillance in that, “whereas surveillance presumes monitoring for specific purposes, dataveillance entails the continuous tracking of (meta)data for unstated preset purposes” (van Dijck, 2014, n.p.). In the era of dataveillance, any single individual is included in numerous data sets collected by a wide range of platforms and actors. Much work has shown that by combining disparate data sets, anonymized data can be re-identified, and personal details about an individual’s life revealed. For example, as early as 1997, Latanya Sweeney dramatically demonstrated how simple it was to re-identify health records by combining them with publicly available voter registration records (Ohm, 2010). Sweeney identified the health records of the Governor of Massachusetts in a corpus of publicly available data in order to demonstrate that merely deleting identifiers was an insufficient mechanism for protecting patient privacy (Ohm, 2010). Since then, computer scientists have developed more sophisticated techniques for preserving anonymity, including approaches known as differential

privacy (Dwork, 2008) and hashing (Kumar, Novak, Pang, & Tomkins, 2007). And yet re-identification continues to occur. In a high profile example, soon after a data set of taxi rides in New York City was publicly released in 2013, numerous analysts were able to de-anonymize the data and combine it with other sources to find out how much celebrities tipped their drivers, and who frequented upscale erotic dance clubs (Metcalf & Crawford, 2016).

A recent development that has accompanied the growth in popularity of mobile phones and location-based services is the availability of mobile phone users' geotemporal location data. Even when gathered only to the precision of the nearest cellular network antenna, de Montjoye et al. (2013) have demonstrated that only four location points are needed to distinguish unique mobility patterns for 95 percent of users. Although they stopped short of combining these unique patterns with other sources of information in order to associate location patterns with names, they noted that it would be trivial to do so (de Montjoye et al., 2013).

But for Solon Barocas and Helen Nissenbaum (2014) the association of names with data should not be our only privacy concern in this day and age. Anonymity, or namelessness, has long been the gold-standard of privacy protection, but they argue that it does not always matter if a name can be attached to a unique user or not. Individuals can be isolated and labeled with a random number or pseudonym, and the absence of a name does not prevent that individual from being targeted; she is still vulnerable to being singled out as an individual. For this reason, Barocas and Nissenbaum (2014) suggest replacing the construct of identifiability with the concept of *reachability*.

Likewise, they argue that the standard of informed consent is also no longer sufficient in this day and age. When data intensive technologies have become part of the fabric of daily life, opting out is not a feasible option (Brunton & Nissenbaum, 2011); and when users must agree to

terms of service that give providers wide berth to collect and share their data in order to use services that have become ubiquitous in society, consent loses its meaning (Barocas & Nissenbaum, 2014). This situation has caused Sadowski and Pasquale (2015) to remark that such agreements represent "the ideal-type of desiccated, hollow, pro forma 'consent' that is better termed obeisance, acquiescence, or learned helplessness" (n.p.). Therefore, Barocas and Nissenbaum (2014) argue, instead of simply being required to obtain consent to use data collected from users, data owners should be held to maintaining a standard of *contextual integrity*, which would account for the "reasonable expectations" that users and citizens have for the flow of information about themselves. For example, Uber's 2012 data analysis that inferred when and where their customers were having one-night stands would probably not pass the test of what a customer would reasonably expect the company to do with their data, even if they had given permission to collect it (Jeong, 2016).

### **Data governance and governmentalities**

Not only are companies amassing mounds of data about individuals' behavior, so are governmental bodies increasingly trying to leverage data and sophisticated computational techniques in making decisions and conducting operations. The administrative use of data is by no means new, and has long been intimately tied to the development of modern structures of governance (Bowker & Star, 2000; Porter, 1995), but recent growth in data availability and the evolution of data-intensive technologies and techniques has opened up a contemporary set of pressing questions and concerns (Kitchin, Lauriault, & McArdle, 2018).

Routinely collected administrative data is now increasingly being employed in predictive analytics and optimization algorithms across a wide array of applications, ranging from law enforcement (Scassa, 2017), to welfare services (Eubanks, 2017), to infrastructure maintenance

(Crawford, 2013). In the hands of the state, concerns with data-intensive technologies already described above—bias, representation, the entanglement of private and public interests, etc.—are amplified in light of the government’s monopoly on force. This makes the use of data analytics in the criminal justice system a particularly pressing concern for critical data scholars. For example, algorithms used to predict the location of future crimes and the likelihood that an individual will commit a future crime have been criticized for being racially discriminatory (Angwin et al., 2016; Saunders, Hunt, & Hollywood, 2016). This is, in large part, because algorithmic predictions of the future must be based on the record of the past, and data from criminal justice systems are already tainted with institutionalized forms of prejudice and discrimination. For example, although whites and blacks in the US use marijuana at roughly the same rates, black people are arrested for marijuana possession at four times the rate of white people (The American Civil Liberties Union, 2013). Such minor drug possession is part of a class of crimes known as “quality of life” offenses that tend to be observed directly by police rather than reported by the public (Shapiro, 2017). This means that such arrests may be more telling of where law enforcement officers are policing than where such behavior is actually occurring. Therefore, if highly biased quality of life offenses are used to predict when and where crime will occur, or who will commit a future crime, we are likely to only further exacerbate the gross racial disparities in arrests and incarcerations that already exist (Shapiro, 2017). Because of the particularly high stakes in the criminal justice system—in which the state has the authority to deny individuals life and liberty—some activists and critical data scholars have suggested that predictive data analytics and algorithmic decision-making should be avoided across the board in this domain (boyd, 2018).

In addition to established forms of administrative data being used in new ways, critical data studies have also examined relatively new, networked, real-time sources of data in the phenomenon that has been called “smart cities.” Although the term lacks a clear and universal definition, it typically captures efforts to embed urban spaces with pervasive sensor networks that capture data about an array of activities and characteristics in order to enable “wider-scale, finer-grained, real-time understanding and control of urbanity” (Kitchin et al., 2018, p. 3). This includes instruments such as license plate readers, wifi sniffers, air quality monitors, closed-circuit television cameras, traffic volume estimators, and more. In the ideal of the smart city, relatively non-invasive sensing technologies (say, pressure plates embedded in pavement that estimate traffic flow) are integrated with more invasive technologies (for example, license plate readers) in what Sadowski and Pasquale call a “spectrum of control” (2015). The problem with the smart city, as they see it, is that “meritorious or merely creepy technologies [are] directly imbricated with deeply disturbing ones” (Sadowski & Pasquale, 2015, n.p.).

Images of centralized control rooms for aggregating and integrating various streams of urban data in smart cities readily lend themselves to Foucauldian critique of disciplinary societies, in which citizens are kept strictly in line through constant monitoring by authorities using technologies that allow for panoptic surveillance (Kitchin, 2014a; Townsend, 2013). Alberto Vanolo (2013) argues that smart cities represent a form of disciplinary governmentality because they “impress a new moral order on the city by introducing specific technical parameters in order to distinguish between the ‘good’ and ‘bad’ city” (p. 883).

Klauser et al. (2014), too, offer a Foucauldian reading of smart cities, but they argue that instead of representing a disciplinary governmentality, smart cities are a manifestation of Foucault’s somewhat lesser-discussed notion of the security society. Whereas a disciplinary

society maintains a sharp binary distinction between permissible and prohibited by punishing nonconformity, a security society is constantly adapting to an expanding range of what is acceptable while orienting itself to the average of that range (Klauser et al., 2014). Klauser et al (2014) see this paradigm at work in smart cities discourse, in which the city is understood according to metaphors of biological systems with the goal of optimizing the functioning of that system. This is not to say that a governmentality of security is neutral or benign, for the “quest for policies benefitting ‘the whole’,” is an approach “in which the claims of the minority or powerless or disenfranchized or non-mainstream groups are considered disturbing factors” (Klauser et al., 2014, p. 314).

Furthermore, smart cities do not actually render its entirety visible. Instead, the sensors, meters, and instruments of wired urban spaces offer only and always incomplete perspectives that bring some characteristics of the city into sharp focus while excluding others beyond the field of vision. According to Kitchin et al. (2016), smart cities, therefore, offer not the panoptic surveillance of a Foucauldian disciplinary dystopia, but an oligoptic vision, in which partial and situated views offer a synecdochic stand-in for the entirety of the city. From this perspective, it is critical to ask not just who is included in big data surveillance and how they are affected by it, but also who is excluded (Lerman, 2013) and unaccounted for in optimized renderings of the city.

Another common critique of smart cities targets the neoliberal agenda that underwrites the phenomenon, and the further entanglement of public mandate and private interest. The smart cities vision has been aggressively promoted and exploited by high tech companies like IBM and Cisco (Hollands, 2015), who see lucrative contractual relationships in the long-term adoption of their technologies in smart cities infrastructure. Söderström et al (2014) have borrowed from

Actor Network Theory in describing the calculated move by technology companies to make themselves ‘obligatory passage points’ and indispensable actors in the network that constitutes smart cities. Authors like Anthony Townsend (2013) have warned that this relationship between the city and technology companies can be “usurious” (p. 294), with governments getting locked into technological dependencies of proprietary systems (Brauneis & Goodman, 2018), possibly losing control over and access to their data (Young, forthcoming), and complicating their ability to protect against cyberattacks and other sources of failure (Kitchin, 2014c).

### **Data in organizations and practices**

Recently, some examples of critical data scholarship have also begun attending to questions of organization and practice in the development and deployment of data-intensive technologies. For example, Robyn Caplan and danah boyd (2018) have examined the relationship between news outlets and online distribution platforms that use algorithms to sort and display news content. They argue that algorithmic mediation leads to institutional isomorphism in the news industry because “organizational contexts are embedded into algorithms, which can then become embedded within other organizational and individual practices” (Caplan & boyd, 2018, p. 1), underscoring “how efforts to increase accountability within algorithmically-mediated fields need to consider the organizational values and institutionalized mechanisms embedded within algorithms” (p. 2). Jim Thatcher and Craig Dalton (2018) have critically assessed how practitioners of data science think of data provenance in a purely technical sense, understanding it to be the capture of information related to time, format, instruments, structure, and other such characteristics. Instead, Thatcher and Dalton (2018) call for data practices that account for the many iterations of meaning that get inscribed into data by including descriptions of purpose, use, assumptions, and lineage of ownership in the

documentation of data provenance. Andrew Selbst and Solon Barocas (forthcoming) have likewise put forth that better documentation practices are a step toward addressing some of the issues arising from the inscrutability of complex computational models, writing from a legal perspective that suggests such practice be mandated by law. Jo Bates (2018), meanwhile, takes a cultural approach to data intensive practices rather than a regulatory one, urging critical data scholars to investigate the value frameworks and philosophical assumptions that inform “what sort of future these practices are in the process of creating” (p. 197).

## RESEARCH QUESTIONS & PREVIEW OF ARGUMENT

Taken as a whole, critical data studies scholarship has succeeded in surfacing many of the dangers, shortcomings, and transgressions of our data-mediated world. Combined with journalism exposing the underbelly of data intensive computational technologies (e.g. Angwin et al., 2016) and the voices of data scientists calling for reform within their own practice (e.g. O’Neil, 2016), critical data studies scholarship has begun to shift the discourse around data science, big data, algorithmic mediation, artificial intelligence, machine learning, data analytics, smart cities, etc. It has tempered the penchant for triumphalism, and drawn attention to the need for caution and reform. But in revealing the excesses, injustices, and unintended consequences of data-intensive technologies, we have identified only the symptoms, and not the causes, of the problem. To truly understand how and why data-intensive technologies come to be as they are, we must understand the organizational practices and structures that produce them. These are questions that have received less attention from critical data scholars to date, though the few aforementioned exceptions suggest that there is an appetite for more such work. My own research fits into this lacuna. I use a practice-based approach to understand the organizational processes and structures that play off of each other to produce data science practice. The two

core, overarching questions that motivate my work concern ethics in data science of the social, and the means by which data science practice is spreading across social sectors and problem spaces.

I ask how data scientists make sense of the ethical questions that arise in their day-to-day work, and what organizational structures and processes support ethical thinking and decision-making. I argue that data scientists are not always the arch-positivists that critical data studies tends to portray; that they are often acutely aware of the shortcomings in their data and the subjectivities involved in the work of data production and analysis. Chapters 3 and 4 can be thought of as a couplet that addresses the issue of ethics in data science of the social. In Chapter 3, I portray ethical sense-making as a form of vernacular theorizing, and argue that in data science of the social, various distinct strains of vernacular theories lend themselves to divergent ethical approaches, each of which reflects an implicit understanding of the nature of sociomateriality. In Chapter 4, I provide an empirical account of two data science projects that both put ethics at the center of their work, and yet take distinct ethical approaches. The first project—an effort to render transaction data from a transit fare payment system useful for analysis—I characterize as “data science as ethical convention,” an approach that seeks to mitigate the potential harms that could result from data science by repairing the practice through methodological rigor. I then identify three organizing processes that support this ethical approach: translating ethical values into technical specifications; incubating ethical thinking by temporarily removing data science practice from the pressures of productivity; and incentivizing the work of ethical sense-making by making its results “count” as valuable and integral contributions to data science. The second project—an effort to build a routing application for people with limited mobility—I characterize as “data science as ethical innovation,” an approach

that seeks to intervene in an extant social injustice by creating novel opportunities for empowerment of a marginalized group. Here, too, I identify three organizing processes that support such an ethical approach: balancing the needs and values of different affected stakeholders; “fractalizing” the problem at hand by connecting it to broader social patterns and systemic issues; and matching the problem to the proposed intervention in a way that avoids technological solutionism.

Rather than exploring all the things that can go wrong as data intensive technologies spread to the social sector, I ask how that development is being facilitated, and explore the consequentiality of these new configurations and processes. Chapter 5 and 6 can be read as a couplet that investigates these questions. In Chapter 5, I introduce the concept of *exostructure* as a temporary, project-based configuration designed to spawn investment in data infrastructures and knowledge infrastructures for data science. Because they are intended to be transported to new contexts and grow into more stable infrastructures, I argue that exostructures are a key mechanism by which data science is being “scaled” across social sectors and problem spaces. In Chapter 6, I return to the two projects introduced in the discussion of ethics and draw out the infrastructural ambitions and exostructural configurations of these projects. I argue that these exostructures are supporting three processes that enable the spread and uptake of data science practice in the social sector: experimenting with new roles and institutional arrangements; mitigating the risk of financial or moral failure; and mobilizing the intellectual labor that data science requires. Furthermore, I discuss how these processes are resulting in emergent roles for the academy and raising important questions about the appropriate relationship between social sectors.

## CHAPTER 2 METHODS

### DATA GENERATION

#### Field site

This study is based on ethnographic fieldwork in the “Data Science Environment” (DSE) at the University of Washington. The DSE is a partnership across New York University, the University of California Berkeley, and the University of Washington that is funded by the Robert and Betty Moore Foundation and Alfred P. Sloan Foundation. It was established to “catalyze a new era of research that enables interdisciplinary approaches to data-intensive discovery” by creating “new types of institutional environments in which these discoveries can take place” (MSDSE, n.d.-a). Across campuses, activities to address the challenges of advancing data science in academia are organized around six thematic “working groups”: careers; education and training; tools and software; reproducibility and open science; physical and intellectual space; and data science studies. Participation in the working groups is generally open to anyone from the host institution, and includes people from a wide range of academic domains and career stages. Although each of the lead organizations at the three universities administers the DSE autonomously on their own campuses, all three universities convene annually for an “all hands” summit, during which the working groups meet to discuss their efforts and plans for the future. At each university, DSE funds and activities are directed by a lead organization—NYU’s Center for Data Science, the Berkeley Institute of Data Science, and UW’s eScience Institute—and each lead organization has a physical space on campus that serves as a point of convergence for DSE activities.

The eScience Institute’s tagline is “advancing data-intensive discovery in all fields,” and the organization has cast itself as the hub for data science activities on the UW campus. Its

physical home, the Data Science Studio, is, indeed, a bustling hub of activity. The organization houses core staff and researchers with appointments at the institute; organizes several seminar series; periodically hosts academic “hack weeks”; conducts peer-to-peer programming boot camps; participates in the development of interdisciplinary data science curricula; holds office hours that are open to the entire university; runs an annual incubator program to provide intensive mentorship to researchers from across campus; provides open space where students and faculty can meet and study; participates in regional and national networks supporting data-intensive knowledge production and technologies; and more. I have been embedded at the eScience Institute as an ethnographer since September 2015, and while I have participated in and observed every aspect of this aforementioned work at to some degree, by far my greatest investment in time and energy has been directed toward participant observation in eScience’s Data Science for Social Good (DSSG) program.

The DSSG program started after someone approached the institute’s founding director, Ed Lazowska, and suggested that eScience should copy the Data Science for Social Good program that the University of Chicago had recently started. Ed and the rest of the staff thought this sounded like an excellent idea, and so, with blessings from Chicago, they launched the first iteration of UW’s own DSSG program in the summer of 2015, after just a few months of planning. eScience decided to combine aspects of Chicago’s program with elements of their own incubator program and came up with the following structure.

The eScience Institute hires a cohort of 15-16 students to work full time for 10 weeks over the course of the summer on data science projects related to social good, and learn new data science skills in the process. The students are divided into teams of four or five that are distributed across three or four projects, which are selected from an open call for proposals. In

the past, accepted projects have been submitted by individuals from the university, local government agencies, nonprofit organizations, and even an industry lab. eScience is looking for projects with methodologically interesting questions that are somehow related to social good, although they intentionally do not define what that means. Previous projects included objectives like predicting outbreaks of foodborne illness from online reviews; generating alternatives to census data from mobile phone records; and detecting traffic congestion caused by circling vehicles. Each project applicant is required to appoint someone from their organization as a “project lead,” who commits to spending at least 16 hours a week during the summer working side-by-side with the rest of the team in the Data Science Studio. Sometimes this responsibility is shared between two people. The teams are also supported by one or two data science mentors from the eScience institute, whose role is primarily to provide technical and methodological guidance, but also sometimes includes project management and other responsibilities. The most typical composition of a DSSG team is: four students, 1-2 project leads, and 1-2 data scientists.

The stories I tell later in this dissertation, in Chapters 4 and 6, come from the DSSG program. However, I don’t consider the object of my study to be “data science for social good.” For one thing, I address issues and questions in this dissertation that are not unique to the DSSG program. And so my unit of analysis is not the program itself, but the various DSSG projects I’ve observed in the context of the program, all of which have a life that both precedes and extends beyond the DSSG program. I view these projects as instances of something larger: as examples of “data science of the social” and examples of “exostructure”-based cross-sector collaborations, terms that will be explained in the following pages.

## **Ethnography**

When I began my graduate program in the Department of Communication at the University of Washington, I intended to do an ethnographic study of women's social media use in Afghanistan. I had conducted my master's research on the development of independent news media in Afghanistan, and spent a year living there between my masters and PhD programs. In part, my objective in that time was to lay the groundwork for future fieldwork by practicing my rudimentary Persian language skills and cultivating a network of friends, colleagues, organizational affiliations, and interlocutors. In other words, I was preparing to do classic ethnographic research, in the vein of anthropological studies of distant lands and peoples.

The ethnographic method was, of course, honed in the discipline of anthropology, a field that coalesced originally around the goal of understanding and explaining universal truths about humankind, aspiring to be the "science of man" (Tylor, 1889). Anthropology came of age in the era of colonization, as European powers fanned out across the globe in search of natural resources, labor, markets, and trade routes. As these Europeans came in contact with diverse cultures, in some cases for the first time, anthropologists tasked themselves with describing, categorizing, and quantifying their customs and characteristics. At first, this cataloguing of culture was done by "armchair anthropologists" who produced second-hand accounts from documents and stories told by worldly travellers (Tedlock, 1991). Over time, however, anthropologists began spending time visiting and living amongst distant communities, learning their languages and customs *in situ*. In 1922, Bronislaw Malinowski published *Argonauts of the Western Pacific*, which would become a sort of template for modern ethnographies in the decades to come (Kuper, 1973): richly descriptive, narrative accounts based on immersive and extended participant-observation among "exotic" peoples.

By the latter part of the twentieth century, in the throes of the so-called crisis of representation in academe (Marcus & Fischer, 1999), critical, feminist, and postmodern scholars began interrogating the foundations of anthropology and the role of ethnographers in furthering an unjust project of colonization (Asad, 1975), reifying stereotypes of non-White Europeans as dehumanized “Others” (Said, 1989), and unreflexively overlooking the power dynamics inherent to their craft (Clifford & Marcus, 1986). Although it remained, for quite some time, standard fare for students of anthropology to spend years studying a foreign language and conducting immersive fieldwork abroad, the genre of ethnographic writing was forever changed by the seismic shift that resulted from this crisis. No longer would it be acceptable to produce functionalist tomes; for many, ethnographies of distant cultures and communities became sites for the production of multi-vocal accounts of the human experience that destabilized readers’ received notions of difference and challenged the pillars of western liberalism.

It was this mode of ethnography that I planned to undertake in my doctoral research on the role of social media in the lives of young Afghan women. I was inspired by Saba Mahmoud’s (2005) ethnographic study of Islamic revivalism in Egypt, which explored the way women exercised political agency through their performance of piety, and called into question core assumptions of secular feminism. I was also motivated by Miller and Slater’s (2000) ethnography of internet use among Trinidadians, which troubled prevailing notions at the turn of the century about socializing on the Internet being “opposed to and disembedded from the real” (p. 4), a myth perpetrated through popular imaginations of “cyberspace,” “virtuality,” and “simulation.” In my mind, these were powerful examples of how ethnography of distant places could be used, not just to offer voyeuristic portrayals of distant others, but to fundamentally shift

perspectives about the construction of our own social world. And that was the kind of work I hoped to emulate.

However, conditions in Afghanistan were rapidly deteriorating, putting my aspirations to do fieldwork there in serious jeopardy. The security situation was already precarious when I returned to the US in late 2013 (although, in fairness, life in Afghanistan has been precarious ever since the revolts that precipitated the Soviet invasion in 1979), and were rapidly devolving further throughout 2014. That year marked the formal end of US-led combat operations in Afghanistan, a resurgence of local Taliban forces (Al Jazeera, 2017), and the emergence of an Afghanistan-based branch of the brutally draconian global militant group that refers to itself as the Islamic State (Middle East Institute, 2016). My closest friends and some of my family members were fleeing the country, and warned me that it wasn't the right time to go back.

At the same time, in autumn of 2014, I was enrolled in a fieldwork methods course taught by Dr. Matthew Powers. For the sake of that class, I needed a site closer to home, where I could conduct weekly observations throughout the 11-week-long academic quarter. With that in mind, I reached out to Dr. Brittany Fiore-Gartland for help. I knew that she had recently been hired as a full-time ethnographer at the eScience Institute to study the data science environment on campus. I had nothing more than the vaguest notion of what data science was at the time, and was not paying particularly close attention to the data-intensive transformations taking place across nearly every aspect of social life in American society, from the intimate spaces of our personal lives to the halls of power. But Dr. Fiore-Gartland and I had bonded over our shared interests (we both studied social dimensions of technology, were drawn to international contexts, and had previously obtained degrees in anthropology) and I thought it would be worthwhile to reach out and see if she could use an extra set of eyes and ears in the field that quarter. Fortunately, she

said yes, and asked me to help her conduct observations of eScience's Incubator program, which pairs a data science mentor from the eScience Institute with an outside researcher to collaborate intensively on a data science project over the course of one academic term. And so I spent several hours a week watching the Incubator participants huddled around a conference table in a windowless room, hacking away quietly on their keyboards, discussing how to fix bugs, diagramming data pipelines, writing pseudo-code on the white board, and weighing the merits of various tools or software packages. I may not have traveled very far to do my fieldwork, but the language and culture of data science were foreign to me nonetheless. I went into the experience without specific research questions and not knowing what would be interesting or important. I remember feeling quite unmoored at first, as evident from my notes at the time:

We talk a lot in class about how our own biases and positionality influence our research, and so that's something I've been prepared to think about as I started this fieldwork. But I didn't expect what really feels like an element of randomness. I'm very well aware that I'm sometimes simply capturing what I'm physically able to capture—not necessarily systematically filtering what I record, but just literally missing much of what is going on because I don't understand, or there are too many things happening at once, or I can only type so fast. There are biases at play for sure, but there's also some amount of just sheer luck in terms of what makes it into my notes—but then those are the things that will end up seeming important down the line, just because they happen to be there.

Fieldnotes, October 2014

Dr. Fiore-Gartland coached me through this period of anxiety, though. This is what grounded theory is all about, she advised. And this is why it's important to truly be immersed in your field site, to stick around long enough that you can see patterns, articulate routines, recognize anomalies, and evaluate salience. And sure enough, by the end of the quarter, I was starting to be able to do that. As I learned more about the eScience Institute itself and got more context for the interactions I observed in the Incubator, I realized that they were part of a well-supported and concerted effort to build data science capacities across new contexts and domains,

part of a broader and consequential movement to make an impact on the way knowledge is produced and decisions are made. And I realized that to really understand why and how that was happening, I would need to stick around.

### **Studying up**

And so it was that I ultimately abandoned my plans to do fieldwork in Afghanistan, shifted my academic focus, and committed to studying the “data science environment” at UW for the rest of my graduate career. In doing so, I claimed my spot among a growing line of ethnographers choosing to study places, communities, and phenomena close to home. George Marcus and Michael Fischer (1999) advocated for this—what they call “repatriated ethnography”—in response to the crisis of representation. In their seminal essay, *Anthropology as Cultural Critique*, they argue that traditional ethnography fell short of fulfilling anthropology’s full potential to offer powerful critique (Marcus & Fischer, 1999). Although ethnographers had been marginally successful in offering critical provocations for readers through “the juxtaposing of alien customs to familiar ones,” Marcus and Fischer argued, (1999, p. 111), their method could be more powerful if its lens were turned directly onto their own culture. They invited anthropologists to draw inspiration from critical theory and “create an equally probing, ethnographic knowledge of its social and cultural foundations” (Marcus & Fischer, 1999, p. 112) by studying communities, institutions, and practices within their own social milieu.

Writing two decades after the call for repatriated ethnography went out, Stephen Crossley (2017) notes that much of the work ethnographers are producing in and about their own backyards have continued to scrutinize the lives of the poor, the marginalized, and the disadvantaged, and that those demographic groups are often exoticized and essentialized just as

distant cultures have been. “Thick description” of the lives of disadvantaged people does little to shed light on the systemic issues perpetuating their marginalization, he argues, and instead, ethnographers should aim for producing “‘thick construction’ of the wider conditions that structure and impinge on those residents that live in disadvantaged areas” (Crossley, 2017, p. 115). To get at this, Crossley compels researchers to “explicitly link the behaviour of rich and powerful groups in society with the conditions experienced by marginalised and less powerful groups” (Crossley, 2017, p. 114). In doing so, he is renewing Laura Nader’s (1972) call to “study up,” an argument that ethnographers should not only study places close to home, but also turn their gaze several steps up the ladder of power, rather than several steps down, as they were accustomed to doing:

Anthropologists might indeed ask themselves whether the entirety of field work does not depend upon certain power relationships in favor of the anthropologist, and whether indeed such dominant-subordinate relationships may not be affecting the kinds of theories we are weaving. What if, in reinventing anthropology, anthropologists were to study the colonizers rather than the colonized, the culture of power rather than the culture of the powerless, the culture of affluence rather than the culture of poverty?"

Nader, 1972, p. 289

The relative powerlessness of informants in traditional ethnographic research is intimately connected to the separateness of their own existence from that of the researcher. The traditional anthropologist enters “a distant, parallel universe,” “inhabited by people who bear little relation to her home society, class, profession, or employing institution” (Forsythe, 1999, p. 6). They often don’t speak English, don’t have access to the outputs of ethnographic research, and hold no sway in the institutions that determine whether an ethnographer’s work meets standards of quality and integrity. As a result:

While they may have a lot to say over whether and how she does fieldwork in their community, they have no power over the way the anthropologist represents them. Indeed,

they may not even know how they are represented in her work. Their reaction to her construction of them has no bearing on the anthropologist's future ability to obtain jobs or research grants, or to publish her material about them.

Forsythe, 1999, p. 6

Such is not the case, however, if one commits to studying up. As Hugh Gusterson (1997) has noted, the problem with studying elite contexts is that "ethnographic access is by permission of people with careers at stake, where loitering strangers with notebooks are rarely welcome, and where potential informants are too busy to chat" (p. 116). Moreover, once access is obtained, the privileged social position of elite interlocutors continues to mediate the relationship between ethnographers and their subjects. "Our subjects are powerful and literate," Gusterson (1997) says of studying up, "and they read what we say" (p. 117). While conducting fieldwork at the Lawrence Livermore National Laboratory where a number of nuclear weapons were developed, Gusterson recounts a peculiar situation that unfolded during a meeting at which he was to present his research to Livermore lab scientists:

I arrived to find that one of the Laboratory's leading weapons scientists had come to my talk wearing nothing but a loincloth and carrying a cane to which he had nailed an animal skull. He shook this at me and grunted whenever my presentation displeased him — which seemed to be quite often.

Gusterson, 1997, p. 117

Gusterson humbly characterizes this interaction as the weapons scientist validly putting the anthropologist in his place. "As he so aptly dramatized for me," concludes Gusterson (1997), "the objectifying, exoticizing language of anthropology is as objectionable at home as abroad, and one is less likely to get away with it" (p. 117). Gusterson's stance that ethnographers should be accountable for respectful representations of their subjects is a noble one, but his implication that there is an equivalency between an ethnographer's ethical obligations to the less powerful

and his ethical obligations to the more powerful is troubling. The anecdote about the Livermore scientist parodying the “naked savage” stereotype from yesteryear’s ethnographies can also be read as a cautionary tale that when ethnographers place themselves in realm of the powerful, they are opening the door to surveillance, coercion, ridicule, and other forms of discipline that may result in censorship or self-censorship. The line between accountability and co-optation can be a blurry one, indeed, and striking the right balance between them is an ongoing challenge in “studying up.”

This is a particularly salient issue when ethnographic access is gained through employment by the very same institution that comprises the field site, an arrangement that has become commonplace among scholars of science and technology studies (STS). The complicated power dynamics of such a situation are taken up by Diana Forsythe (2001), an anthropologist who primarily studied computer scientists and physicians at the same university where she was employed, often in the same department to which she was appointed. In the essay, “Ethics and politics of studying up in technoscience,” Forsythe (1999) is forthright about the challenges of such entanglement. Not only did her informants read, and occasionally challenge, her work, there were times when they were asked to provide her with letters of reference for employment or funding opportunities. And she was well aware that, in her precarious soft-money position, she was competing for resources with people who were simultaneously colleagues and informants. All of these things shifted the power dynamics in research to be something quite different from the traditional ethnographies of anthropology’s colonial past. Even while studying up, of course, the ethnographer retains a degree of power that comes along with the responsibility of representing individuals and communities to the world. That power is tempered, though, by the

entanglement of the ethnographer's interests and those of her research subjects, a situation that Forsythe (1999) has referred to as "mutual vulnerability" (p. 10).

Despite the complications of conflating employers, colleagues, and research subjects, such embedded arrangements have proved valuable for developing insights within the field science and technology studies, while simultaneously advancing the scientific, technological, and commercial aims of the institutions who host, and sometimes hire, ethnographers. For example, in the technology industry, Xerox Palo Alto Research Center (PARC) was an early leader in employing ethnographers to better understand the relationship between people and the machines they built. One of their first hires, Lucy Suchman, not only helped the company design more intuitive products (Chokshi, 2013), but also went on to become one of the most prominent and respected scholars in the academic field of human-computer interaction (CHI Academy, 2010). So many companies have emulated Xerox PARC in recent decades by bringing on ethnographers, as well as other qualitative researchers and social scientists, that such professionals have formed a voluntary association, the Ethnography and Praxis in Industry Community (EPIC). Ethnographers and other social scientists have also increasingly been hired to study the development of scientific collaborations, based on a growing recognition that the insights of those who study people, technology, organizations, and work can "offer both specific recommendations and a knowledgeable perspective from which to weigh social alongside technical and scientific concerns" (Vertesi et al., n.d., p. 1).

It is in this vein of thinking that an ethnographic component was integrated into the Data Science Environment grant shared by the University of Washington, the University of California, Berkeley, and New York University: that a team of ethnographers embedded within the data science environment would not only contribute to general understandings of cultural and

organizational transformations associated with data-intensive computational research, but also that they would contribute to the success of ongoing efforts to institutionalize data science in the academy.

After a brief period of time during which I was conducting fieldwork in the Data Science Environment at UW as part of my coursework, I was hired to continue that work as a research assistant in the Human-Centered Data Science Lab under the supervision of Professor Cecilia Aragon, who served on the executive team of the eScience Institute and would also become a co-chair of my dissertation committee. Dr. Aragon had secured a sub-budget from the grant that provided the lion's share of funding for the eScience Institute to support the ethnographic study of the Data Science Environment, and obtained IRB approval for the study as its principal investigator. This arrangement meant that not only would I essentially be paid by the organization I was studying, but also that my academic advisor had a vested interest in the success of that organization. This employment situation undoubtedly has influenced the course and nature of my research, and created delicate dynamics that needed to be handled with care. For one thing, we realized early on that Dr. Aragon's multiple roles within the Data Science Environment could pose ethical challenges; because she was in a position of power within the organization as a member of the executive committee, we agreed that she would not access fieldwork data related to individuals who were employed by the eScience Institute. Another complication of conflating my place of employment and my field site is that I have never truly "left the field," which is usually considered to be an important step toward clarity in making sense of the experience; backing away from the details of the field site allows one to see the forest, and not the trees, so to speak. I have not yet taken this step back, and while writing, I am still intimately connected to the eScience Institute and deeply immersed in the weeds of the day-

to-day work of data science practice. As such, the analyses I present here do not amount to a grand narrative or definitive account of the institutionalization of data science practice at the University of Washington, but a first step in making sense of a fraction of the rich data that I generated over the course of nearly four years.

Yet another challenge in my fieldwork arises from the fact that I am publicly affiliated with the organization I am studying, which complicates my ability to maintain meaningful confidentiality for my research participants. While I can often obscure individual identities when explaining recurring themes across my field site, the “thick description” (Geertz, 1973) that is characteristic of ethnographic writing, and necessary to understanding the complexities of day-to-day work, would leave plenty of bread crumbs leading readers back to the source of my account. Therefore, with approval from the human subjects division at the University of Washington and with permission from relevant study participants, I have chosen to name the organizations, projects, and interlocutors that are most prominent in my writing. This is both liberating and constraining. On the one hand, it frees me to discuss the intricacies and interactions of data science practice in fine detail. On the other hand, I have an ethical obligation to not cause reputational harm to my research subjects, or cast them in a bad light. This is just one of the reasons I have selectively highlighted stories from my trove of field notes that serve as positive exemplars of reflexive and cautious data science practice, rather than stories of data science practice that is blind to its own shortcomings. This does not mean that the accounts I present here are not veridical, relevant, or representative. In fact, I firmly believe they are essential and timely contributions to the understanding of data science practice. As I discussed in the previous chapter, critical data studies literature has vigorously taken on the task of surfacing the assumptions, indulgences, and transgressions of data-intensive computational technologies,

but has provided less in the way of generative insights into how to improve the design and use of these technologies. The data science community I've been studying is eager for such insights, so in telling the stories of data scientists behaving well and extrapolating practical lessons from their experiences, this dissertation is part of my humble effort to think *with* data scientists about how to improve their practice, not for or against them (Neff, Tanweer, Fiore-Gartland, & Osburn, 2017).

My employment with the eScience Institute has enabled this approach because I am truly a participant in the phenomenon I am studying; I am on the same team as my research subjects, and that means there is an expectation that my research will contribute to their success. Aside from the external publications produced from this long-term immersive study, my ethnographer colleagues and I regularly present analyses of our fieldwork to the eScience Institute and participate in the planning and implementation of their programs. I have been particularly involved in the Data Science for Social Good program that I write about at length in this dissertation; as part of my involvement, I have introduced stakeholder analysis, ethics workshops, and human-centered design mentorship to that curriculum.

Recently, Sarah Pink and Deborah Lanzeni (2018) have called for ethnographers to collaborate more deeply with data science practitioners in order to “practice ethics embedded in ethnographic and big data analytics together as part of a coherent, future-focused, and (new mode of) ‘mixed methods’ research agenda for understanding and acting in the world in an ethical and responsible way” (p. 2). At the same time, they call for the production of “critical ethnographies that provide specific examples of how existing anticipatory interventions based on big data analytics are irresponsible” (Pink & Lanzeni, 2018). But my own experience suggests that it is difficult to operate from a critical perspective and simultaneously work collaboratively

with one's research subjects on a shared objective. Although participant-observation has long been a hallmark of ethnography, the method actually represents a wide spectrum, with some modes of engagement leaning more toward observation and other modes of engagement leaning more toward participation. When an ethnographer is situated far enough toward the participant end of the spectrum that her engagement constitutes collaboration, this comes along with certain commitments that make an unadulterated critical stance untenable. Ethnographic collaboration means authentically sharing in the goals of the community of study, which would seem to foreclose the conclusion that their endeavors are fundamentally misguided or flawed—a possibility that must remain open if one is truly operating from a critical perspective. Collaboration also means starting from a position of ethnographic generosity, assuming that people are acting in good faith and with good intentions; this is also difficult to square with the foundational critical project of revealing the ways actors exert power and perpetuate inequity. This does not mean that a collaborative ethnographer cannot critique or problematize her phenomenon or community of study, but it does mean that she cannot, in good faith, enter the field with a predetermined mission of showing how their efforts are fundamentally misguided or “irresponsible,” as Pink and Lanzeni (2018) have suggested. As such, although I'm conducting immersive ethnographic fieldwork among a relatively elite community close to home, my project is informed less by the critical theories that inspired the original formulations of studying up and repatriated ethnography, and is more aligned with the theoretical commitments of practice scholarship.

## THEORETICAL ORIENTATION

### **The practice turn**

Academic scholars are fond of identifying trends in the study of social phenomena as “turns” toward a promising approach that had previously been overlooked, ignored, forgotten, or undiscovered—the interpretive turn, the discursive turn, and the material turn, to name just a few. In recent decades, some scholars in certain fields have either observed or advocated for a “practice turn,” a focus on the everyday, productive activities that help order our social worlds (Miettinen, Samra-Fredericks, & Yanow, 2009). As Theodore Schatzki (2001) has put it, “thinkers once spoke of ‘structures,’ ‘systems,’ ‘meaning,’ ‘life world,’ ‘events,’ and ‘actions’ when naming the primary generic social thing. Today, many theorists would accord ‘practices’ a comparable honor” (p. 10). This interest in practice is readily apparent in the three overlapping fields of inquiry that most inform my own approach: communication studies (e.g. Craig, 2006), science and technology studies (e.g. Suchman, Blomberg, Orr, & Trigg, 1999), and organization studies (e.g. Miettinen et al., 2009). As we will see, intellectual treatments of practice are heterogeneous and multifaceted both within and across these fields, with practice at once serving as a topical focus, a unit of analysis, an explanatory concept, and sometimes, a methodological commitment.

Although practices are comprised of actions, not all actions are part of practice—a distinction that goes back to Aristotle’s formulation of *praxis* as those actions that arise from practical wisdom (phronesis), as opposed to universal truth (episteme) (Nicolini, 2012). Practices are “doings and sayings” (Schatzki, 2001) bound together as “a coherent set of activities that are commonly engaged in, and meaningful in particular ways, among people familiar with a certain culture” (Craig, 2006, p. 38). Practice scholarship is, in part, a response to dissatisfaction with

what Sherry Ortner (2006) has called “theories of ‘constraint’”—formulations that seek to explain how behavior is “shaped, molded, ordered, and defined by external social and cultural forces and formations: by culture, by mental structures, by capitalism” (pp. 1-2). Scholars from a wide range of disciplines have theorized practice as the concept that can reconcile human agency with the existence of such constraints.

While they share certain concerns and commitments, a unified approach to practice is nonexistent (Schatzki, 2001), and various strains of thought have developed their own specialized vocabularies and methods for understanding practice (Miettinen et al., 2009). Contemporary practice scholars draw on a diverse range of philosophic influences that have been traced and parsed in a number of ways. Here, I largely follow Miettinen et al (2009) who identify three distinct sources of inspiration for practice theory: Wittgenstein and the phenomenology of Heidegger, Marxian materialism, and the pragmatism of Dewey and Mead (for slightly different parsings see Bernstein, 1971; Nicolini, 2012; Schatzki, 2001).

### **Heideggerian & Wittgensteinian influences on practice scholarship**

Some of the threads that tie together the thought of Heidegger and Wittgenstein, and make them both inspirations for practice theory, are their respective emphases on social contexts and ideas about extra-rational thought. In Heidegger’s meditations on being, everyday actions unfold in a seamless web of relationships that give existence meaning (Dreyfus, 2001) . There is no existence (Dasein) outside of existence-with-others (mit-Dasein), which includes both living and non-living beings. For Wittgenstein, language is a practical and social endeavor, with rules that can never be made totally explicit, but rather, require contextual background knowledge that goes unarticulated and unnoticed (Nicolini, Gherardi, & Yanow, 2003). Thus, people must share a “life form” or praxis in order to make meaning or share knowledge (Nicolini et al, 2003, p. 11).

These ideas have influenced three of the most prominent contemporary practice theorists, Pierre Bourdieu, Anthony Giddens, and Theodore Schatzki (Feldman & Orlikowski, 2011), each of whom addresses what Nicolini et al (2003) call “prelexive knowledge”—the way routinized actions unfold without being the focus of explicit thought, and how this stabilizes and structures the social world. Bourdieu (1977), in his development of “praxeology,” introduces the concept of “habitus”—an intuitive “feel” for action that arises out of repeated mimetic behavior, such as an athlete performing the movements of their sport in the midst of a game. Because habitus precludes rational or deliberative thought, it serves as an important mechanism by which social norms and customs are stabilized and perpetuated in the absence of the conscious decision-making that we normally associate with notions of agency. Similarly, Anthony Giddens’ (1983) theory of “structuration,” which accounts for the way action and structure constantly reproduce one another, emphasizes “routines” that are unreflexively executed in the course of practice. Theodore Schatzki (1996) makes a similar move with his concept of “action intelligibility,” which he characterizes as non-explicit sense-making. For all of these thinkers, reflection and rationalization only come into play during practice when the flow of prelexive knowledge is interrupted by breakdown, crisis, or conflict.

### **Marxian influences on practice scholarship**

For practice scholars from a Marxian tradition, though, reflection and rationalization is treated not as a special case, but as a central activity informing practice that is always evolving in the face of ever-present problems, tensions, and misalignments. Although many Marxian scholars have come to emphasize the more deterministic aspects of his materialist thinking, the developers and adherents of Cultural Historical Activity Theory (CHAT, or sometimes, simply Activity Theory) are practice scholars who have retained Marx’s material focus, historical

sensibility, normative orientation, and interventionist mandate, but found openings in his work via Vygotsky (Foot, 2014) to develop ideas about structured agency. CHAT theorists argue that changes within activity systems are precipitated by the activation of one or more “contradictions”—i.e. misfits or paradoxes—within the system (Engeström, 1999a; Foot & Groleau, 2011). In Marxist logic, each of these lower order contradictions flow inexorably from the ultimate and primary contradiction in capitalism: a tension between “the dual construction of everything and everyone as both having inherent value and being an exchangeable commodity within market-based socioeconomic relations” (Foot, 2014, p. 339). Yrjö Engeström, one of the foremost proponents of CHAT, is concerned with how organizations learn and change in response to contradictions through a collaborative process. He articulates an “expansive learning cycle,” which “begins with individual subjects questioning the accepted practice, and it gradually expands into a collective movement or institution” (Engeström, 1999b, p. 381). After collaboratively identifying a problem, the organization engages in an iterative process of solution development—first conducting analysis, then developing and testing a possible solution, then implementing a version of the new idea and reflecting on that process before moving to fully integrate the solution into their practice (Engeström, 1999b, p. 384).

### **Pragmatist influences on practice scholarship**

A third influence on practice scholarship is the pragmatic tradition, especially as articulated by Dewey and Meade. Like the Marxian-influenced approaches discussed above, a pragmatist take on practice foregrounds “the analytical process of deliberate, reflexive thinking” (Simpson, 2009, p. 1337) rather than pre-flexive or extra-rational thought; but unlike those approaches, it does so without the underlying theoretical commitments rooted in a critique of capitalism. In fact, one of the distinctive characteristics of pragmatic practice theory is the

absence of adherence to or search for *a priori* universal truths. Instead, the point is to develop useful understandings of particularly situated practices (Cronen, 2001). For Dewey, practical judgments are not evaluated against some notion of objective truth, but on the basis of the outcome informed by those judgments; as Bernstein (1971) has put it in an exploration of pragmatism's relevance to understanding action and practice, "the actual consequences which issue from our practical judgments can validate or invalidate these judgments" (p. 215 - 216). In other words, from a pragmatist perspective, "knowing does not take precedence over acting; the two are inextricably intertwined dynamics of human conduct" (Simpson, 2009, p. 1343).

For practice theorists inspired by pragmatism, this translates into a concern for developing particularized, situated, and useful understandings of local practices. This does not mean that practice theories cannot be generalized, but rather, that "theoretical inquiry gains its systematic explanatory power in the degree to which it abstracts from the demands of immediate existential situations" (Bernstein, 1971, pp. 216–217). "Within a practical discipline perspective," say Craig and Tracy (1995, p. 248), "theory is conceived as a rational reconstruction of practices for the purpose of informing further practice and reflection." They go on to address the usefulness and applicability of practice theory in the following way:

The purpose of this rational reconstruction is not to discover some inherent, unchanging 'essence' but rather to *construct* a tentative, revisable, but still rationally warranted normative model that is relevant to a broad range of practical situations. The ultimate test of such a practical theory is not, then, like scientific theory, its capacity to explain an existing reality but rather its usefulness for practice and reflection. The underlying philosophy is not realism (theory describes the world) or idealism (theory constitutes the world) but rather reflective pragmatism (theory informs praxis)"

Craig & Tracy, 1995, p. 252

Pragmatism-inflected practice scholarship, then, distinguishes itself by not just theorizing practice, but by putting theory into practice.

## **Salient distinctions in practice theory**

With influences deriving from such varied and distinctive philosophical traditions as phenomenology, Marxism, and pragmatism, it is no surprise that practice scholarship exhibits a wide range of variation. While a comprehensive treatment of these convergences and divergences is beyond the scope of this dissertation, here I will briefly sketch some of the distinctions that are salient to my own work, as a way of charting my course through the practice scholarship terrain.

### *“Theories of Practice” versus “theories of practice”*

On the one hand, some practice scholars are engaged in a theoretical project “aimed at transcending perennial problems in philosophy and social sciences, such as Cartesian dualism and the agency-structure problem” (Miettinen et al., 2009, p. 1312). On the other hand, some practice scholars engage with inductive theory development through close empirical study—by observing, describing, and explicating the consequentiality of mundane, situated, particular practices. Another way to think of this is as the difference between a concern for Practice with a capital “P,” and practice with lower case “p.” Purely theoretical works on Practice hope to inform the way we generally understand the relationship between agency and structure, and the nature of practical knowledge writ large. More empirically grounded works on practice, meanwhile, may either seek to advance middle-range theories that can explain certain aspects of practice, or localized action-oriented theories for temporally, spatially, and culturally circumscribed practices.

Although I have done much of the latter type of localized theorizing in work presented directly to my community of study, the empirical analyses I include in this dissertation fall firmly into the middle camp. Rather than hoping to fundamentally shift the way we see Practice, I

explore the consequentiality of emergent practices in data science of the social, and it is to this particular realm of practice that my theoretical insights can be applied. In my empirical chapter on ethics in data science of the social, my analysis explores the tensions that surface as data scientists make sense of their work's ethical consequentiality, and the trade-offs they make in designing their projects based on that process of sense-making. It is my belief and hope that the lessons to be learned from their experiences are of value beyond the particular program in which their work unfolded, and applicable more broadly to emergent practices in data science of the social. Likewise, in the fifth and sixth chapters, I introduce the concept of "exostructures" to explain how project-based work is implicated in the scaling of data science approaches across social sectors. The cross-sectoral, project-based work that I describe is a common approach in data science of the social, and as such, the concept of exostructure that I introduce resonates beyond the particular time and place I have been studying. But it is also constitutively and definitionally tied to data-intensive, computational work, and therefore may not necessarily help us understand other types of practices, or Practice more generally.

### *Inward gaze versus outward gaze*

Nicolini et al. (2003) also distinguish between practice scholarship that is, on the one hand, primarily concerned with questions about the internal continuity of practice, such as enculturation processes involved in the perpetuation of principles and norms among practitioners, and practice scholarship that, on the other hand, has a more "outward" focus, concerned primarily with the emergent, expansive, and adaptive nature of practice (p. 24). To this, I would add that practice scholarship with an outward focus can also be concerned with the consequentiality of practice, showing how it is situated historically, or related to broader social phenomena. Within this dissertation, I have turned my gaze in both directions. In the chapters

related to sociomateriality and ethics, I not only explore the dynamics of ethical thinking within data science teams and the conditions that allow ethical deliberation to flourish, I also situate their experience within the broader discourse that is taking place around the ethical dangers and transgressions of data-intensive technologies. And in the chapters related to infrastructuring, I not only characterize and theorize the project-based mode of work typical of efforts to institutionalize data-intensive practice across social sectors, I also am concerned with how such work is fundamentally strengthening, challenging, and evolving relationships between academia, government, and industry.

#### *Ancillary practical research versus interventionist practical research*

Practice scholarship is often (but certainly not always) characterized not just by its topical focus on questions of practice, but also by the *practical intentions* of practice researchers; not practice theory, but what (Cronen, 2001) calls practical theory. By this I mean that, in many cases, practice researchers hope in some way to benefit the community they study, or improve its practice. The means by which researchers try to make this happen may vary widely, but can be viewed under the broad headings of two basic types of approaches. In the first, what I'm calling *ancillary practical research*, research questions and findings may be relevant to practitioners of study, but insights or results derived from the research are distributed primarily in typical academic venues. For example, practice research findings in organization studies or critical management journals may eventually work their way into educational programs training a new generation of organizational leaders, and in this way, indirectly or diffusely inform practice. In *interventionist practical research*, however, a researcher's insights are shared directly with practitioners in a manner that is appropriate for their own cultural context, through media that are familiar and accessible to their community, and at a time that is proximate to the researcher's

engagement with that community. This mode of research has much in common with the tradition that has been called “action research,” which is also concerned with “the pursuit of practical solutions to issues of pressing concern to people, and more generally the flourishing of individual persons and their communities” (Reason & Bradbury, 2001, p. 1). But my chosen term is in some ways broader than action research, and in other ways, more specific. For many, action research should necessarily entail a theoretical and axiological commitment to empowering marginalized populations (Kemmis, 2008), while interventionist practical research does not necessarily adhere to this norm. So in this way, the term is more general than action research. But also, action research refers to action on the part of the researcher, and does not necessarily adopt the same theoretical and empirical privileging of action or practice as an object of study. So in this way, my chosen term, interventionist practical research, is also more specific than action research.

My own doctoral work has included both ancillary and interventionist aspects of practical research. My ethnography colleagues and I have regularly provided presentations and written internal documents for our community of study as a way to share our grounded analyses of their practice. These are usually done to coincide with the institute’s programmatic cycles, so that our insights could be incorporated into the iterative planning process that tends to coincide with the periodicity of the academic calendar. In addition to these formal presentations of our work, we also often engaged directly as participants in the planning process, especially in the Data Science for Social Good program about which I write in this dissertation. Although that more interventionist work does not make an appearance in this dissertation, I must acknowledge that it has undoubtedly informed and inflected my more academic products as well. The arguments and analyses I develop here are also intended to be practical, but in the ancillary sense. One of the

particularities of my field site is that most of my study participants are academic researchers themselves, who will likely be curious about what I have to say, and will have access to my publications. Additionally, I intend to translate the results of my dissertation into outputs that are appropriate for the venues where data-intensive computational researchers and the people who study them congregate and share knowledge—spaces like the conferences on Human Computer Interaction and Computer Supported Cooperative Work. Moreover, though, as I take on an increasingly participatory role in the organization, the practical insights I develop herein will inform my own contributions to the community going forward—a situation I will return to in the conclusion of this work.

### **Commonalities among practice approaches**

Despite the distinctions that can be made between various strains of practice scholarship, we can nonetheless glean certain core characteristics that are common across it. Here, I highlight the methodological strengths and commitments of practice scholarship that are particularly salient to my own study.

#### *Focusing on action*

Practice scholarship is first and foremost concerned with action in process, as evidenced by the affinity for using the gerund forms of nouns (Nicolini et al., 2003); a practice approach starts with a concern not for decisions, but for deciding; not for organizations but for organizing, not for interpretations but for sense-making. This linguistic choice “conjures up a world that is always in the making, one in which “doing,” more than “being,” is at the center of attention” (Nicolini et al., 2003, p. 21). Just because active processes are the starting point of a practice orientation does not mean, however, that they are the end-point as well. A focus on process can provide a better sense of how and why other salient categories of the social world come into

being. As Craig and Tracy have noted, for example, with a practice approach, “values and principles implicit in the practice are made explicit” (Craig & Tracy, 1995, p. 252). The point is not to ignore more stable structures or concepts, but “to uncover that behind all the apparently durable features of our world there is always the work and effort of someone” (Nicolini, 2012, p. 3). In this dissertation, the processes that most concern me are sense-making and scaling. In my discussion of ethics, I detail the processes of deliberation and decision-making that two teams undertook to make sense of the ethical implications of their work. And in my treatment of scaling, I discuss how the project-based structure of DSSG work is contributing to an ongoing process of institutionalizing data intensive computational work across social sectors.

### *Understanding context*

Practice approaches also tend to share what can be called a “social ecology” perspective (Nicolini et al., 2003, p. 22). Regardless of whether practice research speaks of communities, organizations, activity systems, or some other collective noun, its primary concern is not with individuals, but with common actions and shared meanings as they unfold in social contexts comprised of heterogeneous beings. This includes both people and things, and the focus is not on understanding any of those beings in isolation, but on understanding the relationships and connections between them. Moreover, ecological contexts for action are not just a backdrop in front of which action plays out, but serve as the structures that both constrain and enable action, and are simultaneously shaped by action. In my empirical chapter on ethical sense-making in DSSG, I explore how the structure of the program facilitated deliberation, and how the deliberations and resulting design decisions contribute to imaginations and reifications of what it means to do ethical data science. In my empirical chapter on scaling, I explore the relationship between the sectors, and how their different logics, incentives, and accountabilities inform their

interactions with each other, and how those interactions are resulting in emergent roles and norms for those institutions.

### *Being there*

The coupling of these two foci—on understanding context and action—lend themselves to a concomitant methodological commitment. There are many ways to gain insight into people’s behavior; by analyzing captured video after the action is over, for example, or collecting digital traces of online activities. But studying action in context seems to require being there to bear witness to action as unfolds in real time, to have the opportunity to hear the backstories that illuminate people’s relationships, to experience the same things they experience, to ask questions about their motivations and interpretations. As Nicolini (2012) notes, most of the goals of practice scholarship “can only be achieved through participant observation, that is watching participants’ activities, interacting with them (e.g. asking questions), and—at least ideally—attempting to learn their activities first-hand” (p. 179). He is, of course, essentially describing the ethnographic fieldwork method, which finally brings me full circle to a discussion of my data.

## DATA ANALYSIS

### **Overview**

After being embedded in the Data Science Environment at UW for over three years, my colleagues and I have amassed a vast trove of qualitative data. Combined, we have collected more than 1,800 pages of field notes, conducted 175 interviews with 133 subjects in total, and collected documents and photos along the way that are relevant to our research participants’ practices, including discursive texts produced by, discussed within, or relevant to the community of practice. For reasons described below, this dissertation is based on a subset of that entire data corpus—the field notes, interviews, and documents that are related in particular to the eScience

Institute's cross-sector collaborations in data science projects that are intended to benefit society. The bulk of that fieldwork was conducted while embedded in the Data Science for Social Good program at the eScience Institute, which runs for 10 weeks every summer from mid-June to mid-August. I observed and participated in three iterations of this program prior to writing this dissertation, in 2015, 2016, and 2017. My role in the program included: participating in planning meetings with eScience staff; conducting workshops on collaboration, ethics, and stakeholder analysis for project participants; conducting daily observations of team work; and interviewing program participants. Additionally, because the eScience Institute's involvement in social-impact data science is enmeshed within regional and national networks supporting such work, I conducted supplementary observations and interviews at two other DSSG programs and eleven related conferences and events around the country in 2016 and 2017. All told, the subset of data informing this dissertation consists of roughly 1,200 pages of notes, 99 interviews with 98 research subjects, and numerous documents related to these observations, including for example, presentation slides, blog entries, and chat logs (see Appendix: Methods, for a summary of the data corpus). This dissertation relies predominantly on observational data generated through fieldwork. Rather than incorporating a comprehensive analysis of all my interview data, interviews are employed herein for the sake of clarifying and illustrating the perspectives of various participants whose work is described.

I have employed three related approaches in three distinct, but overlapping, stages of analysis and theory development. Throughout the period of data collection during participant observation, when seeds of theory were first starting to germinate, I largely followed the guidelines of grounded theory development, as adapted for ethnographic inquiry by Kathy Charmaz and Richard Mitchell (2007). During an initial stage of intensive distillation in which I

honed in on the ideas that would form the core of my dissertation, I relied on situational analysis, an offshoot of grounded theory advanced by Adele Clarke (2003). And in refining these theoretical abstractions and connecting them back to the stories in my data, I followed a retroductive analysis process outlined by Ragin (1994) and Sæther (1998).

### **Germination phase: Grounded theory development**

Since, as I've already discussed, I came into my field site nearly entirely ignorant of the phenomenon I was about to study, I was primed to take a grounded theory approach by default. However, as the grounded theory proponents Kathy Charmaz and Richard Mitchell (2007) remind us, researchers inevitably "hold worldviews, possess stocks of knowledge, and pursue purposes that influence their respective views and actions" (p. 162). This acknowledgment is, in part, what led scholars like Charmaz (1996; 2014; 2017) and Adele Clarke (Clarke, 2003, 2009) to build on grounded theory as originally developed by Glaser and Strauss (2009/1967), and adapt it to the postmodern turn in academic research. It is this adapted approach that I follow here, which retains broad methodological foundations of grounded theory, but eschews the more positivistic tendencies of purist grounded theory that has evolved over the decades, including highly prescribed analytical formulae and the supposition that a researcher could ever enter a field of inquiry as an objective blank slate. As Charmaz and Mitchell (2007) note, the line-by-line coding process associated with Glaser's version of grounded theory works well for structured qualitative data, but is ill suited to ethnographic field notes derived from participant observation, which often consist of some combination of detailed observational descriptions and the ethnographer's own in-the-moment reflections on what is unfolding. Trying to re-establish the "gentle guidelines" that originally characterized grounded theory and move the method "away from technology and turn it toward art" (p. 161), Charmaz and Mitchell (2007) provide a

path forward for adapting grounded theory to ethnographic work that broadly follows these stages of research (p. 160):

1. Simultaneous data-collection and analysis;
2. Pursuit of emergent themes through early data analysis;
3. Discovery of basic social processes within the data;
4. Inductive construction of abstract categories that explain and synthesize these processes;
5. Integration of categories into a theoretical framework that specifies causes, conditions and consequences of the process(es).

In spite of not going into the field with a preconceived hypothesis or research question in mind when I joined the data science ethnography project, I did enter the field with an academic focus on the study of technology and society, and with a theoretical orientation that leaned strongly toward a sociotechnical perspective; in other words, I was already interested in the ways the social world is built with and through technological artifacts, and the ways that technological artifacts are socially constructed accomplishments. While I began with this general theoretical orientation, the particular foci of my research emerged slowly over time. This is consistent with a grounded theory approach that calls for researchers to begin analyzing their data as soon as they begin collecting it, and use those provisional insights to focus future data collection in a process that has been called “theoretical sampling” (Glaser, 1978). The process of constantly reviewing field notes to identify salient themes, anecdotes and questions, was a collaborative endeavor in the case of this study. Although several researchers participated in the ethnography team periodically over the years, Dr. Brittany Fiore-Gartland and I were the primary researchers consistently collecting field data throughout the study period. We would regularly read each other’s notes, make comments where we saw resonance or discord with our own observations,

and discuss prominent themes, peculiarities, and open questions that served to focus our attention in the field.

We quickly realized that one of the core themes in our field site was the community's commitment to cross-disciplinarity, fueled by a position of domain agnosticism—a belief that data science could be applicable to all fields of inquiry, knowledge production, problem spaces, and decision-making. We observed the way actors in cross-disciplinary data science collaborations were navigating the use of different terminologies, epistemological assumptions, technical proficiencies, and values, as they attempted to apply data science across varied domains of inquiry. These themes could be seen in any number of eScience's activities—from their efforts to promote cloud computing, to their involvement in the deployment of large-scale scientific instruments, to their development of data science education curricula, to their interdisciplinary mentorship programs. But questions of cross-disciplinarity and domain agnosticism were thrown into sharpest relief in the community's efforts to apply data science to entrenched social problems. That objective was instantiated most prominently in the organization's flagship “Data Science for Social Good” program, which became the site for the majority of my participant-observational work. It also carried over into the institution's partnerships in urban analytics, and involvement in national networks like MetroLab and the National Science Foundation's Big Data Hubs, all of which will be described at greater length elsewhere. These regional and national collaborations, as well as connections to other Data Science for Social Good programs, led me to include several observational forays at conferences and workshops where actors involved in leveraging data science for social benefit gathered to discuss, share, and reflect upon their work. In all these endeavors, I saw the community not just applying data science of the social across academic disciplines, but beyond the university and

across social sectors as well. How and why this was happening became a central concern in my work. Thus, our ethnography team's combined data on the various programs, projects, and networks supporting these cross-sector collaborations around data science of the social became the largest subset in the corpus of our work.

After identifying emergent themes—in this case, cross-sectoral collaboration and the pursuit of social benefit—a grounded theory approach entails focusing in on “the basic social processes” at play in those themes (Charmaz & Mitchell, 2007, p. 160). Two basic social processes I honed in on were *translating* the techniques and tools of data science across domains, and *sense-making* to negotiate the differing values and priorities of stakeholders from distinct domains. Once those processes are identified, grounded theory development involves “inductive construction of abstract categories that explain and synthesize these processes” and finally, “integration of categories into a theoretical framework that specifies causes, conditions and consequences of the process(es)” (Charmaz & Mitchell, 2007, p. 160). For this analytical phase of grounded theory development, I followed a method described by Clarke (2003, 2009) as “situational analysis.”

### **Distillation phase: Situational analysis**

Clarke's (2003) methodological project is “disarticulating grounded theory from its remaining positivist roots” by developing methods for “provocative yet provisional grounded theorizing rather than the development of substantive and formal theories” (p. 559). Her formulation of situational analysis is complementary to communication scholar Kevin Barge's (2001) argument that analytical mapping exercises can play a role in helping the practical scholar understand “the puzzles, dilemmas, or challenges inherent to a practice and to describe the particular communicative strategies, moves, and structures that manage those problems” (p. 7).

Clarke's (2003) methods of conducting "cartographic situational analyses" (p. 558) include constructing a number of different kinds of maps: situational maps that illustrate connections between relevant social actors and objects; social worlds/arenas maps that identify the relations and negotiations between collective actors; and positional maps that draw out salient differences and relations between discursive perspectives (p. 559-560).

In my chapters on sociomateriality and ethics in data science, I employ the latter analytical exercise. Positional maps "lay out the major positions taken, and not taken, in the data vis-à-vis particular discursive axes of variation and difference, concern, and controversy surrounding complicated issues" (Clarke, 2003, p. 554). Such an analysis acknowledges that social actors, even when engaged in common pursuits, hold multiple positions, interpretations, and motivations that can both complement and contradict one another. Riffing on Geertz (1973), Clarke refers to these maps as "thick analysis," a way to develop mid-range pragmatic theories that articulate salient differences rather than identifying generalities.

In Chapters 3 and 4, I am primarily concerned with the process of sense-making. I introduce a framework laying out various ethical approaches in data science, which emerged from an exercise of mapping various strains of discursive arguments around what counts as ethical in data science. I happened to be immersed in my field site at a time when the community of practice was explicitly and publicly starting to come to terms with the profound dangers, ethical implications, and social responsibilities implicated in data science of the social. Following years of triumphalist rhetoric on the inherent goodness of big data analytics, the latter years of my research saw the emergence of what I have called an ethical crisis. As I document in greater detail in Chapter 3, this time period saw a sudden outcropping of introspective efforts to develop codes of ethics and build institutions focused on the human impact of data analytics,

artificial intelligence, machine learning, and algorithmic mediation. The framework I introduce relies predominantly on the discourses in circulation across the wider field of data science practice, and I argue that these discursive moves should be regarded as a form of vernacular theorizing about sociomateriality, which I then link to scholarly discussions about sociomateriality.

In Chapter 5, I am primarily concerned with the process of translating data science across knowledge domains and fields of practice, and employ a combination of what Clarke (2003) calls “situational maps” and “social worlds/arenas maps.” Situational maps “lay out the major human, nonhuman, discursive, and other elements in the research situation of concern and provoke analyses of relations among them,” while “social worlds/arenas maps” illuminate the “*collective* actors and arenas of commitment within which they engaged in ongoing negotiations” (Clarke, 2003, p. 559). Through these mapping exercises, I honed in on the idea that a key mechanism by which translation occurs is through the temporary, project-based collaborations that I observed everywhere in my field work. I argue that the collections of people, ideas, data, tools, and code that comprise these projects can be conceptualized as “exostructures”—sociomaterial configurations that allow data science to “jump contexts” and establish itself in new domains of knowledge or fields of practice. I connect this concept to literature on information infrastructures, and argue that such exostructures are designed to be a temporary, *ad hoc* arrangements that are eventually outgrown and replaced with more permanent data infrastructures and knowledge infrastructures for data science.

### **Refinement phase: Retroductive analysis**

In each case, I started with situational analyses, developed a provisional framework for understanding the relationships that emerge from those analytic exercises, then connected those

frameworks back to salient bodies of literature in order to further develop my theoretical argument. This is not the end point of my analysis, however. I adopt a retroductive analytical approach as discussed by Ragin (1994) and Sæther (1998) to develop further insights from my field site. Retroductive analysis involves working back and forth between empirical data and theoretical ideas in an iterative process that involves both deduction and induction. In retroductive analysis, researchers inevitably start with some *a priori* theoretical foundation (even if this is an implicit paradigmatic orientation rather than an explicit explanatory theory), which informs the analytic frames they employ. At the same time, they inductively distill their data into what Ragin calls “images,” (1994) and Sæther says are “idealized cases, constructed through the process of abstraction (or idealization process), where the abstraction process has a specific grounding in evidence” (1998, p. 247). Researchers move back and forth iteratively between theory, analytical frames, images, and data until they have developed a “representation of social life” that helps us better understand the world. In my case, once I developed the framework for ethical approaches in data science (Chapter 3) and concept of data science exostructures (Chapter 5), I returned to my data to develop the “images” or idealized cases that help illustrate and develop those frameworks. Following each of the chapters in which I present those theoretical concepts, in Chapters 4 and 6, I present the cases of two projects, the ORCA Project and the AccessMap/OpenSidewalks project. I craft what can be called “decision stories” (Eisenhardt & Bourgeois III, 1988; Maitlis & Lawrence, 2003)— narrative collections of key moments in the timeline of these projects in which project team members grappled with major decisions that impacted the trajectory of their work. In doing this, I intended not only to simply illustrate different positions within the theoretical frameworks I had previously outlined, but also to return to my data to perform another iteration of analytical work, this time drawing out particular

dynamics within and between those cases that further the nuance and complexity of the theoretical contributions. Through the presentation of these cases, I ask what worlds are being born of different approaches to ethics in data science, and how the novel arrangements of exostructures, in spite of their temporariness, might impact the long-standing roles and relationships of different social sectors.

## CHAPTER 3 SOCIOMATERIALITY IN “DATA SCIENCE OF THE SOCIAL”: ETHICAL APPROACHES AS VERNACULAR THEORIZING

### INTRODUCTION

Scholars of technology and society would very much like to put a nail in the coffin of the well-trodden debate between technological determinism and social constructivism. In fact, Jonathan Sterne (2014) advises faculty not to teach this dichotomous argument anymore, “even as a historical curiosity” (pp. 126–127). But he also very reasonably wonders, “why are we so compelled to have it and what are we to do about it?” (Sterne, 2014, p. 126). I maintain that this is because, while pure technological determinism and the most extreme versions of constructivism may seem intellectually naive these days, their juxtaposition does authentically speak to a deep-rooted ambivalence that people feel in their day-to-day experience of technology. We wring their hands over what technology is doing *to* us, at the same time that we revel in what we can do *with* technology. But the scholarly conversations that have displaced the technological determinism versus constructivism debate do an unsatisfactory job of accounting for such ambivalence. The theoretical language we’ve developed for describing a more nuanced understanding of sociotechnical phenomena—whether it’s symmetry (Latour, 2005b), imbrication (Leonardi, 2012), or mutual shaping (Boczkowski, 1999)—implies a passive harmony rather than a dialectical tension.

I argue that instead of artificially resolving these tensions, we need to understand why such divergent interpretations of the human-technology relationship endure, and what difference they make in the world. To this end, I introduce a theoretical framework for Vernacular Sociomateriality. Vernacular Sociomateriality accounts for the multiple and contrasting ways

people actually experience and make sense of their relationships with technology. It integrates vernacular discourses and practices with established academic theories of technology to show how those theories—which are sometimes discussed in scholarly circles as if they are competing for the one true version of reality—are enacted in the way people produce technology, and produce meaning with technology. I demonstrate how vernacular sociomaterial theories have real-world impact by discussing how they manifest in different approaches to ethics in the data science of the social.

## VERNACULAR THEORY

By vernacular theory, I am referring to the ordinary ways people make sense of their world by situating their own experiences within larger patterns and connecting local circumstances to broader phenomena, and how this sense-making is informed by implicit theoretical and philosophical positions. In his book, *Street Smarts and Critical Theory: Listening to the Vernacular*, literary scholar Thomas McLaughlin (1996) develops the concept of vernacular theory while showing how ordinary people critique received assumptions of dominant culture by speaking a “critical language grounded in local concerns, not the language spoken by academic knowledge-elites” (p. 5-6). In portraying “the subject in vernacular culture as an active, productive consciousness, historically and socially placed, but not shaped inexorably into a passive victim of ideology” (p.11), McLaughlin (1996) draws on the work of British cultural studies, feminist studies, and pedagogy of the oppressed. Unlike those traditions, however, in which focus is firmly centered on vernacular sensemaking among marginalized populations, McLaughlin (1996) widens his gaze to show that “membership in a marginalized group is not the only entry into vernacular theory” (p. 21-22). McLaughlin (1996) writes about vernacular theorizing among avid fans of popular culture, among political and cultural activists, among

visionary or prophetic seekers, and among expert practitioners. His treatment of this latter category is of particular relevance here:

Practitioners of a given craft or skill develop a picture of their practice—a sense of how it is or ought to be practiced, of its values and its worldview—and many are quite articulate about this "theory," aware for example that there are competing theories, that not all practitioners work from the same premises. These practitioners' theories may contrast sharply with the theories of their practice constructed by academic theorists. Ask any elementary teacher if his or her theory of teaching is the same at the end of a year of practice as the theory provided by schools of education.

McLaughlin, 1996, p. 22

In this case, the distinctiveness of vernacular theory does not arise from the difference between oppressed and oppressor, elite and non-elite, or expert and non-expert, but between the practitioner whose theory is part and parcel of day-to-day work and the scholar whose theory is part of an academic exercise. Vernacular theories of expert practitioners emerge “from within the institution they are theorizing” (McLaughlin, 1996, p. 102). In writing about the advertising profession, McLaughlin (1996) contrasts the way critical theorists deconstruct the pervasive power of advertising and the way advertising professionals defend their work against accusations of “manipulation and trickery.” He observes that “one might think that their busyness would preclude self-reflection. But in fact advertising professionals routinely reflect on the premises of their work and its implications. They would never *define* themselves as theorists, but rather as hardheaded practitioners” (McLaughlin, 1996, p. 101). And yet, McLaughlin (1996) sees “persistent self-reflection and scrutiny” (p. 102) in the discursive spaces of their community, such as trade publications, professional conferences, textbooks, and public appearances. Herein, they develop “what they see as a dissident theory” of “what advertising contributes to society, how it addresses consumers, how it stimulates economic development, and how it derives from what they see as the basic nature of human being” (McLaughlin, 1996, p. 104).

McLaughlin (1996) applies the designation of vernacular theory not to all forms of reflection, but to reflection on the “fundamental questions” of practice. For example, deliberations about how readers might react to a particular advertisement may be informed by theory but are not a case of theorizing itself, whereas deliberations about “what do we mean by reader reaction itself” are part of vernacular theorization (McLaughlin, 1996, p. 103). He discusses how advertising directors intentionally seek to create “extra meaning and symbolic value,” for consumers to purchase along with the product itself (McLaughlin, 1996, p. 105). As such, they exhibit an acute postmodern sensibility in their articulated theory of how “value resides not in objects, but rather in the subject’s perceptions of those objects, which is determined by the subject’s position within a cultural system” (McLaughlin, 1996, p. 106). McLaughlin (1996) argues that these vernacular theorizations “ought to be recognized alongside more academic theories of advertising if we are to understand how advertising looks from the inside as well as how it looks when subjected to unfriendly critique” (p. 102).

McLaughlin’s (1996) work in the tradition of literary theory has resonance with practice-oriented scholarship at the intersection of organizational studies, science and technology studies, and communication studies. Like McLaughlin’s (1996) work, this heterogeneous clustering of approaches takes as a central concern not the pursuit of universal truths, but the pursuit of situated and mundane knowledge-making. However, in its attention to action and materiality, such practiced-based scholarship stands in contrast to the textually-based conceptualization of vernacular theory developed by McLaughlin (1996). Scholars of practice seek to understand how knowledge “is expressed in the capacity to carry out a social and material activity” (Nicolini, 2012, p. 5) in a specific place and time, such that “discursive practices are not seen as ways to represent the world as much as ways to intervene and act on it” (Nicolini, 2012, p. 5). Therefore,

practice-based scholarship is concerned not only with what people say and think, but what they do and how they do it. It explores how knowledge is created and acquired in the course of situated action, as well as how practice reproduces structure and is simultaneously produced by structure. It seeks to understand the situated and particular ways in which the world “is routinely made and re-made in practice using tools, discourse, and our bodies” (Nicolini, 2012, p. 2).

I contend that such a focus on action and materiality can enrich the concept of vernacular theory, and that, likewise, the concept of vernacular theory is a useful contribution to practice-based approaches. When scholars of practice refer to “practice theory” or “practical theory,” they are typically referring to etic theories *about* practice developed by scholars rather than emic theories developed by practitioners themselves. Davide Nicolini, (2012) for example, treats “practice theory” as theories about practice that are united by a shared set of ideas: that meaning is made within practice, that practice is a social accomplishment, that practices are historically situated and materially mediated, and that power is deeply implicated in practice. In a 2001 special issue of the journal *Communication Theory* that is dedicated to practical theory, although guest editor Kevin Barge (2001) characterizes Katherine McComas’ (2001) piece on public meetings in that issue as uncovering the “underlying practical theories” used by the government officials in her study (p. 7), McComas (2001) herself portrays practical theory to be what results from her analysis as a researcher. She sees her task as providing “a starting point for the development of a practical theory of public meetings grounded in the experiential knowledge of those frequently mandated or encouraged to conduct public meetings” (2001, p. 50), in the hopes that this can serve as “a useful ‘road map’ or set of guidelines for public agencies and their officials” (2001, p. 41). This resonates with Vernon Cronen’s (2001) take on practical theory as well, in which the theorist provides “formalizations” of practitioner sense-making that can aid

those practitioners in their own efforts. In all these treatments, practical theorizing or theorizing about practice is something that is accomplished by academic theorists on behalf of, or in conjunction with their interlocutors; the ideational efforts of practitioners may provide source material, but their activities and discourses are not regarded as theories until the practice researcher comes along and turns them into such.

What I'm arguing, though, is that practitioners themselves engage in theorizing by reflecting on and responding to discursive critique that emerges both within their community and from outside of it. This process is distinct from the development of practice theory or practical theory that academic researchers of practice develop, and yet we don't commonly employ language that recognizes it as theorizing in its own right. So at the very least, "vernacular theory" is a useful term for acknowledging the theorizing done by practitioners in the thick of practice and disambiguating it from the theorizing done by academics *about* practice. I would argue, though, that this disambiguation is not merely clarifying but also generative. By creating language that accounts for the distinctiveness of theories that emerge from within practice, we end up with an analytical tool for exploring the interplay and entwinement of this vernacular theory with practice theories and other academic theories. In fact, my intention is not to draw a bright red line between these distinct variants, but to show how they play off of one another, and suggest ways of enriching the dialogue between them.

This point is taken up by McLaughlin (1996) as well, with regard to vernacular theory in critical cultural studies. Taking cues from Paulo Freire, James Sosnoski, and bell hooks, McLaughlin sees the role of the educator being not to transmit formal theory, but to draw upon and strengthen their students' own inclination to question the circumstances of their worldly experiences:

We can get students to do what the academy calls theory about the culture they inhabit, but we should remember that students have been doing vernacular theory all their lives, and not just in school settings. It is important to assert, though, that a pedagogy for vernacular theory would only begin with student culture and student theory, not end there. The theoretical strategies developed in academic culture can only help the vernacular theorist become more adept. And reading challenging and unfamiliar texts can only sharpen theoretical understanding.

McLaughlin, 1996, p. 154

According to McLaughlin (1996), what the academic educator can provide these budding vernacular theorists is “an opportunity for encounters with radically different subjects with radically different histories” (p. 157). While they may intuitively critique their own circumstances, “vernacular theorists need to know that the world can be experienced differently from different cultural and subjective positions, and educators in the humanities and social sciences are uniquely placed to provide students encounters with historically, geographically, and culturally strange texts, whether canonical or multicultural” (McLaughlin, 1996, p. 157). McLaughlin’s (1996) primary concern in developing “a pedagogy of vernacular theory” is the relationship between professors of cultural theory and their undergraduate students. But just as he broadens the scope of vernacular theory to include theorizing by expert practitioners, so can we ask what would a pedagogy of vernacular theory look like in professional practice? How can academic theorists be put into meaningful dialogue with vernacular theorist-practitioners, in a way that draws upon practitioners’ own instinct and need for reflection, while guiding them toward considering alternative perspectives in the course of that reflection?

These are questions that I take up in earnest in the context of data science of the social. I start by reviewing the divergent premises underlying academic theories of sociomateriality, and show how these same premises inform critiques of data science of the social emerging simultaneously from academics, law and policy experts, journalists, and data scientists

themselves. I argue that as the data science community engages with these critiques and grapples with how to develop a robust set of ethical principles and practices in response, they are engaging in vernacular theorizing. Then, just as McLaughlin (1996) calls on educators to strengthen their students' vernacular theorizing by putting them in dialogue with other vernacular and academic perspectives, I draw out the variations in the vernacular theories I see emerging within this community of practice and put them into dialogue with one another, with critics, and with academics. In other words, I am creating a practical theoretical framework by mapping vernacular theorizing alongside academic theories of sociomateriality. In drawing out their theoretical convergences and divergences, overlaps and juxtapositions, I hope to create a tool that can help orient ongoing conversations and developments related to ethics in data science of the social.

To be clear, conversations about ethics in data science of the social are already taking place outside of any simplistic notions of academic and professional siloes. For one thing, the “practitioners” I’m concerned with in data science for social good—the people cleaning the data, writing the scripts, and building the models—are often academic researchers themselves, but not necessarily academics who are trained to think about social theory. Furthermore, people who are practicing data science of the social are in many cases already in dialogue with critical voices raising ethical concerns about big data, data science, machine learning, and artificial intelligence. Forums like the ACM Conference on Human Factors in Computing Systems (CHI) and Computer Supported Cooperative Work (CSCW) showcases work by critical scholars such as Lucy Suchman (1993) and Lilly Irani (Irani & Silberman, 2013) alongside research from industry labs at technology companies like Facebook and Google. The Fairness, Accountability and Transparency in Machine Learning conference was co-founded by critical data scholar Solon

Barocas, and draws speakers and participants from the tech industry and universities alike. At the Bloomberg Data for Good Exchange, participants from government, academia, industry, and non-profits decided to launch an effort to develop a Data Science Code of Ethics (Bloomberg, 2017). These are just a few of the many places where such dialogue and practitioner-centered critique is going on. My job then, is not to fabricate this dialogue, but to help make sense of it, to connect the dots and surface tensions.

## ACADEMIC THEORIES OF SOCIOMATERIALITY

I employ the term sociomateriality along the lines of Orlikowski and Scott (2008), as an “umbrella” concept referring to a suite of intellectual strands that are unified by their ontological position on the entanglement of the material and the social. In other words, these positions broadly acknowledge that all technology is inherently social, and all sociality is technologically mediated. But within this broad outlook, two axes of important distinctions can be identified. As will be discussed in detail below, along one axis, a given sociomaterial approach might alternately emphasize what I refer to as “material activation” or “material mediation”; along the other axis, an approach might exhibit either an “intrinsic perspective” or an “extrinsic perspective.”

### **Material activation versus material mediation**

A position concerned with material activation seeks to understand how technology exerts influence on the world, and is concerned with the consequentiality of ‘the physical character and existence of objects and artefacts that makes them useful and usable for certain purposes under particular conditions’ (Lievrouw, 2014, p. 25). Theorizations that emphasize material activation include, for example, work that treats objects as “actants” capable of influence commensurate with human agency (Latour, 1991), notions of “autonomous technologies” that serve as surrogate

political operatives for those who design and deploy them (Winner, 1980), and treatments of “technological affordances” that focus on the ways in which technology enables and constrains certain behaviors (Hutchby, 2001).

A position concerned with material mediation, on the other hand, places a stronger emphasis on how people act with, through, and upon material objects, including how things are materialized through human action and expression. Mediation theory, as articulated by Leah Lievrouw (2014), accounts for a “mutually determining relationship” between objects, actions, and structures, while highlighting the ways people reconfigure, reform, and remediate each of those components. Theorizations that emphasize material mediation include, for example, Bechky’s (2003) description of how engineering drawings mediate jurisdictional struggles in the workplace, and Burrell’s (2012) analysis of how the seemingly immaterial phenomenon of rumor is mediated by material infrastructure and implicated in a web of material consequences.

### **Intrinsic perspective versus extrinsic perspective**

Sociomaterial theories of technology also vary in their positions about how to analytically approach the entangled relationship between humans and technology. On one side of this spectrum lies an intrinsic perspective, which focuses on how the social and the technological are *co-constituted* and analytically inextricable. As Orlikowski puts it:

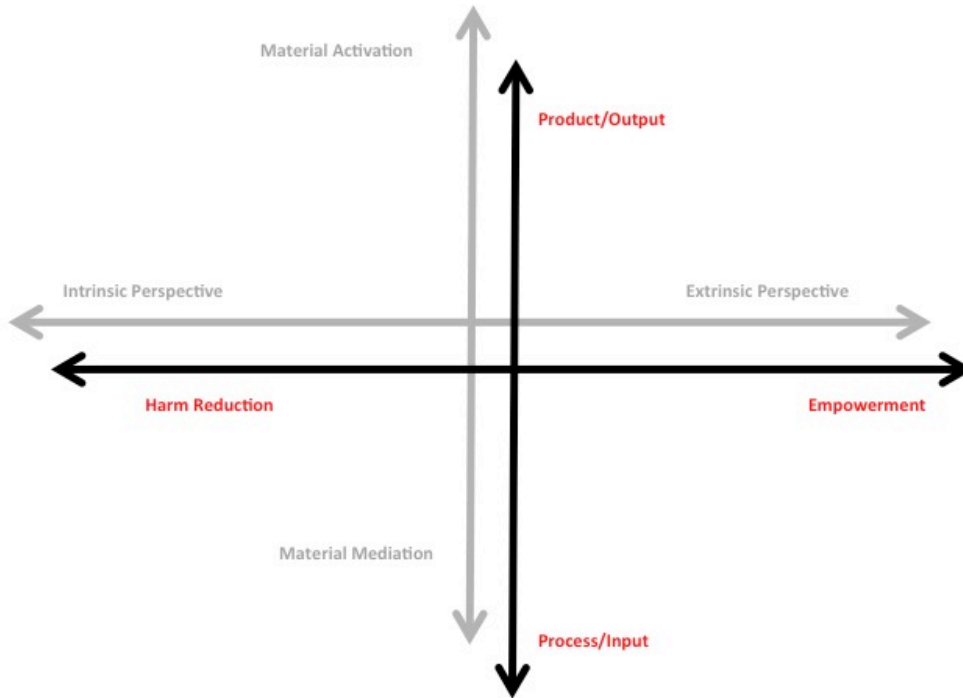
... the social and the material are constitutively entangled in everyday life. A position of *constitutive entanglement* does not privilege either humans or technology (in one-way interactions), nor does it link them through a form of mutual reciprocation (in two-way interactions). (Orlikowski, 2007, p. 1437)

Leonardi (2012) favors the metaphor of “imbrication” to capture this relationship because, unlike concepts such as “mutual shaping,” it doesn’t imply ontologically distinct categories that influence each other in a cascading chain of cause and effect. To Leonardi (2012),

material and social agency are like the imbricated tiles of a terracotta roof or the imbricated scales of a fish—comprised of the very same building blocks arranged in an uninterrupted pattern. As such, an intrinsic perspective seeks to show how the sociotechnical world is built *de novo* from these materials, and avoids assuming and deconstructing an *a priori* social order. One of the most forceful declarations of this position comes from Actor Network Theory, in which the point of analysis is to account for the web of connections that bring an object of study into being. As Latour (2005) has put it, if the social world is understood to be assembled of people, things, and the ties that bind them, “then it can be *reassembled*” (p. 129) by the analyst. Tracing these connections requires that objects of study be “opened up, de-fragmented, and inspected,” (Latour, 2005, p. 259), but ANT warns against looking only for “traditionally conceived social ties” (p. 233) in that process. Otherwise, the analyst may end up “simply repeating that they are woven out of the same tiny repertoire of already recognized forces: power, domination, exploitation, legitimization, fetishization, reification” (Latour, 2005, p. 249). While I am using Actor Network Theory to represent a crystallization of the intrinsic perspective, I do not mean to imply that all theorizations exhibiting some variation on this position share the same prescriptions (or proscriptions) of ANT. What they do share, though, is an analytical lens capable of showing how the social and material are co-constituted, and therefore how sociotechnical phenomena come into being—exercises that lend themselves particularly well to studying moments of technological genesis, change, or evolution.

In contrast to the intrinsic perspective is the extrinsic perspective, which also views the social and material as entangled, but extricable for analytical purposes. A more apt characterization of the relationship between them is one of *mutual shaping* as opposed to co-constitution, in which the building blocks of the social and material are qualitatively distinct, and

an *a priori* social order can serve as the starting point of an analysis that deconstructs the relationship between them. For example, in Boczkowski's (1999) study of online communications in an Argentinian expatriate community, nationalism is treated as an *a priori* social phenomenon that is not inherently technologically mediated. Nonetheless, Boczkowski (1999) argues, the nationalism exhibited by users of the group's email list becomes implicated in a cycle of mutual shaping between the user community and the technical features of the mailing list. Feelings of nationalism spark expatriate Argentinians' interest in creating a shared digital artifact to memorialize their community in a particular moment in time, but their collective act of building that artifact sparks discursive reflection that shapes users' sense of national identity. In this analysis, nationalism exists on its own as a phenomenon, as does the mailing list technology; the point is not to show how they are inherently mutually constituted, but rather how they are mutually shaped upon being brought into relation with one another. As such, rather than a focus on the origins of sociotechnical phenomena, the extrinsic perspective lends itself to analysis of the ways in which enduring social orders are either altered or sustained in conjunction with the development, deployment, and adaptation of technology.



**Figure 3-1. Vernacular and academic perspectives on sociomateriality.** This diagram depicts the relationship between vernacular perspectives on ethics in data science of the social (red) and underlying academic perspectives on sociomateriality (gray).

### VERNACULAR THEORIZING IN DATA SCIENCE OF THE SOCIAL

My main purpose in drawing these distinctions between perspectives on sociomateriality is ultimately to demonstrate that the differences between these positions are not merely matters of academic debate. In everyday encounters, people confront both materiality and materialization: they often acutely feel technology pushing and pulling on them (material activation), and simultaneously recognize their own agency in making sense of and with that technology (material mediation). They also intuitively grasp the degree to which their social world is built through technology (intrinsic perspective), at the same time they recognize that entrenched ideologies and social categories make useful starting points for understanding divergent human conditions (extrinsic perspective). Most people are capable of oscillating between various everyday understandings of their relationship with technology, and act on their

own theories in consequential ways. When a father decides his toddler shouldn't have access to a tablet computer because he's afraid it might destroy her attention span, when a newly divorced 60-year-old tries online dating for the first time and contemplates how much more complicated romance has become since the last time she was single, when a patient with chronic pain tracks his daily activities and sensations to validate his experiences to his doctor, they are all forming and acting upon implicit theories about what technology does, and what they can do with it.

This multiplicity of ordinary sense-making about technology's everyday role in social life is what I call *vernacular theories of sociomateriality*. These are not generalized or consistently applied across sociotechnical phenomena, but rather are specific to particular technologies, situations, or contexts. The subset of vernacular theories I'm interested in exploring here are those associated with data science of the social. I argue that classic academic theorizations of sociomateriality correspond to a set of vernacular theories in this space, that these vernacular theories in turn inform distinct approaches to ethics in data science of the social, and that they therefore have profound implications for our social world.

### **Harm reduction versus empowerment as primary ethical concern**

Many ethical values and concerns can be brought to bear on data science. For example, scientific reproducibility and integrity may be ethical concerns for many data scientists, environmental sustainability may be an ethical concern for others, and many more examples of ethical concerns can and do exist within the practice of data science. Here, rather than attempting to provide an exhaustive treatment of all these ethical concerns, I hone in on one of the foremost ethical questions facing data science of the social: how it impacts vulnerable, marginalized, or protected populations. Vernacular theories informing the ethics of data science mirror academic theoretical positions in the following ways: An intrinsic perspective manifests itself in the idea

that data-intensive and algorithmically-mediated systems inevitably reflect the values, judgments and biases of their designers and the social milieu in which they are embedded, and that those values, judgments, and biases are inevitably influenced by the designers' own interactions with technology. When foregrounding this perspective, ethical approaches in data science are framed in terms of mitigating harms to vulnerable populations that can result from these inevitabilities. A more extrinsic perspective, on the other hand, manifests itself as the idea that deeply entrenched disparities can either be alleviated or exacerbated by new technologies. When foregrounding this perspective, ethical approaches in data science are framed in terms of the way technologies can either further marginalize or empower. In other words, a vernacular instantiation of the intrinsic-extrinsic theoretical divide in data science is whether one's primary ethical concern related to marginalized populations is related to *reducing harm* or *producing empowerment*.

### **Product versus process as primary ethical response**

Likewise, how one responds to those ethical concerns can vary in ways that reflect the difference between a focus on material activation and a focus on material mediation. A focus on material activation locates ethical responses in the *products* or outputs of data science efforts; such an artifact should be designed to act in ways that address the primary ethical concern and further the ethical goals or commitments of the community. In contrast, a material mediation stance locates ethical responses in the *process* of doing DSSG; in other words, the emphasis is on aligning the practice and culture of the community with its values and morals.

### **SOCIOMATERIAL FRAMEWORKS**

The fields of science and technology studies, computer supported cooperative work, communication, organizational studies, and others, have developed a rich set of theoretical tools

with which to understand the sociomaterial nature of technological artifacts and society. Identifying two axes of theoretical orientations, as I have done above, and attending to the intersections of those orientations, as I will do below, allows for the construction of an overarching framework that organizes a number of varied theoretical perspectives into families of resemblance.

Such an abstraction of complex and nuanced ideas that have enriched our understanding of myriad empirical phenomena may be seen as a disservice to the individual scholars and theories it draws upon. It admittedly stays on the surface of those ideas and collapses their nuanced arguments. But if we follow the truism that there is no creation without destruction, there may be something to be gained from this razing of subtlety and complexity. The point of my exercise is not to negate the importance of these distinctive contributions, to attempt the development of a unified theory, or to resolve differences in their orientations. Instead, what I ultimately aim to do is show how the divergent ways that academic theorists understand technology and society mirror the divergent ways that people design, use, and make sense of technology in their day-to-day lives.

In what follows, I will explore the theoretical positions that arise from the intersection of the epistemological dimensions or axes I've outlined above, highlighting particular scholarly works as exemplars of each position. My choice in focusing on discrete pieces of writing rather than cohesive schools of thought or the collected works of any given scholar is intentional. This is because distinctive theoretical traditions have evolved over time, and because scholars may engage with different positions in different works. The fact that certain traditions or scholars may alternately adopt different positions is actually part of my point: that our relationships with technology and our efforts to come to terms with those relationships are full of tensions and

contradictions that play out in different circumstances and situations. We do this at the level of academic theorizing, as well as at the level of vernacular discourse and practice. In other words, we often adapt our theories of technology and society to accommodate particular situations and phenomena that we want to explain or intervene in.

For both academic theories and vernacular theories of sociomateriality, I offer what Adele Clarke (2003) calls a “positional map.” According to Clarke (2003): “positional maps lay out the major positions taken, and not taken, in the data vis-à-vis particular discursive axes of variation and difference, concern, and controversy” (p. 560). Based on the discursive axes of variation I’ve identified thus far, I build two related frameworks: A framework for academic theories of sociomateriality and a framework for ethical approaches to data science of the social, which I have cast as an example of vernacular theorizing in practice. The practice-based vernacular framework highlights a range of alternative “situated ideals” that, according to Craig & Tracy (1995), are implicated when practitioners engage with existential problems of practice:

At the most abstract level, a practice can be reconstructed in the form of elaborated normative ideals and overarching principles that provide a rationale for the resolution of problems. In reflecting on what to do about the problem, alternative 'situated ideals' may be available from which to derive reasons for resolving the problem in one way or another, accepting certain trade-offs among competing goals, and thus choosing to use certain communicative strategies and techniques rather than others. A practice can thus be reconstructed by articulating these situated ideals as explicitly philosophical positions.  
Craig & Tracy, 1995, p. 253-254

The relationship between such situated ideals can be revealed in a mapping of schools of thought within a field of practice. In Figures 3-2 and 3-3, I do this for academic and vernacular theories of sociomateriality. An *Intrinsic-Mediation* perspective is conducive to practice-oriented academic theories, and in the vernacular setting of data science, this corresponds to an ethical approach that can be characterized as “*data science as ethical convention.*” An *Intrinsic-Activation*

perspective is conducive to network-oriented academic theories, and in the vernacular setting of data science, this corresponds to an ethical approach that can be characterized as “*data science as ethical interrogation.*” An *Extrinsic-Activation* perspective is conducive to politically-oriented academic theories, and in the vernacular setting of data science, this corresponds to an ethical approach that can be characterized as “*data science as ethical innovation.*” An *Extrinsic-Mediation* perspective is conducive to culturally-oriented academic theories, and in the vernacular setting of DSSG, this corresponds to an ethical approach that can be characterized as “*data science as ethical participation.*”

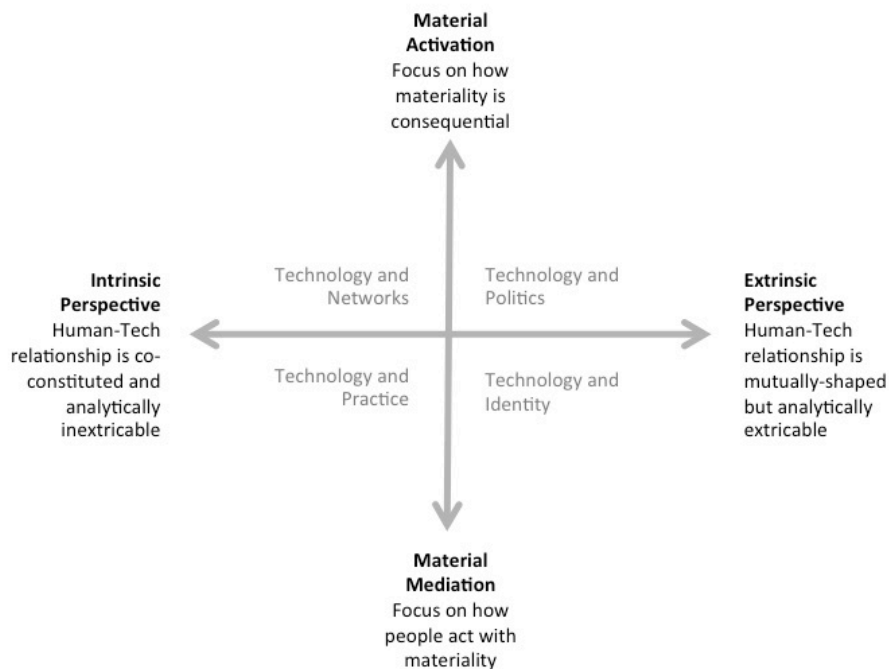


Figure 3-2. Framework for academic theories of sociomateriality.

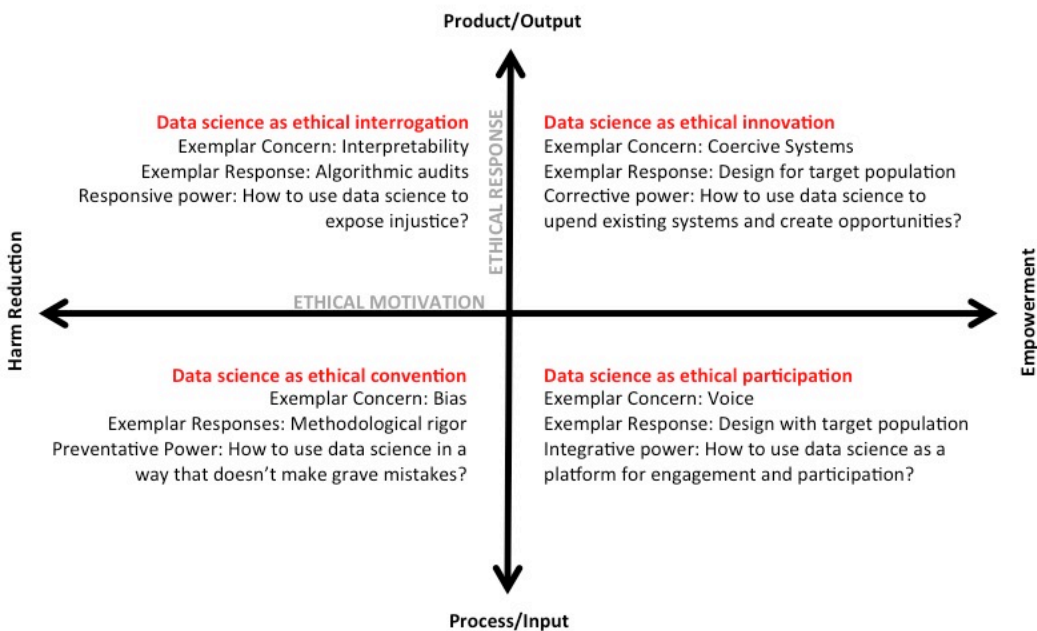


Figure 3-3. Framework for ethical approaches in data science of the social.

### An intrinsic perspective with a focus on material mediation

*Academic theorizing: Technologies and practice*

An *intrinsic* view of the imbricated relationship between humans and technological artifacts, coupled with a focus on *material mediation*, or how people make sense and relevance with technological artifacts, can be seen in Wanda Orlikowski’s (2000) study, “Using technology and constituting structures: A practice lens for studying technology in organizations.” Orlikowski (2000) investigates the adoption of a new software tool, and compares its roll-out across various departments of a single consulting firm. Finding that these different divisions—each with their own distinctive mandates, incentives, and routines—ended up using the software in divergent ways, Orlikowski (2000) argues that it is only through recurrent use that technology gains structure; in other words, it is through situated practice that technology becomes a resource with

rules of use associated with it. Applying Giddens's structuration theory to the use of technology, she notes that, "rather than starting with the technology and examining how actors appropriate its embodied structures, this view starts with human action and examines how it enacts emergent structures through recurrent interaction with the technology at hand" (2000, p. 407).

Janet Vertesi (2015) takes a comparable approach in her ethnographic study of scientific work supporting the production of images from a Mars Rover expedition. Vertesi (2015) also adopts the position that social organization and technological configuration are "inseparably intertwined," and deftly argues that the calibrations, negotiations, and transformations that go into the creation of each digital image not only shape the technological artifacts, but also reproduce the organizational structure of the Rover team itself. Technological structures and social structures, then, are both constituted through local interactions with tools and artifacts, such that, in the case of the Rover team, "images of objects are images of subjects too" (2015, p. 244).

This lens has also been applied to academic scholarship on the increasing use of big data in planning and governance of urban spaces. Jo Bates (2018) is concerned with how the practice of data-intensive work emerges within the context of certain sociomaterial constraints, and simultaneously gives shape to the sociomaterial configurations of the future. According to Bates, such a perspective allows us to focus our attention "where structure meets agency" (2018, p. 198) in order to see how biases and assumptions inevitably get embedded into digital data and digital artifacts through culturally-informed and materially-constrained data practices at every step, a verisimilitude that once prompted Geof Bowker to quip that, "raw data is both an oxymoron and a bad idea" (2005, pp. 183–184). For Bates (2018), the stakes are high, with real consequences for the future of cities hanging in the balance. She argues that a sociomaterial

perspective acknowledging the entwinement of practice and materiality can ultimately “contribute to the development of more critical and reflexive forms of data practice” (2018, p. 198).

*Vernacular theorizing: Data science at ethical convention*

The preceding academic theorizations of technology in practice correspond with prominent vernacular discourses on ethics in data science of the social. This can be seen in critiques emanating both from within the community of practitioners and from outside observers whose work is being circulated and discussed by practitioners, becoming a part of their vernacular discourse. Research organizations established by critical data scholars specifically to promote critical—and often, qualitative—investigations of big data and data science, such as Data and Society and AI Now, have succeeded in producing work that is commonly referenced in the discursive spaces where practitioners of data science of the social discuss their community’s accomplishments, methods, values, problems, and norms.

The ideas of critical data scholars are being discussed alongside similar critiques made by data scientists themselves. A notable example of critical practitioner voices is Cathy O’Neil (2016), a mathematician with extensive experience doing data science in both corporate and civic settings, who wrote the highly influential and bestselling book, *Weapons of Math Destruction*, released by popular press publisher, Crown Random House. In it, O’Neil discusses examples of data science gone awry, such as an algorithmic system put in place in Washington DC to purge the public school system of “bad” teachers. According to O’Neil (2016), the algorithm was based on highly problematic standardized test scores and led to the unwarranted firing of some excellent teachers. She explains how predictive models are inherently problematic because they can only predict the future based on what’s happened in the past; this means a

predictive model based on data from a prejudiced criminal justice system will end up making prejudiced predictions, a point that has also been illustrated in journalistic investigations into recidivism algorithms used in determining whether or not defendants are released on bail (Angwin et al., 2016). O’Neil’s position can be summed up by this quote:

If we back away from them and treat mathematical models as a neutral and inevitable force, like the weather or the tides, we abdicate our responsibility. And the result, as we’ve seen, is [Weapons of Math Destruction] that treat us like machine parts in the workplace, that blackball employees and feast on inequities. We must come together to police these WMDs, to tame and disarm them. My hope is that they’ll be remembered, like the deadly coalmines of a century ago, as relics of the early days of this new revolution, before we learned how to bring fairness and accountability to the age of data. (O’Neil, 2016, p. 218)

In this and the preceding examples of discourse about ethics in data science of the social, the intrinsic perspective is evident in the way data-intensive and algorithmically-mediated systems are portrayed as inevitably reflecting the values, judgments and biases of designers and society, and the concern with **mitigating the harm** that can result from this inevitable entanglement. This is coupled with an emphasis on material mediation, in that the proposed solutions focus on altering the **process** of doing data science by forging new cultures, norms, canons, and routines for data science practitioners in response to ethical concerns. As such, I characterize this particular vernacular instantiation of theorizing about technologies in practice as “*data science as ethical convention*”: the idea that we need to train data scientists to think about the ethical consequentiality of their work, recognize the damage it can do, and develop methods, approaches, techniques, and norms that can mitigate that harm.

In recent years, the data science community has taken up this call. Recently, a grassroots organization called Data for Democracy led a Bloomberg-sponsored push to craft a code of ethics and set of community principles for data science (Bloomberg, 2017). The collaborative,

crowd-sourced process was primarily organized through Slack and Github (platforms favored by software developers and other computationally-oriented teams for managing communication and version control, respectively) along with a few in-person meetings. The resulting “Community Principles on Ethical Data Sharing” was compiled by more than 80 working group members from across academia and industry, several of whom I have interviewed and observed in the course of my doctoral research. The principles include the following values:

**Fairness:** Understand, mitigate and communicate the presence of bias in both data practice and consumption.

**Benefit:** Set people before data and be responsible for maximizing social benefit and minimizing harm.

**Openness:** Practice humility and openness. Transparent practices, community engagement, and responsible communications are an integral part of data ethics.

**Reliability:** Ensure that every effort is made to glean a complete understanding of what is contained within data, where it came from, and how it was created. Extend this effort for future users of all data and derivative data.

(“Community Principles on Ethical Data Sharing,” 2018)

Each of these principles offers a way forward for repairing data science practice by introducing norms to mitigate future harms. Efforts like the Community Principles on Ethical Data Sharing are coupled with a growing area of specialization in developing methods, tools, and techniques to address the biases and privacy concerns inherent in big data, and to develop techniques for mitigating the damage they can do. A number of venues have been cropping up in recent years for promoting and sharing progress in this area of computational expertise, including workshops and seminars hosted by the Responsible Data Science Project on issues of fairness, accuracy, confidentiality, and transparency, abbreviated as FACT (van der Aalst, Bichler, & Heinzl, 2017), the Conference on Fairness, Accountability, and Transparency, abbreviated as FAT\* (“Conference on Fairness Accountability and Transparency,” 2018), and industry labs such as Microsoft’s Fairness, Accountability, Transparency, and Ethics in AI group (“FATE:

Fairness, Accountability, Transparency, and Ethics in AI,” 2018) (FATE, 2018), and the Ethics and Society wing of Google subsidiary DeepMind (Hardin & Legassick, 2017). In the classroom, as well, universities are paying more attention than ever to the ethical quandaries raised by data intensive work (Singer, 2018).

But it is important to realize that, even removed from this growing chorus of voices publicly and formally calling for more ethical practices in data science, practitioners are often acutely aware of the shortcomings in their data, the value-laden nature of their technical choices, and the potential consequences of their work. As my colleagues and I have discussed elsewhere (Neff et al., 2017), the daily conversations and technical choices made by data scientists in the course of their work often surface many of the very issues raised by data science critics. To illustrate this, in Chapter 4, I present the story of a data science project I closely observed over the course of two summers, detailing how the team members on this project dealt with one of the most pressing and salient ethical issues in data science: the potential for data-intensive technologies to codify and reify bias.

### **An intrinsic perspective with a focus on material activation**

#### *Academic theorizing: Technologies and networks*

An intrinsic perspective that sees the social and the technological as being inextricably *co-constituted*, coupled with a focus on material activation is evident in theorizations of how agency is distributed across heterogeneous networks comprised of humans and technological artifacts that together comprise the social world. An exemplar of this is Edwin Hutchins’ research on distributed cognition (1995). His work was a rebuke to psychologists and anthropologists who studied cognition among lone individuals in a controlled lab environment, instead opting to study “cognition in the wild” among people and their surroundings as they

naturally interact in situated practice. In the course of ethnographic observations aboard a navy vessel, Hutchins realized that the knowledge needed to navigate the ship was greater than any one individual could keep in his head; instead cognitive demands were off-loaded onto technological instruments in the surrounding environment. Cognition, then, from Hutchins' perspective, is an accomplishment distributed across a network of people and their technological implements.

The philosopher Luciano Floridi (2013) takes a similar approach in developing the concept of distributed morality. According to Floridi (2013), we live in a world of multi-agent systems comprised of human and computational actors. This raises questions about our conventional means of making moral judgments and assigning moral responsibility. Historically, when we consider whether or not a human should be accountable for his or her actions, we look for three criteria: a clear causal connection between the person's action and the outcome, awareness of the possible consequences of their action, and freedom to choose a course of action. But in a world where algorithmically mediated systems function autonomously or semi-autonomously in the world, can those standards really be applied? What does it mean to hold a machine accountable? Even determining which humans are responsible for the creation and deployment of those algorithms can be difficult, when it is often large teams—sometimes distributed across the globe—that contribute to their design. And these questions get further exacerbated for a class of algorithms that can learn and adapt in response to stimuli once deployed. To deal with these issues, Floridi (2013) advocates for an “infrastructure” of moral enablers, a “framework of implicit expectations, attitudes, and practices that can facilitate and promote morally good decisions and actions” (p. 738). These include mechanisms for ensuring

accessibility, transparency, and openness in information systems so that we can begin untangling and understanding the complex web of accountabilities.

Legal scholar Frank Pasquale (2015) similarly calls for prying open opaque algorithms that profile individuals and make financial decisions. “The values and prerogatives that the encoded rules enact are hidden within black boxes,” he writes. “Faulty data, invalid assumptions, and defective models can’t be corrected when they are hidden” (2015, p. 18). In addition to calling for regulation, Pasquale (2015) advocates for deploying technology to cut through algorithmic opacity and reveal the contents of those black boxes. “In healthcare for example, regulators are deploying technologically savvy contractors to detect and deter fraud, abuse, and unnecessary treatments. Similar techniques can and should be applied to keep banks, search engines, and social networks honest” (2015, p. 16). Such an approach of investigating what is inside the blackbox of sociotechnical networks echoes Actor Network Theory’s call to “follow the actors,” which include both human and nonhuman entities (Latour, 2005, p. 29).

#### *Vernacular theorizing: Data science as ethical interrogation*

Certain arguments of ethical import in the vernacular discourse of data science practice resonate with these previously outlined academic treatments of technologies in networks of distributed agency. A key issue in this space concerns the opacity of complex algorithms that act on the world in consequential ways, and the difficulty in holding them accountable. One of the most famous and respected computer scientist ringing this alarm bell is Latanya Sweeney, a professor at Harvard and a former chief technologist of the Federal Trade Commission under the administration of Barack Obama. One of Sweeney’s most famous contributions is a study widely known and discussed in the data science community, in which she demonstrated the racial bias of algorithms that display ads in Google searches (Sweeney, 2013). When a user searches for an

individual by first and last name, it is common for that action to generate advertisements for companies that perform background checks by accessing public records. These ads can follow a number of templates that incorporate the first and last name that was used in the search, such as “We found Jane Doe,” or “Jane Doe, arrested?” Sweeney (2013) found a statistically significant difference in the way “ads suggesting arrest tend to appear with names associated with blacks, and neutral ads or no ads appear with names associated with whites,” regardless of whether or not there was actually an arrest record associated with the names (p. 4). This bias can have profound real-world ramifications, warns Sweeney: for example, employers may form a negative opinion of a job applicant if they search for their name and see implications that the individual may have been arrested. Sweeney (2013) goes on to discuss how it is difficult to know exactly why and how this bias arises because proprietary algorithms determine which ads appear to which users. “Why is this discrimination occurring?” she asks “We don’t yet know, but navigating the terrain requires further information about the inner workings of Google AdSense” (2013). Armed with a general understanding of various advertising services offered by Google, she is able to trace the relationships between the search operator and its advertisers, and infer the likely algorithmic logics that determine which advertisements appear with which names:

Google understands that an advertiser may not know which ad copy will work best, so the advertiser may provide multiple templates for the same search string, and the “Google algorithm” learns over time which ad text gets the most clicks from viewers. It does this by assigning weights (or probabilities) based on the click history of each ad. At first, all possible ad texts are weighted the same and are presumed equally likely to produce a click. Over time, as people click one version of an ad more often than others, the weights change, so the ad text getting the most clicks eventually displays more frequently. This approach aligns the financial interests of Google, as the ad deliverer, with the advertiser.

Sweeney, 2013, p. 14-15

This means that the algorithm is essentially learning and reflecting back the biases in a population of internet users who are more likely to click on ads suggesting the arrest of black

people than white people. Sweeney’s tactic of exposing the ethical transgressions of technological systems and uncovering their underlying logics is one that has gained traction among practitioners, manifesting in efforts to impose what is often called “algorithmic accountability” (Donovan et al., 2018). For example, there is a movement afoot to conduct algorithmic audits (Sandvig et al., 2014) by gathering data generated by algorithmic systems, running statistical tests to expose bias against protected classes of people, inferring the algorithmic logic that resulted in the biased output, and compelling developers to alter their algorithms in a way that reduces this bias.

Like the efforts identified above to practice data science as ethical convention, the community of practice focused on algorithmic accountability is working on making intellectual and technical progress in developing ethical data-intensive computational technologies. The distinction I’m drawing is that in the former approach, the focus was on training data scientists to mitigate the harm that can come from their own work if their practice is not imbued with ethical ideals, whereas this approach is focused on using the products of data science to expose and address ethical transgressions perpetuated by other people and technologies. As such, I characterize this approach as “data science as ethical interrogation,” a distinctive and complementary set of discourses and actions that is, nonetheless, not mutually exclusive to data science as ethical convention. In a sense, it is an effort to force the hand of technologists, shaming them into adopting ethical conventions in their practice.

### **An extrinsic perspective with a focus on material activation**

#### *Academic theorizing: Technologies and politics*

When a focus on material activation is combined with an extrinsic view of the “social” and the “technological” as entangled yet analytically extricable categories, we see theories about

the ways in which political logics, agendas, and ideologies are intentionally inscribed into the design of artifacts for the creation or maintenance of a particular social order. Langdon Winner (1980) takes this approach when exploring the histories of particular technologies designed to purposefully unleash a certain “set of consequences logically and temporally prior to any of its professed uses” (p. 125). For example, he discusses how new automated technology at a Chicago factory in the late 19th century was introduced not for the sake of a superior product, but as a tactic to displace skilled laborers and weaken their union. Winner’s (1980) thesis is that technologies are often designed and deployed by the powerful with their own interests in mind, and, once established in the world, act autonomously to advance those interests. He critiques scholars of technology and society who don’t account for entrenched power dynamics at the outset of their analyses, and for focusing on the uncertainty and contingency surrounding technological origins at the expense paying attention to social consequences once a technology has become entrenched (Winner, 1993).

Attention to such political intentions and consequences is what Brian Pfaffenberger has called the “technological drama” (Pfaffenberger, 1992). In the burgeoning area of literature on social studies of data practices, data cultures, and data economies, politically oriented scholarship explores how data intensive technologies concentrate power, perpetuate marginalization, and transform publics, citizens, and subjects. Alison Powell (2014) argues that faith in data analytics as the preeminent way to understand society is rapidly becoming the norm in cities, fundamentally transforming relationships between governments, citizens, and commercial interests through their roles in the production, exchange, and brokerage of data. This new configuration “shifts from seeing citizens as those with civic responsibilities and engagements, to classifying them as consumers who purchase services from providers” (n.p.). In

Melissa Gregg's (Gregg, 2015b) work, on the other hand, people become not just consumers in a data economy, but also the product, as technology companies scramble to exploit the "infinite possibilities" (p. 43) for business profit afforded by gathering and connecting ubiquitous traces from the day-to-day actions and interactions of citizens.

The role of data-intensive technologies in political power is also a core theme running through Virginia Eubanks' (2017) deep dive into algorithmic systems used in the provision of social services by public agencies. Her investigations of algorithmically assisted decision-making in the determination of eligibility for welfare services, the assignment of shelter to the unhoused, and the prediction of which children will become victims of abuse by a caretaker, lead her to the take-away that these systems are part of long-standing and deeply entrenched policies that perpetuate marginalization. Eubanks (2017) focuses on the history of poverty in the US and argues that American society has always punished the poor rather trying to authentically help them, characterizing new data-driven systems as a "digital poor house"—a 21st century version of the physical poorhouses of yesteryear. She questions the underlying logics of data-based computational systems in the public sector, premised on efficiency and optimization. While technologists may think they're doing "good" by more efficiently matching homeless people to resources, for example, they are actually participating in a political system that was never designed to help as many people as possible, but rather is geared toward reducing the number of people on public assistance. While Eubanks (2017) does touch on the importance of ethical convention as I've characterized it earlier, she also admonishes data scientists for asking the entirely wrong questions in the first place.

As we create a new national narrative and politics of poverty, we must also begin dismantling the digital poorhouse. It will require flexing our imaginations and asking entirely different kinds of questions . . . . What would decision-making systems that see poor people, families, and neighborhoods as infinitely valuable and innovative look like?

It will also require sharpening our skills: high-tech tools that protect human rights and strengthen human capacity are more difficult to build than those that do not.

Eubanks, 2017, p. 212

In other words, if technologists want to help the poor, they need to start by asking what the poor need.

*Vernacular theorizing: Data science as ethical innovation*

The solution that Eubanks (2017) proposes in response to ethical issues raised by data-intensive computational systems is fundamentally different from the ethical approaches discussed thus far—data science as ethical convention and data science as ethical interrogation. Those approaches, in keeping with the intrinsic perspective that underlies them, are focused on identifying harm that arises along with data-intensive computational technologies, and mitigating those harms. Coming from an extrinsic perspective, on the other hand, Eubanks (2017) focuses on the way such systems are situated in historical continuities of a deeply flawed social system. To be sure, on both sides of the spectrum, critics acknowledge the existence of entrenched social biases. But they differ in terms of how they problematize the relationship between the technology and the pre-existing social bias. For example, Latanya Sweeney's (2013) work on racial bias in ad delivery is premised on the existence of racism, but the point of her analysis is not to demonstrate that biased algorithms make racism worse overall, but to show how racism and algorithmic technologies combine to produce *racist algorithms*. In other words, technology is the *explanans*, not the *explanandum*. Eubanks (2017), on the other hand, wants to show that algorithmic technologies are a tool employed to further a longstanding project to marginalize and punish the poor, rather than help them. The solution, then, is not to merely tweak the technologies, but to tear down the social system and replace it with something else. Technology has a role to play in that reconstruction, but much more must be asked of it. For the goal isn't just

to make the technology less harmful, but to design technologies that empower the marginalized and build a different world. As such, I characterize this approach as “*data science as ethical innovation.*”

Such an ethos can also be found in the vernacular discourses and practices in some corners of data science. For example, in 2017, a group of data scientists with the mission of “using data science to create concrete and measurable change in the lives of Black people” convened the inaugural “Data for Black Lives” conference on the campus of MIT in Boston (“About Data for Black Lives,” 2017). One participant (Watson-Daniels, 2017) who recapped the conference in a blog post highlighted the conference’s focus on the capacity of the black imagination to forge a more equitable future through technology:

When we understand that social ideologies are strengthened when people use data to engineer a narrative like white supremacy and embed it into the fabric of our society, we can begin to think about decolonization as a project of reverse-engineering or even a task of redesign. Our data has to be wrapped up in more inclusive and equitable narratives.... Remember, what we are talking about is black futures and what is possible with this unleashing of black imagination.

Watson-Daniels, 2017

The Data for Black Lives conference does what Eubanks (2017) has suggested is necessary; instead of asking how can we make sure our technologies do not inflict further harm to a marginalized black population, it asks how do we develop technologies that originate with the needs and questions that are of central concern to black communities. For example, algorithms predicting which individuals are more or less likely to recidivate are being used to help judges determine which defendants should be granted bail, and have been notoriously criticized for discriminating against black defendants (Angwin et al., 2016). Rather than seeking to make an unbiased recidivism prediction algorithm (which, according to Chouldechova, 2017

may not be entirely possible), a data science as ethical innovation approach would start by asking what other kinds of technology might be invented to keep black people out of prison, given the disproportionately high rate at which they are incarcerated. For example, a number of startup companies have recently begun devising technological interventions to help defendants navigate the bail bond system—one that is often viewed as discriminatory because wealthy defendants can afford bail while poorer defendants (often people of color) either languish in jail or become indebted to bond companies that charge them hefty interest rates on bail loans. One app, called “Appolition,” lets donors round up the cost of all their purchases to the nearest dollar amount and contribute the spare change to the National Bail Out fund, a grassroots organization that posts bail for people who can’t afford it (V. Law, 2018). Another, funded by the performer and businessman Shawn Carter (who also goes by the stage name Jay-Z), helps defendants track their court appearances and other legal obligations in order to help them avoid violating the terms of their bail (Mahoney, 2018).

### **An extrinsic perspective with a focus on material mediation**

#### *Academic theorizing: Technologies and identity*

Theories of technology and society that come from an extrinsic perspective and focus on material mediation explore the ways that pre-existing social categories manifest in people’s lived experience of technological artifacts or systems; in other words, they are concerned with how technology mediates social roles, positions, and identity. This has been a central concern for feminist technology studies (e.g. Haraway, 1988; Lucy Suchman, 2002; Wajcman, 2010), which aims to generate “reconstructive engagement with received conceptions of the human, the technological and the relations between them” (Suchman, 2005). In her classic essay, *A Cyborg Manifesto*, Donna Haraway (1991) muses on how technological mediation of embodied

experience allows for the rejection of essentialist categories of “natural” identity and makes room for the embrace of infinitely heterogeneous bonds of affinity. Valuing the multiplicity of such heterogeneous perspectives is the political and epistemological agenda of feminist standpoint theory, which seeks to dispense with the notion of objectivity as a “view from nowhere” and replace it with the notion of objectivity as “situated knowledges” that make visible the social and historical positioning from whence they were derived:

... feminist embodiment resists fixation and is insatiably curious about the webs of differential positioning. There is no single feminist standpoint because our maps require too many dimensions for that metaphor to ground our visions. But the feminist standpoint theorists' goal of an epistemology and politics of engaged, accountable positioning remains eminently potent. The goal is better accounts of the world, that is, 'science.'  
Haraway, 1988, p. 590

From this perspective, generalized or universalizing claims are never adequate; if our aim is to understand the social world as it is, we must acknowledge the multiplicity of the human condition, reach across borders and boundaries that circumscribe our own existence and situated knowledge, and make room for the situated knowledges of others. Lucy Suchman and others have brought this perspective to the domain of technology design, emphasizing the need to bridge perspectives and welcome multiple standpoints into the design process. Suchman has problematized the cloistered world in which technologists typically conduct their affairs, and advocated for a reimagining of the duality between designers and users:

... we need to begin by problematizing the terms 'designer' and 'user' and reconstructing relevant social relations that cross the boundaries between them. Attempts to avoid this conclusion lead to various sorts of surrogates, proxies, stand-in's for 'the user,' designed to allow the creation of usable technologies in the absence of these other relations.  
Suchman, 2002, p. 94

Without such revisions, says Suchman (2002), technologists will continue “operating within a limited sphere of knowing and acting that includes variously crude or sophisticated conceptualizations of the others” (p. 96).

*Vernacular theorizing: Data science as ethical participation*

In the world of data science, this is a powerful argument for including marginalized communities in the design of data-intensive technologies. Even when data science is imagined to be a vehicle for democratic innovation, computational work involves high barriers to entry. For example, the ethnographer Thomas Lodato (2016) has talked about the experience of attending a civic hackathon that ostensibly welcomed people of all technical abilities to participate. Even with some professional programming experience under his belt, however, he found that the work was so complex, he was relegated to doing the repetitive and menial labor of uploading data through a web browser. This was a crucial task that had to be done, but nonetheless felt a far cry from being a meaningful contribution, leaving Ladato (2016) feeling “cheated” and unlikely to return, were it not for his desire to continue conducting ethnographic observations.

Not only is technical expertise distanced from other ways of knowing, the work of data science is often distanced from the people it affects most: the people who are represented in data by their digital traces, who use services that are algorithmically augmented, who are governed by institutions making decisions based on data-informed cost optimization. For example, danah boyd likes to point out that, unlike doctors, data scientists rarely come face to face with the outcomes or consequences of their work, even when that work is implicated in making decisions with life or death consequences (boyd, 2018).

Barriers to entry and distances between practitioners and the populations they affect become even more problematic when considering the notorious lack of diversity in

computational professions, including in data science (Priceonomics, 2017). This means that the people making decisions about what technology looks like, deciding what questions should be asked, and interpreting what patterns in data mean, are predominantly white and male. Similar to Suchman's (2002) concern over the dichotomy between designers and users, these conditions—the barrier to entry in data-intensive work, separation between the context of production and context of consequence, and lack of diversity in computational professions—set up serious cause for concern over the dichotomy between data scientist and data subject.

Recently, then, there have been calls in the vernacular discourse of data science for practitioners to recognize their own cloistered positionality and to invite and involve the participation of others in their craft. For example, the aforementioned “Community Principles on Ethical Data Practice” calls on practitioners to “foster diversity by making efforts to ensure inclusion of participants, representation of viewpoints and communities, and openness” (“Community Principles on Ethical Data Sharing,” 2018). Inclusive participation is thought to be necessary for ensuring that data science initiatives not only do no harm, but also “maximize positive impact.” Suggestions for how to foster such diversity include “being conscious of, and owning the results of actions, regardless of intent; promoting the voices of marginalized groups; acknowledging and self-checking privilege; accepting checks of privilege by others in good faith, and using privilege to advocate for equity” (“Community Principles on Ethical Data Sharing,” 2018).

An example of participatory data practice is taking place in Atlanta between a community organization called the Westside Atlanta Land Trust (WALT) and a research studio at Georgia Tech called the Public Design Workshop (Public Design Workshop, 2018). WALT represents communities that are expected to rapidly gentrify with the development of a new sports stadium

in West Atlanta and put long-time residents at risk of displacement from their neighborhood. Therefore, the community is trying to create a public land trust by buying up all vacant properties in the neighborhood, and are working with the researchers at Georgia Tech to make a data-driven case for their efforts:

Working together, the Public Design Workshop and WALT produce custom datasets, maps, graphics, videos, and other informational media to help make the case for a community land trust in the English Avenue and Vine City neighborhoods.

Public Design Workshop, 2018

Like this project, when data science is practiced as ethical participation, instead of asking what kinds of technologies marginalized communities might need, it asks what those communities are already doing and how we can help leverage data in service to their efforts.

## CONCLUSION

In this chapter, I have argued that practitioners engage in vernacular theorizing, and that this vernacular theorizing can be considered in relation to academic theorizing in order to create generative dialogue between them. In particular, I have shown how academic theories of sociomateriality are implicitly reflected in vernacular theorizing that informs various approaches to ethics in data science of the social. I have explored a range of perspectives on ethical concerns related to the impact of data science on marginalized populations, exploring how those approaches frame problems and enact solutions. This includes the *data science as ethical convention* approach, which is informed by an underlying acknowledgment that the social and technical reinforce and recreate one another, and seeks to develop techniques and norms for avoiding the production of unintended harmful outcomes in the course of practice. Another variant is what I have called the *data science as ethical interrogation* approach, which reveals an underlying understanding of technologies as block boxed sociotechnical systems that must be

pried open and investigated in order to hold them accountable. A third approach I've characterized as *data science as ethical innovation*, which is predicated upon an understanding of the existence of powerful and entrenched social orders that can either be reinforced or unsettled by the development of technology. The final ethical approach I discussed is *data science as ethical participation*, which sees community identity and empowerment as emerging from embodied and technologically mediated experiences, and advocates for the direct involvement of marginalized communities as the path forward for producing ethical sociotechnical systems.

In mapping these different approaches, I have surfaced how the implicit, shifting, and partial understandings of sociomateriality have consequences for how data-intensive technologies are designed, deployed, and enacted in practice. This analysis can be thought of in terms of three interrelated theoretical levels employed by scholars when reconstructing practice (Craig & Tracy, 1995). According to Craig & Tracy (1995), at the “philosophical level,” the practice scholar elaborates “normative ideals and overarching principles that provide a rationale for the resolution of problems” (p. 253). I have done this by revealing the underlying and implicit perspectives on sociomateriality that inform data science of the social. At the “problem level,” practice scholars identify the particular “interrelated web of problems that practitioners experience” (Craig & Tracy, 1995, p. 253). I have addressed this level of analysis by calling attention to the ongoing ethical crisis in data science of the social, and by tracing the varied ways in which practitioners are problematizing and addressing these issues. The final level in the reconstruction of practice is what Craig and Tracy (1995) call the “technical level,” which reveals “a repertory of specific communicative strategies and techniques that are routinely available to be employed within the practice” (p. 253). In the next chapter, I turn my attention to this third level of analysis by exploring in detail the way two teams in the eScience Institute's

Data Science for Social Good program made sense of the ethical challenges and implications of their work. One of these teams adopted the data science as ethical convention approach that I have outlined above, and the other adopted a data science as ethical innovation stance. At this technical level of analysis, I use their stories to draw out the particular processes that play a key role in supporting in ethical thinking in those respective approaches.

## **CHAPTER 4 ETHICS IN ACTION: CASE STUDIES OF ETHICAL APPROACHES IN DATA SCIENCE FOR SOCIAL GOOD**

### **INTRODUCTION**

In this dissertation, I engage in retroductive analysis and argumentation, in which I tack back and forth between data and the exposition of theory. In the last chapter, I took a discursive approach to addressing what Craig and Tracy (1995) call the philosophical and problem levels of practical theory by highlighting the underlying sociomaterial premises informing ethical approaches in data science of the social, and mapping the different ways ethics were evoked in that space. I introduced a practical theory framework outlining four distinct, though not mutually exclusive, ethical approaches: data science as ethical convention, data science as ethical interrogation, data science as ethical innovation, and data science as ethical participation. In this chapter, I shift to what Craig and Tracy (1995) call the “technical level” of practical theory, to examine the specific strategies, activities, and processes at play in ethical approaches to data science of the social. I hone in on two ethical approaches in particular—data science as ethical convention and data science as ethical innovation—as they manifested in situated data science practice during the Data Science for Social Good (DSSG) program. I introduce accounts of two DSSG projects as exemplars of those respective approaches, and use empirical vignettes to develop more nuanced understandings of the practical framework introduced earlier, probing the implications of how such vernacular understandings of sociomateriality play out in the day-to-day practice of data science.

The tales I tell are examples of what Maitlis and Lawrence (2003) call “decision stories”—a chronological account of sense-making episodes in which choices are made that definitively impact the trajectory of practice. The first vignette I present concerns the ORCA project, which was an effort to make electronic fare transaction data from a regional transit

system useful for analytical purposes. I explore the sense-making and decision-making that go into “data science as ethical convention” through a descriptive account of the ORCA team’s deliberations about the biases in their data. In the second story, I present the AccessMap/OpenSidewalks (AMOS) project, which was an effort to build a pedestrian routing application for people with limited mobility. I explore the trade-offs and compromises that go into “data science as ethical innovation” through a descriptive account of the AMOS team’s development of a data schema that they hoped would be adopted as the functional standard for an open-source mapping platform.

Making a claim of “doing social good” is an act with inherently ethical implications, and so I begin each story by illuminating how the teams’ leaders framed and communicated their notions of why and how their projects counted as social good, and the visions that animate their work. This also provides a sensible starting point for introducing the projects, as it explains the motivations and origins of the work. I then follow in detail how the DSSG teams—comprised of the project leads, DSSG students, and data scientists from the eScience Institute—attempted to enact that vision for social good while balancing multiple priorities, negotiating competing interests, and wrestling with divergent values. Within the body of scholarship that could be considered to fall under the emergent field of inquiry called critical data studies (Andrew Iliadis & Russo, 2016), technologists and data scientists are often portrayed as arch-positivists who blindly assume the neutrality and objectivity of data and data-intensive methods. As I’ve argued elsewhere with my colleagues, this is simply not always the case (Neff et al., 2017). In both of the projects I discuss in detail below, we see two teams putting ethical issues at the very center of their work.

After presenting detailed accounts of how the ORCA team and the AMOS team came to understand, frame, and enact the subjective and value-laden nature of their projects, I address the practical implications of their work for the ethical convention approach and the ethical innovation approach to data science, drawing out the key processes supporting ethical thinking within those respective approaches.

## THE DSSG SCENE

On a beautiful June day in the Pacific Northwest, all the participants of the Data Science for Social Good program are gathered in the Data Science Studio, the open-plan workspace that serves as the home of the eScience Institute. A bold patchwork of red, orange, and purple carpet tiles gives off a cheerful glow, and the design features of the space reflect the organization's emphasis on collaboration: a handful of cushioned sofas and easy chairs are arranged facing each other, living room-style, at the center of the studio; several clusters of standing desks are closely nestled in pod formation; two large rooms for meetings and seminars flank the sides of the space; several smaller rooms for break-out sessions and private meetings are tucked away into the corners; and nearly every wall is covered in glass or dry-erase paint, turning virtually the entire studio into a giant whiteboard. Often, nearly every section of the wall is filled with mathematical annotations, diagrams of computational pipelines, and mock-ups of data visualizations.

Perched atop the sixth floor of one of the tallest buildings at the University of Washington, the space boasts some of the best views on campus. Eight-foot tall windows look out onto the looming mass of Mt. Rainier to the southeast, the slender profile of Seattle's iconic Space Needle can be seen in the southwest, and, far to the west across Puget Sound, a chain of snow-capped peaks in the Olympic Mountains peek out on particularly clear days. This happens to be one of those pristine summer days in the Pacific Northwest... but at the moment, no one

seems distracted by the vista. Their attention is turned to the front of the conference room, because they're finally about to learn why they are here in the first place.

The DSSG fellows—16 graduate and undergraduate students selected from a competitive pool of about 200 applicants—started their 10-week long fellowship a week ago, but they still know next to nothing about what they'll be doing for the remainder of the summer. They have spent the first several days of the program in tutorials covering the holy canon of data science: crash courses in Python, R and SQL programming languages, workshops on using the Github version control platform, and lessons on the principles of software design. Now, they're chomping at the bit to roll up their sleeves and get to work.

They're all gathered together around a large rectangular conference table to hear presentations from the program's "project leads," researchers who will be directing each of this summer's four DSSG projects. These individuals were selected into the program after submitting project proposals earlier in the year, and have committed to spending about half of each work week in the studio this summer working side-by-side with the student fellows and data science mentors from eScience who have been assigned to their projects. Today, they've been asked to give a short presentation introducing their project to all the program participants before the group splits up into their respective teams to have their first planning meeting of the summer.

## THE ORCA PROJECT

### **Decision story: The ORCA team confronts bias**

*Data that tells you what people actually do*

The first presenter is an engineer named Mark Hallenbeck. Mark has salt-and-pepper hair, boundless energy, and boyish dimples that deepen when he's making one of his frequent self-deprecating jokes about talking too much or wandering off topic. He has the lanky frame of

a former competitive track and field athlete, and he habitually shows up to meetings in a trademark tie and a pair of cycling cleats. As a research scientist at the University of Washington, Mark runs an outfit called the Washington State Transportation Center. Unlike faculty, who are typically paid at least in part from tuition dollars, research scientists at UW are entirely dependent on soft money; essentially, they create their own salaries by obtaining grants and contracts from outside sources. Mark has been supporting his work in this manner for the last 30 years, primarily by winning research contracts from transportation agencies to do applied research that is directly relevant to their operations. He's a self-proclaimed transportation data wonk, and he's accustomed to presenting to other transportation data wonks.

But this crowd is different. The students come from a dizzying array of disciplines: political science, anthropology, applied math, finance, geography, psychology, and more. Not one among them has a background in transportation. So instead of appealing to them by emphasizing how this project will impact the transit system, Mark opens with one of the most enticing promises of big data, something that that is a dream come true for most researchers no matter what field they come from: the data I'm going to give you isn't just what people *say* they do, he tells them, it's what they *actually* do.

The gold standard in transportation planning has long been data from household transportation surveys, which are periodically conducted by the US Department of Transportation and regional planning authorities. These surveys ask scientifically sampled respondents to provide information about where members of their households travel, how they get there, and how long it takes them. The downsides to household transportation surveys are that they are extremely expensive to conduct, aren't collected very often, and aren't highly granular. But, Mark tells the group, transportation and planning agencies now have access to an

alternative source of information—a constant stream of “free” data that could reveal how people use the transit system in finer grained spatial and temporal detail. If only they could figure out how to use it.

The data Mark is referring to are generated by the electronic transit fare payment system called “One Regional Card for All,” so named because it works across six different transit agencies in the greater Seattle metropolitan area. But colloquially, it’s known simply the ORCA card. The governing board that oversees ORCA has records of every financial transaction made by ORCA users, including boardings on local buses, regional trains, and certain ferries. On its own, ORCA data has limited value because there is no geospatial metadata attached to it. So if you want to paint a picture of where, when, and how people are using their ORCA cards, you have to take each transaction record, figure out which vehicle it came from, and use another data set to locate that vehicle in space and time. But joining these data sources isn’t computationally trivial, and doing so could make it easier to re-identify individuals in the anonymized data, which raises concerns over privacy. So although the ORCA system has been in place for seven years, so far, no one has tried analyzing the data from it: it’s simply too complicated and too sensitive. But now that it’s in the hands of academic researchers who can secure the data and protect privacy, the ORCA data could yield analyses that help transportation planners better understand how people use the transit system, and ultimately make better planning decisions.

As Mark’s presentation draws to an end, the very first question from the audience is a stumper: Just how representative is the ORCA data?

Mark’s initial response is blunt and emphatic: I would love to know that!

### *The centrality of the bias question*

This question ultimately becomes a central concern for the ORCA team this summer, as they decide that finding biases in their data will be the team's primary objective. But what they mean by "bias" and how they plan to address it remains up in the air a while longer, as the team juggles multiple meanings of the term. And as we'll see, some of these different understandings of bias can be seen as arising from their different ethical orientations.

For now, Mark's response to the question from the audience about representativeness makes it clear that, although he is bullish on the potential for the ORCA data to yield valuable insights, he remains clear-eyed about its problems and limitations. On most of the public transit options in the Seattle area, he explains, passengers can pay either with the ORCA card or with cash. And, based on his general knowledge of the transit system, Mark strongly suspects that the ratio of ORCA customers to cash-paying customers is not equally distributed across geographies or sociodemographic groups. For one thing, many of the region's largest employers—for example, the University of Washington and Microsoft—subsidize ORCA cards for their employees. This means that the routes serving those locations would likely have higher rates of ORCA use than many other routes. Moreover, people with employer-subsidized ORCA cards are likely to be highly educated and middle class. If these hunches are true, then an analysis built solely on ORCA data could produce a skewed picture of the transit system, one that excludes cash-paying and lower-income riders, and over-represents ORCA-paying and higher income riders.

When the whole ORCA team gets together for the first time following this presentation, Mark sums up all these problems by saying, "We don't know what populations we have and don't have." This is a perennial issue in data science, a hallmark of which is the repurposing of

secondary data (Pasquetto, Randles, & Borgman, 2017), and the use of ‘organic’ rather than ‘designed’ data. Instead of ensuring representativeness with a rigorous sampling method at the time of data collection, data scientists repurposing organic data must figure out how to do *post-hoc* analyses and transformations that can render the data representative.

Mark tells the group that one of the resources they have at their disposal to help in making such a correction is the “automatic passenger count” (APC) generated by a pressure-plate sensor that detects when someone steps onto the bus. This number can serve as their “ground truth,” allowing them to see how many people in total got on the bus and compare that to how many people paid for their trip with the ORCA card. This comparison should provide insight into how representative the ORCA data is of total ridership across the service region. There’s a hitch, though: automatic passenger count sensors aren’t uniformly distributed across buses in the entire ORCA region. While a couple agencies have 100% APC coverage, King County Metro (by far the largest of the public transportation providers), has APC sensors on only 15 percent of its fleet. These get shuffled around between different routes on a weekly basis in a manner that is variable, but probably not totally random. This means getting at the “truth” of how many people are actually boarding buses would not be straightforward.

Later in the day, the ORCA team is working through a stakeholder analysis exercise that my colleague and I have introduced to the program. We’ve asked each team to identify the stakeholders in their projects, to discuss the risks and benefits for each of those stakeholders, and to map them based on their relative degrees of power and interest in the project. While the ORCA team is arranging colorful sticky notes on a glossy four-quadrant square, the students quickly pick up on the implication of Mark’s earlier warnings in the data briefing: if they can’t correct the bias in the data, their analyses could lead to decisions that make the transit system

worse instead of better, especially for marginalized populations that need public transit most. To reduce the harm that could unfold, then, they need to exercise diligence in correcting those biases—an exemplary position in what I’ve characterized in the previous chapter as the “data science as ethical convention” approach.

*Coming to a shared understanding of what bias means*

Although everyone is in general agreement with this position, it takes several more somewhat chaotic meetings to come up with an actual plan for how to proceed. During one such conversation, the team is supposed to be discussing their “project charter,” which is a document where the teams have been asked to outline their vision, objectives, success criteria, communication strategies, and deliverable schedule. The students are eager to map a direct route to their end goal, but instead, they are engaged in an iterative process of diving into the weeds of their data, proposing possible analyses, and exploring potential methods.

While discussing the existing, but insufficient, pipeline for processing and structuring the ORCA data, the group slips into brainstorming mode about what kinds of analyses they could do. There are different types of ORCA cards, they have learned—a general card for adults who pay the full transit fare, and three different categories of government-subsidized fare cards: one for youth; one for seniors and riders with disabilities; and a relatively new one called “LIFT” for people who meet a certain low-income threshold. The team could compare usage across these fare types, they propose ... or they could add sidewalks to their suite of datasets to see how the pedestrian network affects ridership ... or they could compare the subset of users who have employer-subsidized cards with the rest of the ORCA user population ... or they could look at how ORCA usage has changed since the new low-income LIFT program began not long ago.

They've been in free-flowing brainstorming mode for a while, but this last proposition brings them back around to thinking about bias, which they had already agreed would be a top priority. If they want to understand how low-income riders are using the system, they realize that the low-income ORCA LIFT card is a limited proxy, as it excludes people who pay their fare with cash. This underscores for them, once again, the importance of figuring out just how biased their data is. But as they puzzle over how to figure this out, it becomes clear that they don't all share the same understanding of what that bias is, why it is important, and how they should address it. For example, someone starts to explain, "we're trying to estimate ridership to some true world we don't know—", when someone else interrupts to say that they actually *do* know the truth, because the automatic passenger count tells them how many people *actually* get on the bus. But then someone else questions whether the automatic passenger count is the "truth" that actually matters, pointing out that since they don't know anything about the demographics of people being counted with the APC sensors, it won't help them understand the representation of different socioeconomic groups. They all can see that the data is imperfect and biased, but biased compared to what reality?

If this account of the conversation sounds confusing, that's because the conversation was confusing. Suddenly, a student named Jamie (a pseudonym) breaks in and asks for clarification. There's bias in how representative ORCA data is compared to the automatic passenger count, Jamie says, and there's bias in how representative ORCA LIFT is of low-income riders who don't use a card. Aren't those two separate questions? At this point, another student, Robin (a pseudonym), stands up from the table, hands waving in the air. "Help, I'm feeling confused!" Robin says in exasperation. A third student, Jordan (a pseudonym) concurs: "I think we are talking about different kinds of biases." Jordan gets up and walks over to the whiteboard to start

mapping out the different meanings of the term “bias” that are being bandied about in this wide-ranging conversation. But then Jamie reminds everyone they’re supposed to be working on the project charter, and so they should probably table the bias conversation for now. Which, for the time being, they do.

Over the next few days, the team starts exploring their data and preparing it for analysis. They establish a secure process for accessing the data on the cloud, start annotating and documenting variables, join various datasets, run descriptive statistics, and make exploratory visualizations. But they still haven’t finished their project charter, and the students are feeling unsure about how to proceed as a team, especially about which questions to address first, and how to divide their labor. Mark is absent today, and the students have called a meeting with their data science mentors because they want help coming up with a more concrete plan. They tell the data scientists that by the end of the summer, they want to have their own individual research questions, digging into an analysis that is interesting to them. But first, they plan to tackle the bias issue together as a team.

The students start recapping for the data scientists what their conversations about bias have been like thus far. “We’re all thinking about bias in a different way,” says Robin. One of their data science mentors suggests that they write their thoughts on the whiteboard as they talk, so Robin picks up a marker and approaches the board as Jamie starts to sum up the different kinds of bias they’ve discussed so far: there’s bias in how the general ORCA users compared to low-income ORCA LIFT users, and bias related to how representative ORCA data is of the total passenger count on the buses. Then there’s bias arising from the fact that the largest agency has automatic passenger counts for only 15 percent of their routes, and that’s not a random sample. So three different biases, Jamie concludes. But Jordan adds, there’s also the bias of the transit

system overall and who it's serving. Jamie responds that this is the most difficult bias to ascertain because it is "outside the data set;" they could only determine how biased the transit system is by adding other data to their analysis, such as geospatial socioeconomic data from the census.

Jamie now revises that earlier bias count: So four or five different biases.

"This sounds like four or five dissertations!" interjects Pat (a pseudonym), the fourth student on the team.

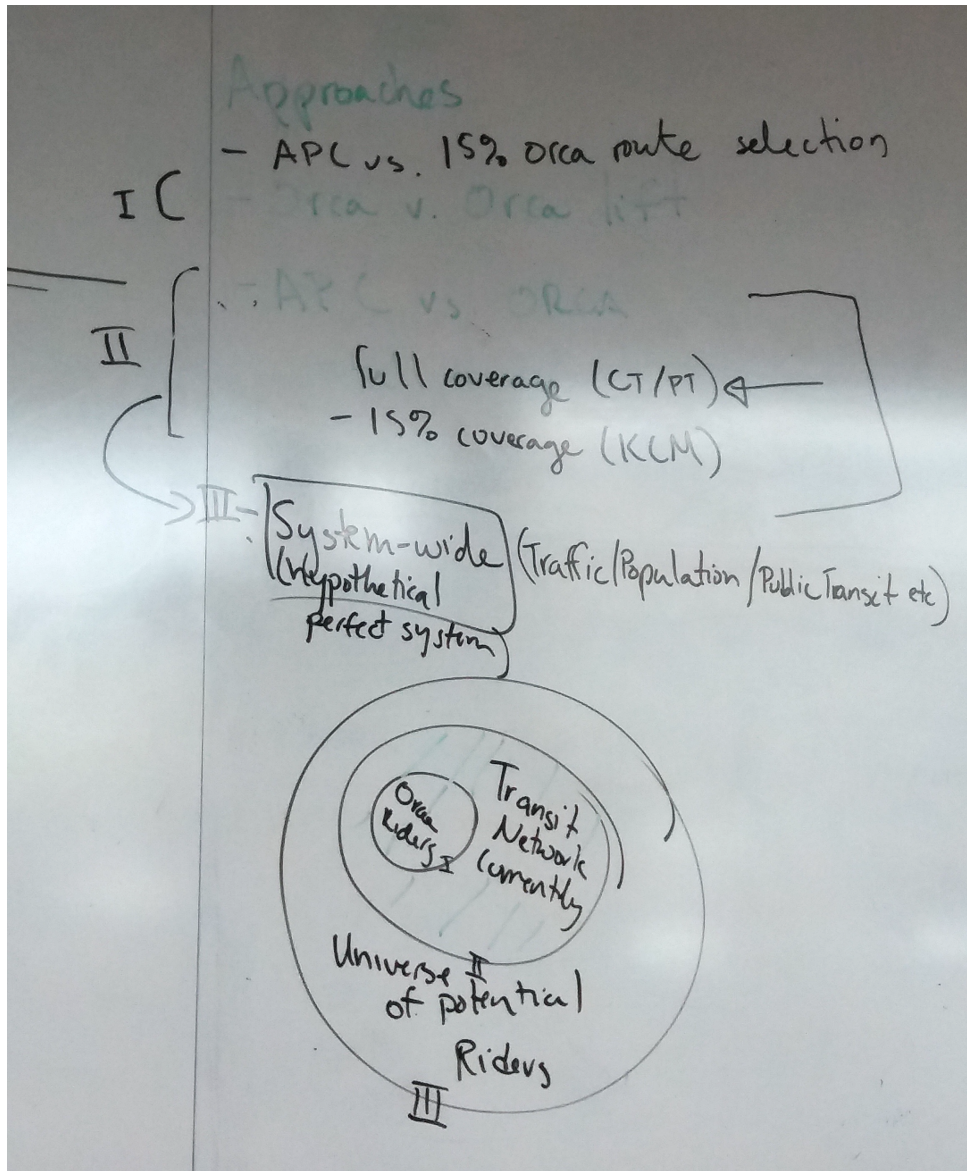


Image 4-1. ORCA team's diagram of the various biases in their data.

The students and data scientists agree that each one of the bias questions they've identified so far is a huge undertaking, and since they don't have time to resolve all of them, they should pick one to focus on. "In Mark's language, there are three 'levels' of bias," says Jamie. As Jamie continues talking, Robin captures this idea of bias levels with an illustration, sketching a nested diagram made of three concentric circles that represent the three different levels (Image 4-1).

Robin labels the innermost circle “ORCA riders,” which consists of all the transit customers who use the electronic fare payment system. Next to it, Robin places a numeral I depicting the first type of bias they’ve discussed, the discrepancies between low-income ORCA LIFT customers and general ORCA customers. In the first decision they make to narrow down which type of bias they’ll focus on, the students decide not to pursue an analysis of this “Level I” bias, because as Jamie points out, the question is just a straightforward comparison. “It seems like none of us are really interested in that,” Jamie says. “Obviously they’re going to be different, they’re different populations.”

Inside the middle circle, Robin writes “transit network currently,” referencing all the people who use the public transit system, and places a numeral II next to it, indicating bias between ORCA users and the entire population of transit riders. Robin suggests that it makes sense to look at this type of bias first because they can figure that question out with the data sets they already have. Plus, it would be useful for the transit agencies to know how representative the ORCA data is, and this is the question that Mark most cared about anyway, they reason—the issue that had started the whole conversation about bias in the first place. And if the team is going to use the automatic passenger count (APC) as their “ground truth” in doing that bias calculation, they’ll also have to deal with the bias related to the fact that King County metro only has APC sensors on 15 percent of their buses.

Finally, inside the outermost circle Robin writes, “universe of potential riders,” to capture the population that could potentially use the system, and places a numeral III next to this to indicate the systematic ways in which ORCA data may reveal bias in transit service availability for certain geographies or demographic groups. The students realize that this is something they could only ascertain by drawing in additional data sources such as the US census, which they

decided just a moment ago is beyond the scope of the work they can do in the remaining weeks of the summer. So they decide to table that question as well, even though this is the kind of question that several of the students care about most.

As the team wraps up this marathon discussion a couple hours after it began, they ask Jamie to take a photo of the diagram they've created on the whiteboard. While Jamie pulls out a phone to snap the picture, Jordan sarcastically jokes, "this will be what we put on our cv's." The comment seems to reveal a degree of frustration with the amount of time and effort it has taken the team to arrive at this place of shared understanding, and an accompanying anxiety that they won't be able to accomplish enough over the summer. Regardless of the sarcasm, though, the diagram does in actuality prove to be an important visual tool for explaining and justifying their work, and appears in a number of subsequent blog posts and presentations the team produces. And the conclusions the team came to during this episode of collective sense-making turn out to be foundational in creating a narrative about the project's importance, even as their relationship with the bias question fizzles over the course of the summer.

### *The bias question gets put on hold*

After the discussion I just described, the team decided that they would model bias by comparing the ORCA data to total ridership, as measured by the automatic passenger count (APC), and generate a numerical correction that would render the ORCA data more representative of overall ridership. Over the next several weeks, the students did manage to generate some helpful insights related to bias. For example, they confirmed their suspicion that in King County, buses equipped with automatic passenger count (APC) technology—the "ground truth" they were hoping to use in assessing how representative the ORCA data was—weren't evenly distributed geographically. Instead, the students found that the sensors were

concentrated in the northern reaches of the region. In King County, the southern neighborhoods and suburbs are generally known to be less affluent than the northern neighborhoods and suburbs, so this raised a red flag for the students. When they brought the finding to Mark, he immediately had an explanation for the discrepancy: the north has more cables installed for powering electric buses, which also happen to be the newer buses that come equipped with automatic passenger count technology. So while King County Metro rotates the buses with APC sensors through different routes, the electric buses with APC counters could only be assigned to routes with electric cables, and the electric cables were more prevalent in northern Seattle; therefore, the uneven distribution of APC counters was a byproduct of the uneven distribution of electrical bus infrastructure.

Aside from insights like these, however, the team never realized their ambition of modeling the bias of the ORCA data during that first summer. That's because once they started tackling that question, the students realized just how messy, inconsistent, and error-riddled their data was. For example, when plotting the location of buses based on their GPS coordinates, some of the buses showed up in the middle of Puget Sound, and at certain stops, the number of ORCA taps was somehow much higher than the total number of people reported to have gotten on the bus by the automatic passenger count sensor. They had to figure out why such impossible things were showing up in their data. "We kind of stopped looking at the bias problem itself," recounted Pat, "and started data detective work, and that pretty much had nothing to do with bias anymore." The team ended up spending the overwhelming majority of their time that summer dealing with errors in their data, and engaging in a cycle of breakdown, investigation, insight, and repair that my colleagues and I have identified as a common, integral, and generative aspect of data science practice (Tanweer, Fiore-Gartland, & Aragon, 2016). As Robin put it:

The bias question got really conflated with the data cleaning question. Because investigating bias was a really effective way to identify all the ways that the data just didn't make sense, right away. Because it's substantively an important question, but the practical implementation is comparing two sets of measures. And that's a really good way to find out where your measures go crazy. Because when you get spikes on one, and troughs on the other, you get really crazy. So, the bias investigation everyone was on together at first, and everyone went, "Holy shit, none of this makes sense." The data just doesn't make sense, and then we all got distracted by data cleaning. Which is not very satisfying, or very fun.

Robin, DSSG student on the ORCA team

Eventually, the team followed the suggestion Pat made earlier in the summer, turning their attention to conducting analyses with the data even though they hadn't yet corrected for its biases or repaired all its errors, so that they would have some results to "show for" their work. In Chapter 6, I discuss how those analyses were important to furthering Mark's long-range infrastructural vision for the project, even though they were not reliable findings. The false starts, dead ends, temporary fixes, and provisional results from the DSSG program were not viewed as failures by Mark and his stakeholders in government, but as incremental steps toward the ultimate goal of developing a more stable infrastructure that could support the ORCA data in the long term. Mark continued to have students work on the project over the course of the academic year, and returned to the DSSG program the following summer, with a new group of students picking up the work started by the first DSSG team. One of those students took an interest in the bias question and eventually made progress in developing a provisional method for modeling bias in the ORCA data.

### **Analysis: Implications for organizing in data science as ethical convention**

I turn now to exploring the implications of the ORCA team's effort to make sense of bias. In the course of their work, the team had to come to a shared understanding that one of their chief objectives would be identifying inherent biases in the data so that downstream uses of it would not do harm. As such, I have portrayed the efforts of the ORCA team to deal with biases

in their data as an exemplar of the “data science as ethical convention” approach. As I discussed in Chapter 3, the data science community is increasingly aware of the ethical perils of data-intensive computational work, and there are concerted efforts underway to infuse data science practice with ethical thinking. Data science practitioners themselves are calling on their community to acknowledge the potential harm that data science can unleash, to develop techniques, methods, and tools that mitigate those harms, and to adopt principles, codes of conduct, or oaths upholding ethical values.

In fact, it is safe to say that the need for attention to ethics is widely acknowledged within computational fields. For example, in a recent survey of about 90 thousand software developers on Stack Overflow, one of the most popular online platforms for knowledge exchange among coders, about 80 percent of respondents agreed that they have a personal responsibility to “consider the ethical implications of their code” (Stack Overflow, 2018). However, more than 40 percent of respondents go on to say that, at least under some circumstances, they would write unethical code anyway, if asked to do so. Perhaps this is because the overwhelming majority of respondents indicated the belief that someone else is “ultimately most responsible for code that accomplishes something unethical” (Stack Overflow, 2018).

These results speak volumes to the mismatch in the way we view ethical thinking, on the one hand, and ethical decision-making on another. We tend to see ethical thinking as an individual act of moral judgment, and yet, we realize that individuals are entangled in a web of organizational structures and power dynamics that can render their ethical thinking irrelevant. In other words, personal judgment makes little difference if organizations do not facilitate ethical decision-making, and incorporate ethics into the fabric of day-to-day practice. Here, I ask what the ORCA team’s approach to data science as ethical convention can teach us about the

organizational arrangements that facilitate ethical data science practice. How do we actually instantiate data science as ethical convention in organizational structures and cultures?

I suggest that at least three lessons can be learned from their experience. In keeping with my commitment to a practice-based approach, I identify core processes that can support data science as ethical convention. The processes I discuss include: translating values across disciplinary boundaries by leveraging ethical issues as boundary objects; incubating ethical thinking by creating a protected time and space that is somewhat insulated from the pressures of productivity; and incentivizing ethical thinking by acknowledging it as a valuable contribution in its own right.

*Translating: Employing ethical issues as boundary objects*

The above decision story is a tale of translation in action. The ORCA team had to work with and across different ethical stances and definitions of bias in order to orient themselves toward a shared objective. At the outset of the story, various members of the team had different implicit understandings of bias that needed to be made explicit through a series of wide-ranging discussions and diagramming sessions at the whiteboard. Although the students ended up thinking of the different kinds of bias in their data in terms of “levels,” there were also important semantic differences in the way they employed the term. In the first type of bias they identified, the one between users of the low-income ORCA LIFT card and users of the regular ORCA card, bias seemed to mean “*distortion*,” a phenomenon in which two distinct groups within a complete universe of data might exhibit differentiated patterns of behavior. On the other hand, the second level of bias they identified seemed to mean “*unrepresentativeness*” in the statistical sense. In comparing ORCA data to the automatic passenger count (APC), the team was interested in finding systematic regularities in the extent to which ORCA data over- or under-estimated total

ridership, and the extent to which the 15 percent sample of King County Metro routes with APC sensors was not randomized. On the other hand, the final type of bias they discussed, the one between the existing system and a hypothetical equitable system, is more aligned with the meaning of “*unfairness*,” or the degree to which the status quo deviates from morally defined ideals of equity.

Given these multiple understandings, their task was to translate across what Paul Carlile (2002) has called a “semantic boundary”—not to generate a single unified understanding, but to find common ground that would allow them to agree upon a shared approach. Heterogeneous teams from different backgrounds and social worlds regularly manage to collaborate with the assistance of “boundary objects” that facilitate the process of translation and coordination:

Boundary objects are objects which are both plastic enough to adapt to local needs and the constraints of the several parties employing them, yet robust enough to maintain a common identity across sites. They are weakly structured in common use, and become strongly structured in individual-site use. These objects may be abstract or concrete. They have different meanings in different social worlds but their structure is common enough to more than one world to make them recognizable, a means of translation.

Star & Griesemer, 1989, p. 393

In other words, Star and Greisemer (1989) have shown that total agreement or shared understanding isn’t necessary for actors to productively collaborate. As we’ll see, even though the team never fully agreed on what bias meant and why it was important, the concept of bias served as an abstract boundary object around which to orient their work, which was necessary because members of the ORCA team came into the program with different priorities and expectations. In part, this is because multiple priorities and expectations are built into the very design of the DSSG program: it is at once about training students to improve their technical proficiency in data science methods, about enacting social good, and about advancing the goals

of the stakeholders who serve as project leads. These different expectations for the DSSG program are depicted in Figure 4-1, along with their particular instantiations in the ORCA project. As I'll explain below, on the ORCA team, the expectation for social good manifests as a concern for equity, the expectation for advancing stakeholder objectives manifests as the goal of making the ORCA data more reliable for transit agencies, and the expectation for data science learning manifests itself broadly as desire to work on a problem that is methodologically challenging.



**Figure 4-1 Expectations in the DSSG program and on the ORCA team.** The diagram on the left depicts three concurrent expectations for the DSSG program: that the projects will result in social good, that they will advance the objectives of partnering stakeholders, and that they will contribute to the students' learning data science methods. The diagram on the right depicts how those expectations played out in more specific terms in the ORCA project, in which the expectation for social good manifests itself as a concern for equity, the expectation for advancing stakeholder objectives manifests as the goal of making the ORCA data more reliable for the transit agencies, and the expectation for data science learning manifests itself broadly as desire to work on a problem that is methodologically challenging.

It was clear from the beginning of the summer that the students needed to believe in the social good aspect of their work in order to feel genuinely invested in it. Although I never saw the group try to come up with a shared, explicit definition of “social good” as a team, in their conversations, they would indirectly bracket what did or didn't count as social good, and their

tacit definitions usually were oriented toward addressing issues of social marginalization and equity. For example, when the students were introducing themselves to each other at the outset of the program, Jamie claimed to be motivated to work on this project out of a concern for transportation access issues among low-income populations. When Mark told the students they had free rein to ask whatever questions they wanted of the data for the individual research questions they planned to pursue, Robin anticipated that, “most of us will gravitate to things with a social good dimension, equity issues.” And Jordan explicitly defined social good in terms of equality during an interview:

I have a very specific definition of social good. I think that I define social good as something that reduces inequality. I'm not utilitarian about it; it doesn't need to reduce inequality for the most number of people. I think that inequality in a broad sense is bad for all of society. I think that when there are marginalized groups, it disproportionately affects them, obviously, but I think society would be a better place if there was less inequality, for everybody. I think anything that reduces that is a social good.

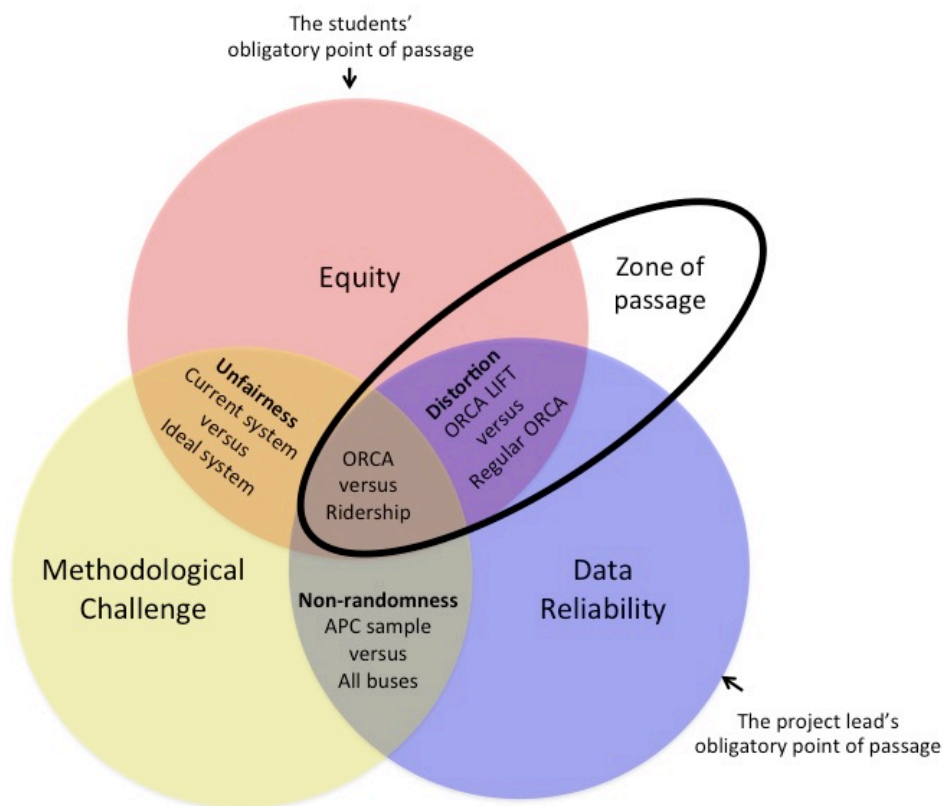
Jordan, DSSG student on the ORCA team

The students brought to the program an instinct for what I have previously (Chapter 3) called “data science as ethical interrogation,” a position that seeks to use the results of data science analysis to expose social injustices. Their project lead, Mark, on the other hand, came into the program with a decades-long history of close cooperation with transportation agencies. His primary concern was not exposing existing bias in the transit system as a whole, but identifying and correcting bias within the data set over which he had immediate control, so that the data could be trusted and used by the transit agencies for future analysis. He knew that correcting biases in the data was just one of many important steps that could render the data reliably useful to transit bodies.

Mark was happy to let the students ask questions of the data that were near and dear to their hearts, but was clear that his own motivation and perspective on social good were different from theirs. In one of their early scoping meetings, he told them that he had two goals: to convince people to use data, and to use data responsibly. In particular, he wanted to convince the transit bodies that the ORCA data was reliable for analysis, and that it would be possible to create software tools to answer questions relevant to planning. It didn't necessarily matter what those questions were for the time being, they just needed to demonstrate proof of concept, and show Mark's stakeholders "what the data is good at representing and what it is not good at representing." I discuss the importance of this project-based, proof-of-concept approach to building data-intensive capacities at length in Chapters 5 and 6, but I bring it up here to illustrate the different goals of team members on this project. The students were inclined to frame their work as being in service to marginalized populations, while Mark was inclined to frame the work as being in service to the transit agencies. The students were motivated by marginalized people's experiences of inequities, while Mark was primarily motivated by a drive to improve regional transportation overall and a conviction that data-intensive work is a superior way of planning and operating a transit system. From the students' initial perspective, their work had the potential to hold transit agencies accountable in the event that they were not fairly serving marginalized populations, while for Mark, the transit agencies had the power to make decisions that would benefit the entire population, and it was his job to enable them to do that better.

These different priorities expressed by the student and their project lead can be thought of as obligatory points of passage, to borrow a phrase from Michel Callon (1986). Obligatory points of passage are anything—be they people, ideas, expectations, values, consequences, material constraints, etc.—that direct convergence around a particular understanding, purpose, course of

action, or decision. The students needed to feel that the project was making a positive contribution to issues of equity, so this can be considered as an obligatory point of passage for them, while Mark needed the project to be improving the data’s reliability, making this his obligatory point of passage. In Figure 4-2, I’ve returned to the Venn diagram of expectations and priorities on the ORCA team, in order to label these two obligatory points of passage. and identify the area where they overlap as the “zone of passage.” In the areas of overlap for each of the three simultaneous expectations in the project, I’ve indicated which of the various types of bias spoke to those multiple expectations. Below, I further explain the rationale and significance of these placements by returning to the deliberations and decisions made by the team.



**Figure 4-2. Obligatory points of passage.** This diagram a) illustrates how different types of bias addressed different priorities on the ORCA team, b) locates the obligatory points of passage for the students and the project lead, and c) demarcates the zone of passage in which both of their priorities could potentially be accommodated.

### *1. Bias as unfairness*

In Figure 4-2, I have situated the bias question related to unfairness at the intersection of the expectation for methodological challenge and the expectation for a project that addresses equity concerns. This bias analysis, which would entail comparing the existing transit system to an idealized hypothetical system, was the one that the students initially thought was most important. As we have seen in comments made throughout the program, from their initial introductions to the interviews I conducted at the end of the program, most of the students expressed a desire to use data in exposing marginalization and inequities in the transit system. This bias question was also deemed to be methodologically challenging, as it would require the acquisition of multiple, disparate data sources and the time-consuming work of making them interoperable with the ORCA data. As such, this bias topic resides at the intersection of the concern for equity and the desire to work on a question that is methodologically challenging (Figure 4-2). But, in fact, it would have been so challenging that the students realized they wouldn't have time to pursue this line of inquiry. Moreover, as the students noted in their discussion, this wasn't a question that overlapped with Mark's primary concern of rendering the data more reliable for the transit agencies. I would argue that this latter issue is not totally separate from their lack of time to pursue the question, though. The additional data sets the students would have needed were not already available because the project had not been conceived or designed with the idea in mind of interrogating the fairness of the transportation system, and retrofitting it to accommodate such an approach would have taken an extraordinary amount of work. In other words, although the project was presented as something of a blank slate, and Mark encouraged the students to pursue any research questions they wished, obviously, their options were already constrained by the design decisions made to that point.

## *2. Bias as non-representativeness*

I have placed the bias question related to how randomly the automatic passenger count sensors were distributed across buses at the intersection of the expectation for technical challenge and the expectation for rendering the data more reliable (Figure 4-2), because it wasn't on its own perceived to be an analysis directly related to equity. Instead, it was understood to be a complementary and necessary step toward answering the bias question related to the distribution of ORCA usage across all ridership, as measured by the automatic passenger count. And that is the question that the team ultimately decided met all three of the major expectations in the program.

As we have seen, several of the students on the ORCA team came into the program hoping to make a social good impact by revealing the existence of social inequities in the transit system, but they eventually came to understand their role in repairing the ORCA data as a kind of social good in and of itself. They saw that if the ORCA data was used without accounting for its biases, it had the potential to “snowball inequity” in the future, as the team put it in one of their group presentations. Ultimately, the team came to a shared understanding that correcting biases in the ORCA data could prevent further harms and injustices that would result from assuming that the data was accurate, representative, or objective. In adopting that position, instead of pursuing data science as ethical interrogation, the team settled on an approach that elsewhere I have called “data science as ethical convention,” a perspective that essentially seeks to prevent data science practices from resulting in harm through methodological rigor. As Jamie noted, “luckily, that actually dovetails quite nicely with some of Mark's own objectives,” even though “he thinks about the bias thing in a much more technical way than the four of us do.”

Mark, for his part, let the students know that he had initially thought he would be assigned a team of computer science whiz kids who would spend the summer building a sleek architecture for the ORCA data; what he got instead was a team of four social scientists with respectable programming chops and an enthusiasm for equity. Once the team decided that bias would be their main focus, though, he saw the students as the perfect match for the task at hand. “You all heard me last week disparaging you as not being CS [computer science] enough,” he needled the team of four social scientists, “and the fact that we are now looking at bias means that who you are is even better.”

In light of their different positions, then, working on the issue of this “second level bias,” as the students put it, created common ground where they could all agree they were doing something important. But this was ultimately a compromise, and over the course of the summer, the students would occasionally express doubt that what they were doing really counted as social good. For example, during one conversation when the team was discussing how to compare ORCA and automatic passenger count data at individual bus stops, Pat stopped the conversation in its tracks to ask, “What is the ‘good’ that we’re concerned with? Because there is a lot of, ‘it would be cool to visualize this . . .’ but then it’s disconnected from the issues.” And when I asked the students in interviews to characterize the social good that their project was contributing to, this is how Jamie responded:

At least the way I justify it to myself is, if I feel like I'm doing good work, and work that I feel like I'm comfortable with, or is analytically rigorous—I don't know even if that's the right word to use—I'm trusting Mark that if I give him good stuff, after this program, he in his position, will be able to take these things and to go to different transit agencies and say, ‘you guys should do things differently.’ Hopefully that will make a difference, or do some social good. That's what the four of us have been talking about when we're implementing these things. That's sort of how I hope or I trust that some social good will come out of it.

Jamie, DSSG student on the ORCA team

In spite of the agreement the team reached, this statement is full of qualifications and hedging. The characterization of this response as a “justification” implies that Jamie doesn’t quite wholeheartedly believe the statement, but had to be convinced that it is true. This underscores that the ORCA team never fully reconciled their different understandings of social good or their different priorities, but that they did manage to reach partial understanding and agreement, in order to organize and coordinate their activities around bias—a flexible boundary object that allowed them to retain some version of their own expectations for their work.

### *3. Bias as distortion*

The final type of bias is one the students did not pursue, the one that I’ve characterized as *distortion*. This bias was related to examining the difference between various populations of ORCA users—in particular, between users of the reduced fare program for low-income riders known as ORCA LIFT, and users of the regular fare ORCA card. I’ve placed this type of bias at the intersection of the equity priority and the data reliability priority, which also falls in the “zone of passage” where the students’ and Mark’s priorities come together (Figure 4-2). But this choice of placement on my part requires some explanation, because, while everything else in this diagram reflects the way the team itself discussed and understood their project, the students did not necessarily perceive the overlap in priorities and expectations that I’m suggesting here. This is how Jamie articulated their rationale for dropping the bias question related to ORCA and ORCA LIFT:

It's kind of like an evidence thing. If you actually have a good way to statistically test for it, then the evidence will more than likely show that there are differences between different types of ORCA users. From an analytical point of view, of course they're different. That's why they use different passes. For us, that wasn't particularly interesting. It's like, this is what we already knew and doing that would give us evidence to back it up.

But why they felt this way deserves some further exploration. After several of the team members had made known their concerns for issues of equity, access, and marginalization, Mark assumed that they would be interested in understanding the relationship between low-income and non-low-income ORCA users. Picking up on the students' implicit definition of social good, during one of their early brainstorming sessions, Mark suggested that they might want to pursue analysis of ORCA LIFT data, "since some of you are interested in the social good side," as he put it. This would have been useful to him and his transit stakeholders, as well, because, as he put it before, they need to understand "what the data represent and what they don't represent." So Mark initially perceived this question to be an area of overlap between the students' priorities and his own. Anat Caspi, who will be introduced in relation to the second project I discuss below and who also served as a co-project lead for the ORCA team, likewise thought that analysis of the low-income fare would align with the students' interests in equity, and seemed to push for that line of inquiry.

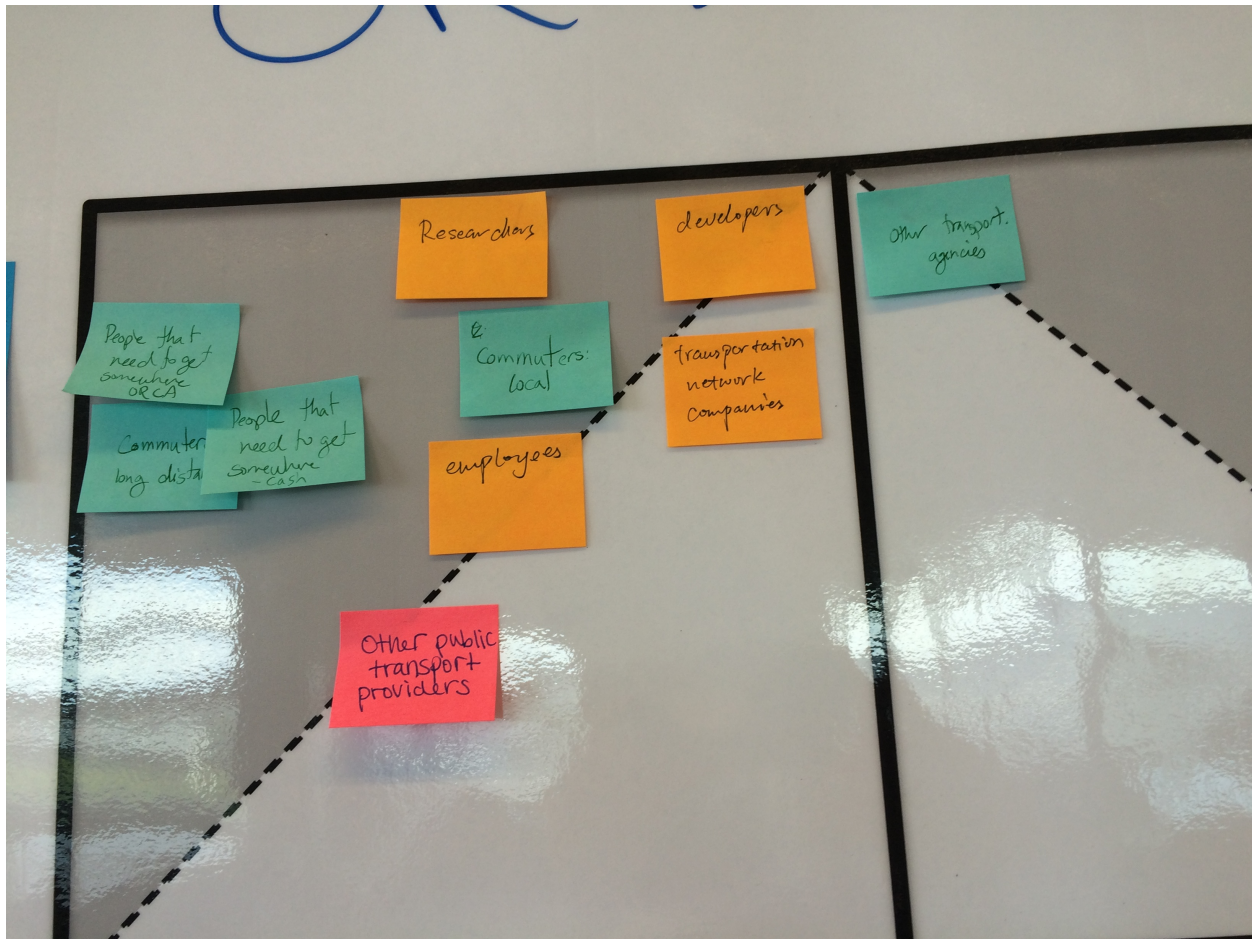
But as it turned out, the first kind of bias the students eliminated from consideration was the distortion bias between reduced-fare ORCA Lift users and regular-fare ORCA users. They dropped this question not because it was too hard, but because it seemed too simple; not because it would take too long, but because they didn't see how this question revealed anything useful, including anything that was related to their concern for equity.

Decision-making always necessarily involves closing certain doors, and aborting futures that may have been. As Iris Marion Young has put it, "each social reality presents its own unrealized possibilities.... it does not have to be this way, it could be otherwise" (Young, 1990, p. 6). Understanding the significance of the decisions made by the ORCA team requires looking

also at the options they did not choose, the possibilities they foreclosed. In the case of the ORCA LIFT data, a counter-narrative was possible.

When the low-income ORCA LIFT program was introduced in 2015, it was only the second program of its kind in the country, and was celebrated as a major victory by Seattle area activist groups such as the Transit Riders Union (Transit Riders Union, n.d.) and the Transportation Choices Coalition (Transportation Choices Coalition, 2015), which had spent years advocating for a low-income fare. Back in the mid-2000's, I had worked with an advocacy organization focused on transportation equity for black communities in Pittsburgh, and my first thought was that similar organizations in Seattle—those that had successfully campaigned for the low-income fare program—would probably be keenly interested in understanding the needs and experiences of reduced-fare ORCA riders. Because of my background working with grassroots transportation activists, I saw an opening for the data to be used, not just in service to the transportation agencies that were Mark's primary stakeholders, but also in service to the civic groups that represent and advocate for low-income riders. The students thought it wasn't worth doing an analysis comparing regular fare and low-income fare activities because it was obvious that they would find statistical differences among different categories of ORCA users. But beyond just acknowledging that a distinction exists at all, one can imagine that a better understanding of when, how, and to what degree those groups diverge could have important implications for particular questions related to transportation equity. Are bus routes that are frequented by low-income fare ORCA users more crowded than bus routes that are frequented by regular-fare ORCA users? Do they tend to run less frequently? Do low-income users have to transfer more or less often than regular-fare users?

Instead of seeing an opportunity to help the advocates of low-income transit riders, the students saw a boring academic exercise. That they didn't recognize any potential in this data set to address the equity issues with which they were concerned does not result from a lack of imagination, but from an absence of knowledge and experience in the specific problem space of transportation equity. In a program that brings together researchers and students from dramatically different disciplinary backgrounds with little to no prior expertise in the subject matter with which they will temporarily concern themselves, most of the DSSG students are quite simply not familiar with the political and historical contours of the social issues to which they have been assigned. The absence of this specific knowledge was apparent in the stakeholder analysis exercise the ORCA team completed at the beginning of the program; the team identified many broad categories of stakeholders like "people that need to get somewhere," "commuters," "employees," and "researchers," but very few specific organizations with questions, expertise, or perspectives that could be brought to bear on their project (Image 4-2). They seemingly weren't familiar with the history of the reduced-fare ORCA LIFT program as a grassroots victory, and they weren't aware of the existence of the advocacy groups that played key roles in that victory; so naturally they couldn't imagine ways for this data to be useful to stakeholders they didn't know existed.



**Image 4-2. ORCA team’s stakeholder analysis.** This partial depiction of the team’s stakeholder analysis illustrates that the students had a general understanding of the categories of stakeholders that would be impacted by their project, but that they didn’t have specific, nuanced knowledge of the problem space they were working in.

I am in no way arguing that the students necessarily *should* have pursued a comparison of regular ORCA users and ORCA LIFT users. Nor am I critiquing them for not having knowledge of the history and complexity of the low-fare program. Rather, I am trying to point out how their view of what was even possible with the data was constrained by their own experience or inexperience with the issue at hand. Such inexperience should not be understood as a shortcoming of the students themselves, but as a structural characteristic of a program in which diversity of disciplinary and subject matter expertise is consciously and purposely selected for. And in fact, the choices made in the structuring of the DSSG program are—as I discuss at length in Chapter 5—rooted in a culture of disciplinary agnosticism that is a hallmark of data science

practice, a belief that the tools and techniques of data science are applicable and transferable across domains and problem spaces. My point here is to show how such an organizational structure can limit the depth of engagement on particular social issues, and constrain the way ethical concerns can be employed as boundary objects in the process of translating across divergent expectations and priorities. Bias served as a boundary object for translating across the ethical perspectives and priorities of the team members—but only a mediocre one that left some of the students feeling less than certain of about the value of their work. I am arguing that a deeper engagement with the problem space could have opened up additional options and more satisfying compromises. So while there may be promise in a “data science as ethical convention” approach that employs issues like bias as boundary objects to bridge concerns for equity and concerns for methodological reliability, the experience of the ORCA team indicates that this process of translation may yield richer results if informed by a more contextualized understanding of the specific issues at hand. In the conclusion of this chapter, I suggest a way forward for integrating the development of such contextualized understanding into practice in data science of the social.

*Incubating: Creating protected spaces for ethical thinking and decision-making*

As I discuss at length in Chapter 6, in the DSSG program, the ORCA project was sheltered to some extent from pressures that typically accompany academic, governmental, or commercial research. There was no expectation that the students should be able to publish final, unassailable analytical results or produce a polished, durable technological artifact by the end of the summer. Rather, their main task was to produce a patchwork proof-of-concept that would be iterated upon in the future. In Chapter 6, I characterize such an arrangement as an “exostructure,” and discuss how these experimental, low-stakes arrangements allow infrastructural elements to

jump contexts and establish a platform upon which more stable knowledge infrastructures and data infrastructures can grow. The ORCA project demonstrates that the DSSG program can provide this space, but it means relaxing expectations for an “implementable solution” in 10-weeks time.

Here, however, I suggest that this type of protected environment can also allow for the incubation of ethical thinking and decision-making. In the ORCA project, it was crucial that the team had the freedom and flexibility to engage in a series of time-consuming, unwieldy conversations in which they struggled to define what they meant by bias and identify a path forward for addressing this issue in their work. In part because of such wide-ranging conversations, it wasn't until the team was three weeks into a 10 week long program that they came to a shared understanding of bias and formed a coherent narrative about the ethical mandate of their work that they would stick with for the rest of the summer. Although participants in these conversations at times seemed frustrated with the redundant backtracks, far-flung tangents, and abundant ambiguity that characterized them, the team also seemed to recognize the importance of the intellectual labor that went into each episode of collective sense-making. As the team put it in a blog post about their work:

After much deliberation, we also agreed on a project charter and a timeline for the rest of the summer. We found this process generative, as our discussions around project ethics, goals, and deliverables directly informed the technical details and workflow we ended up with. In particular, our vision of transit equity and social good led us to the major collaborative component of our project this summer, where we will develop different bias estimates for ORCA datasets.

In the end, the team ran out of time to actually resolve the bias issue, but given the way the work was envisioned and configured, this wasn't a serious problem. After seven years of sitting on the data, the transit agency stakeholders weren't in a rush to get results, and Mark was

content to provide them with incremental updates showing the potential of the data without claiming perfection or certitude—just enough to justify continued interest and investment. For their part, none of the students that first year were working in their primary area of focus or expertise, and so they didn't feel an enormous amount of pressure to come up with publishable results. In other words, by developing the ORCA project outside the contexts in which the data is normally used, and by engaging with researchers outside the contexts in which they usually work, the DSSG managed to create a protected space away from intense pressures to produce, and this enabled a lengthy and iterative process of ethical sense-making to unfold.

This may seem counterproductive in some lights. In some cases, a pedagogical approach in which divergences from expectations are viewed as lessons rather than failures can interfere with the need for implementable results (Tanweer & Fiore-Gartland, 2017). But this is not the best way to characterize the ORCA project, even though, as we have seen, the students were not under pressure to come up with an implementable solution over the course of the summer. In the case of the ORCA project, the DSSG is a modular component of a much longer-term institutional collaboration, ensuring that there will be an opportunity for the students' work to be continued and further developed in the future. It is this robust and ongoing relationship that allows the temporary, modular configuration of the DSSG program to offer the protective space I've characterized, in which the team is relatively free from productivity constraints, yet integrated into an iterative approach.

Creating a separate, protected space for incubating ethical thinking may also seem, at first blush, to be contrary to the view that the process of ethical thinking should not be extricated and shunted off from the process of doing data science. Many would argue that rather than being relegated to special classes or distinct steps in the process of project planning, ethics should be

seen as an integral part of data science, something that is continually evaluated and recalibrated throughout the work. But with the ORCA project, it is not the case that the act of ethical thinking was separated from the work of doing data science. Rather, the work of doing data science was insulated from the pressures of publication and implementation for a period of time that allowed ethical thinking to flourish and become more deeply integrated into the work. Creating a flexible, low-stakes environment and taking incremental and iterative steps toward exploiting a new data source can go a long way in terms of ethical thinking. The culture of data science originated in the private sector among technology companies in Silicon Valley, where the mantra of “fail fast” holds sway. Experimentation and the pursuit of novel data sets and methods lies at the heart of data science practice, and failure is an inevitable outcome some of the time. But the experience of the ORCA team tells us that data science as ethical convention might require an amendment to the embrace of failure: “fail slow, fail small, and fail safe.”

*Incentivizing: Making ethical thinking and ethical progress “count” as contributions*

Another implication of the ORCA story specifically and the data science as ethical convention approach more broadly, is that it is important to recognize and reward the results of ethical thinking on their own merit as valuable contributions to the data science endeavor. After the ORCA team had wrapped up a marathon discussion in which they tried to tease out the different kinds of bias that lurked in their data, Jordan joked about the hand-drawn whiteboard diagram they produced being the only contribution they would be able to include on their CV's. Jordan was either being pessimistic about what the team would be able to accomplish over the summer, or hyperbolic about the importance of their lengthy discussion, but what if such sense-making actually was regarded as a first-class contribution to data science? What if a thorough explication of ethical issues and concerns in data science projects were recognized as a

finding, output, or product? In data science more generally, analytic findings and finished software products are not the only contributions that gain recognition from peers. A novel data set, a replicable method, a useful software library, an intuitive visualization technique—increasingly, all of these things may garner recognition, appreciation, and citation in the field. Given the pressing and widely recognized need to address the ethical issues of big data and data science, so too could systematic ways of identifying, describing, and addressing ethical challenges in the work be considered valuable contributions to the field.

Indeed, there is currently a growing research community oriented around fostering work that explicitly promotes a set of ethical values, with particular emphasis placed on the potential for data intensive analysis and applications to magnify social biases and perpetuate unjust social dynamics. In the Netherlands, the Responsible Data Science Project advocates for foundational research on the issues of fairness, accuracy, confidentiality, and transparency (FACT) in data-intensive computational work, hosting a series of workshops and seminars on those topics. In the U.S., the conference on Fairness, Accountability and Transparency in Machine Learning (FAT ML) has gained traction since its inaugural meeting in 2014, recently dropping the “machine learning” qualifier and replacing it with a wildcard asterisk (FAT\*) in order to be more inclusive of computational techniques beyond machine learning. The FAT\* gathering features research on computational techniques that advance the eponymous values of the conference, as well as tutorials on how to apply such techniques. The development of approaches that promote fairness, accountability, transparency, and interpretability is a growing area of specialization in industry as well, as evidenced by Microsoft’s launching of their Fairness, Accountability, Transparency, and Ethics in AI (FATE) group, the Ethics and Society wing of Google subsidiary DeepMind, and other research units like them. Given this momentum, one can expect in a few years that

specialized journals and graduate certificate in these areas of ethical concern will begin to crop up, meaning that the work of figuring out how to practice data science as ethical convention may already be well on its way to being considered a primary intellectual contribution.

## THE AMOS PROJECT

### **Decision story: The AMOS team addresses the social construction of disability**

It's the very first day of eScience's inaugural Data Science for Social Good program in 2015, and Nick Bolten is standing in front of the program participants to introduce the OpenSidewalks project. Nick is a young man with pale skin, tousled dirty-blond hair, rectangular glasses, and a dimpled grin. He speaks softly and parsimoniously. A graduate student in electrical engineering, Nick's own dissertation work focuses on automating repetitive experimental protocols in biology labs. The project he's here to work on this summer, though, is his passion project.

Nick opens the presentation by sharing a story about a man named Scott. Scott uses a wheelchair, and one day as he was traveling through downtown Seattle, he came across a section of the sidewalk that was closed due to construction of a new building—a common occurrence in the fastest growing city in the U.S. (Balk, 2018). A construction worker pointed Scott to a temporary pedestrian bridge that would get him safely across the construction zone, and he set out on this detour. But as he approached the bridge, Scott's wheels got stuck in the soft tarmac of the ramp that had recently been laid, and someone had to come help him get unstuck.

Had Scott known that he would encounter a construction zone with a closed sidewalk that morning, he could have planned a different route and avoided the whole fiasco. But unfortunately, there just aren't good informational tools for planning your commute if you have a disability, Nick tells the group. People have figured out how to use certain tricks, like searching

for bicycle routes in Google Maps to find paths that minimize elevation gain since hills are difficult or dangerous to navigate in a wheelchair. But these are just hacks—patchwork improvisations that take a lot of time and energy, and leave large gaps in information. This is why, at a recent event sponsored by the City of Seattle called “Hack the Commute,” Nick and his teammates came up with the idea of AccessMap, a routing application that is similar to tools like Google Maps or Waze, but optimizes for specific needs of people with limited mobility. This means in recommending routes, the app would take into consideration features of the built environment such as steepness, sidewalk closures, crossing signals, and curb ramps.

“Hack the Commute” was a hackathon-style event (Johnson & Robinson, 2014; Trainer, Kalyanasundaram, Chaihirunkarn, & Herbsleb, 2016), an intensive three-day long competition in which teams of volunteer programmers were challenged to develop a tool that would “help Seattle commuters adapt to the City’s fast growth and constant construction” (“Hack the Commute Seattle,” 2015). The team that came up with the winning idea would be awarded prizes to support the continuation of their work: cloud computing resources from Microsoft Azure, Kindles from Amazon, space at a local co-working studio, and educational credits from the tech-focused career training company General Assembly. Experts in various transportation-related issues would be on hand to mentor the participants by reality-checking their ideas and pointing them to helpful resources. Anat Caspi, a professor in the School of Computer Science and Engineering at the University of Washington and Director of the Taskar Center for Accessible Technology, was there in this capacity, to mentor participants who were interested in issues of accessibility. This turned out to be Nick Bolten and his other teammates, Veronika Sipeeva, Allie DeFord, and Reagan Middlebrook.

After this team, which adopted the name “Team Hackaccessibility,” won the hackathon competition with their prototype for AccessMap (Adolph, 2015), Nick and his colleagues paired up with Anat and the Taskar Center to continue working on the project. They heard about the upcoming DSSG program run by the eScience Institute, and thought it would be a great opportunity to keep the momentum going by having a group of students to do some focused, intensive work on the project.

Now, just a couple months after their big win at Hack the Commute, Nick is giving the DSSG students their first glimpse of the project they would be working on that summer. For the DSSG, Nick and Anat have jointly taken on the role of “project lead,” and have scoped a subset of the AccessMap project that they think a team of four students should be able to tackle in the span of 10 weeks. The DSSG students will be working on creating a connected graph of all the sidewalk segments in Seattle, which will allow AccessMap’s routing algorithm to generate turn-by-turn directions. They have access to an open data set of all the sidewalk segments in the city from the Seattle Department of Transportation, but the individual sidewalk segments don’t line up perfectly when their coordinates are mapped, leaving thousands of little gaps and overlaps that are impossible for a routing algorithm to traverse. So the DSSG students will have to fix this by making all sidewalk segments properly aligned. This is the main technical challenge they face, and if they solve it, they will also be able to conduct analyses of the data. Since the DSSG students will not be working on developing the AccessMap application itself, but rather focusing on the underlying data that feeds the map, Nick and Anat have decided to call this complementary effort the “OpenSidewalks” project. In future mentions, I use the name AccessMap when referring specifically to the routing application, and OpenSidewalks when referring to the specific objectives of two years of consecutive DSSG teams. And in

acknowledgement of the intertwined objectives of these two strands of work and their interdependence on one another, I'll use the acronym AMOS (for AccessMap/OpenSidewalks) when referring to the overall project and overlapping team membership, regardless of the differentiation in tasks that sometimes characterizes their work.

### *Ethical issues in the AMOS project*

As already mentioned, the AMOS project was by no means contained to the 10 weeks of the DSSG program in 2015. The project got its start several months prior, and it lived on well beyond the program. Nick and Anat led a second team of DSSG students in 2016, whose work we'll hear more about in the following pages. At the time of writing in early 2018, the project is still deep in development with Anat and Nick at the helm, leading a crew of undergraduate and graduate students who rotate in and out of the AMOS team, some of them earning academic research credit for their contributions to various aspects of the work. The project has entailed numerous kinds of specialized labor: different team members have been alternately focused on defining data schema, writing algorithms to automatically clean data, developing apps and interfaces for manually collecting and editing data, communicating with stakeholder groups, and organizing outreach events.

Obviously, the project has a lot of moving parts and my treatment of it here will only cover a sliver of that work, glossing over much of the project's complexity. The team encountered and grappled with ethical questions at every step of the process (Tanweer et al., 2017). But in this chapter, I will highlight the ethical concerns that served as prime motivations for the work. The team's overarching goal was to empower a marginalized community, and prompt people to question the status quo of how they interact with the built environment. Their vision is first and foremost to create a world that is more just and accessible for all. In other

words, ethical concerns are the very *raison d'être* of the project, and it is this more existential ethical orientation that I take up here. As we will see, their work is premised on strong convictions about what counts as social good, and how technology is implicated in producing marginalization and empowerment—positions that I have characterized in the preceding chapter as indicative of the “data science as ethical innovation” approach. The team’s convictions would become very clear following Nick’s presentation on that first day of the DSSG program.

### *The social model of disability*

As Nick wraps up his introductory talk presenting the need for AccessMap and OpenSidewalks data, he opens the floor to questions from the audience. Samuel (a pseudonym), one of the data science mentors from the eScience Institute, raises his hand and says he has a “50 thousand foot question.” You know the sad story of the iBOT, he begins. “It flopped, but why isn’t *that* the solution?”

Samuel is referring to a powered wheelchair invented in the 1990’s by Dean Kamen, who also gave the world the Segway, a motorized personal transportation device (Golson, 2015). The iBOT was a four-wheel-drive wheelchair that could “climb up and down stairs and curbs, roll across varied terrain, raise a seated user to eye-level-standing height by rising up and balancing on two wheels, and travel in this mode — all while relying on sophisticated sensors and gyroscopes to maintain the chair’s balance” (Vogel, 2016). The device came on the market in 2003 with a price tag of \$24,000 that insurance companies balked at, and was discontinued in 2009 due to slow sales.<sup>1</sup> In framing his query as a “50 thousand foot question,” Samuel is signaling that the issue he raises may be orthogonal to the project team’s immediate work, but is more broadly fundamental to the way we approach disability in general: should we be focused on

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<sup>1</sup> At the time of writing, the iBOT was soon to be reintroduced to the market, sold by Toyota at a lower cost than the original version. See Vogel, 2016.

building a world that is accessible to the disabled, or on equipping people with disabilities to access the world as it is? Anat briefly responds to Samuel's question by highlighting Medicaid's role in influencing the development of accessibility technologies in the US, and how that played a part in the iBOT's demise. Then she quickly redirects the conversation back toward the informational questions their team is focused on.

But a bit later, when the group has broken up into their assigned teams so that the students can learn more about their projects and get acquainted with their project leads and data science mentors, Anat circles back around to the issue Samuel raised. First, she clarifies what that exchange was about in case it went over some of the students' heads, letting them know what the iBOT was. She explains that essentially Samuel was asking if it wouldn't be more efficient and cost-effective to invest in wheelchairs that can go up stairs than to redesign the built environment to accommodate disabilities? Then she takes the opportunity to share her perspective on disability with the students. In the US, we tend to treat disability as a medical problem, she says. But we can also think of disability as a situationally determined social construct, something that happens because the world is designed only with certain abilities in mind, not with the abilities of all.

Anat was essentially introducing the students to what is known as "the social model of disability." According to this perspective, first articulated by Michael Oliver in *The Politics of Disablement* (1990), disablement is not an inherent quality of individuals, but rather arises from a built environment that is not designed for diverse needs. This means that if the built environment were universally designed to accommodate an exhaustive range of needs, people of different abilities would be *able* to access and navigate the world with greater ease (Story, Mueller, & Mace, 1998). For example, if a door opens with a straight lever handle rather

than a round knob, people who can't grip well due to arthritis or some other physical limitation can still open the door on their own (Cash & McCall, 2014). They would not be *rendered* disabled in that situation.

The question Samuel raised about high tech wheelchairs, and the response it evoked from Anat, reveals the perspective of AMOS leadership regarding the relationship between technology and society and the role of technological innovation in bringing about empowerment. Cultural assumptions lead us to see limitations in ability as deviations from normal, and categorize them as medical problems to be fixed rather than inherent differences to be embraced and accommodated. These assumptions inform our design of the built environment for “normal” abilities, which gives rise to the embodied experience of inaccessibility.

Because, from this perspective, technological design reinforces a stigmatized view of difference, the design of technologies become a logical and meaningful point of intervention. Our informational systems are “built” just as the doors, buildings, and roads that we normally associate with the “built environment” are. If Scott, the gentleman whose story Nick told earlier, had known to avoid the construction zone, he wouldn't have gotten stuck in the soft tarmac. Similarly to the doorknob example, if the informational built environment were designed to accommodate his needs, Scott could have found an alternative so that he didn't find himself in a situation that rendered him disabled.

But the AMOS team's position is that technological innovations can't be solutions without acknowledging the deeply social nature of the problem at hand. Anat is unquestionably an accomplished technologist; her entire corpus of work is focused on developing technologies that can improve accessibility. Yet she takes issue both with the attitude that technology can provide a quick fix to disability, and efforts to address disability without acknowledging its

deeply social roots. In other words, she is skeptical of what Evgeny Morozov (2013) has called “technological solutionism.” Her gentle rebuke to Samuel’s question was not leveled at him or the iBOT itself, but at the existence of a narrative that we should just give all people with disabilities fancy wheelchairs that “fix” their problems instead of addressing the cultural assumptions, political incentives, and sociotechnical systems that have created those problems.

It is true that the AMOS teams wants to build a tool specifically for people with limited mobility. But as we will see, they do this while simultaneously addressing the broader culturally-derived assumptions that lead to limited informational resources for people with disabilities. The informational built environment had been designed with a “normal” mode of travel in mind—one that privileges travel by automobile and optimizes by default for the quickest way to get from Point A to Point B. To build a tool that could help people with disability, they first had to challenge those assumptions, and redesign the informational built environment for a different set of priorities.

### *Optimizing for delight*

In their second year of participating in the DSSG program, this goal was particularly pronounced. After developing a process and toolkit for automatically cleaning municipal sidewalk data the summer before, the team decides to adopt a base layer map that would allow them to replicate AccessMap in cities across the U.S. and the world (this ambition is addressed at length in Chapter 6). As such, they decide that the open source OpenStreetMap platform would be a great choice, as it had global coverage of geospatial mapping data. But the problem with this plan was that the de facto data standards for adding sidewalks and other pedestrian features to OSM is not ideal, in ways that will soon be explicated. So their task for this summer is to develop a new data schema for sidewalks that the OSM community would embrace.

In preparation for their second summer participating in the DSSG program, Anat and Nick hold several meetings with data scientists at eScience to make sure they are all on the same page before the summer begins. On a sunny day in late spring, a data scientist assigned to the project, Carlton (a pseudonym), arrives to one such meeting carrying a single wheel electric skateboard at his side that he leans against the wall before taking his place at a small round table. “I’ve been paying a lot more attention to Seattle’s sidewalks since I started using that thing,” he says, gesturing to the device behind him. It consists of a platform about the size of a regular skateboard affixed to the axle of a single fat tire that takes up the width of the board and juts out below and above it, so that the rider straddles this central wheel with one foot on either end of the platform while it is in motion.

Anat seizes on Carlton’s comment as identifying yet another population that could potentially benefit from their project. Although AccessMap itself is designed specifically with mobility-impaired individuals in mind, information about the condition of sidewalks is relevant to a lot of pedestrians, such as people pushing shopping carts and baby strollers, people dragging wheeled suitcases, and people like Carlton who are taking advantage of the expanding options in electric-enhanced pedestrian mobility. And their vision for OpenSidewalks is even broader than this: to make sidewalks a central concern in an otherwise car-centric society; to get people to think about the city as pedestrians, and therefore change the way they imagine and plan for mobility. Google maps only optimizes for time and distance, says Anat, but if you facilitated the creation and sharing of data that is relevant to pedestrians, what else would they care about? On hot days, might they want to know what route offers the most shade or has a water fountain along the way? In the spring time, might they want to know which neighborhoods are full of blossoming fruit trees?

“In other words,” says Carlton, “how do you optimize for delight?”

*Focusing on more than disability*

Compared to the social justice issue of people with disabilities being cut off from access to the same sorts of resources and opportunities that able-bodied individuals enjoy, optimizing for delight may seem frivolous at first blush. But the AMOS leadership sees that mentality as part and parcel of the social transformation needed to ensure that the informational built environment is universally designed for diverse abilities, persuasions, and activities. To support the informational needs of people with limited mobility when navigating cities, sidewalks first need to be documented and treated as data of the first class. Which means that people need to care about sidewalks enough to record data about them; they have to think about sidewalks as something important and valuable.

And so, during the second year that the AMOS team is participating in the DSSG program, they shift their framing to emphasize the value of OpenSidewalks for more generalized purposes and multiple populations rather than focusing narrowly on the case of people with mobility impairments—even while openly discussing AccessMap as the “motivation” for their work. Reflecting this broadened scope, as well as their goal of enabling the collection of sidewalk data anywhere in the world, they amend the team name with a new qualifier, becoming the “Global OpenSidewalks” team.

In the second year of the DSSG program, as Nick introduces the project to a brand new cohort of DSSG students, he emphasizes the boundless possibilities enabled by their work:

Our project is not going to be exclusive to disability, whatsoever. This is just an example of what you can do when the information is available....I have talked a lot about accessibility because that's my bias, but there's all kinds of things you could potentially do if you had this kind of information. You could make a way better walk score, for example, for given cities. You can make a whole company just based on sidewalk data if

you wanted to. You could talk about connectivity if you had this huge graph of sidewalks.

Nick, Project lead, AMOS Team

So the AMOS team needs to come up with a schema that will allow them to build a tool specifically for people with disabilities, but they also need to make sure that it will be useful for other purposes as well. They are fully cognizant of how choices in the representation of data are value laden and consequential, enabling some uses while inhibiting others. For example, in one conversation, the team discusses how they will account for “street furniture” like benches in a cost function for AccessMap routing. If it narrows the sidewalk, perhaps it should be labeled as an obstruction to someone in wheelchair, they pondered; but to someone walking with a cane who needs a brief rest, perhaps it is an important amenity. Such trade-offs in representing data were an ongoing theme for the group throughout the summer, becoming one of their primary concerns.

In the final presentation of their work, the team lets the audience know that over the summer, one of their main tasks had been developing a strategy to better capture sidewalk data in OSM. A student on the team named Eric (a pseudonym) sums up their approach perfunctorily. “How do we do that?” he asks. “We draw sidewalks as lines, we draw crossings as lines, and we draw curb cuts as points.” The simplicity of his statement belies all the painstaking work and careful deliberation that went into crafting that recommendation, which I detail below.

#### *Sidewalks as lines: Considering the needs of the OSM*

The team knew one of their objectives would be to develop a schema for pedestrian data in OSM that could become the “functional standard” on a platform that doesn’t actively enforce any true standards, but promotes agreed-upon best practices. In addition to considering how AccessMap users would interact with the data, the AMOS team also must carefully consider how

these proposed changes would affect the OSM community. Like with most mapping technologies, the norms in OSM have been developed primarily with automobile travel in mind, not pedestrian travel, and so in most cases, sidewalks are documented only as attributes of streets—essentially, as metadata rather than data in their own right, a tag on a road indicating if a sidewalk existed on its left or right side. This makes OSM sub-optimal for pedestrian purposes for several reasons. First, sidewalks most typically are not visually represented on the map as their own shape; this makes it hard for map contributors to physically see whether a sidewalk was accounted for or not, and the AMOS team guesses that this is one of the reasons many places on the map lack sidewalk data at all. Second, sidewalk tags inherit the location information of the street they are assigned to, and so they can't be mapped with precision, causing problems when a sidewalk doesn't follow a direct path adjacent to the street. Third, it is difficult to attach further relevant information to the sidewalk tag because map contributors have to wade through several layers of documentation in a cumbersome user interface in order to provide that information—a concern for a platform that relies on user-generated contributions.

So for their own purposes, and for the sake of any future pedestrian-centric mapping applications, the team sees the need for sidewalks to be included not as attributes of streets, but as first-class features of the map that are prominently visualized, precisely located, and intuitively annotated with information relevant to pedestrian travel.

But how should sidewalk segments actually be represented on the map? They could document sidewalks as lines or polygons, for example, but these would afford different functionalities. Polygons would allow for mapping the precise dimensions of sidewalks and would be helpful in documenting any characteristics of the sidewalk related to surface, such as pavement texture. If they went with lines instead of polygons, they would lose the dimensionality

and surface precision, but would gain the ability to do routing. Since routing was the team's primary objective, this was a fairly straightforward choice on their end. Lines it should be.

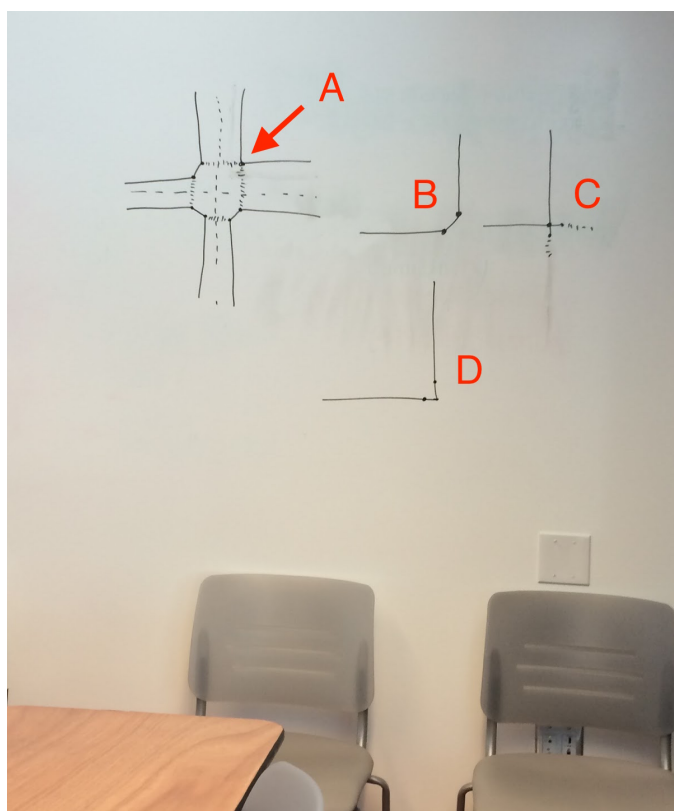
But they also have to consider how this will affect the OSM community, and whether or not they will be receptive to the proposed change. Carlton, the eScience data scientist assigned to be a mentor on the project, has extensive experience with OSM, and is able to help the team think through reasons the community might have concerns about their proposal. It would take more server space to add sidewalks to the map as lines rather than a metadata tag, and that might be an important consideration, he warns them. "I don't think anyone is going to stand up and say, 'screw people with disabilities,'" he reasons. "They're going to do a cost-benefit analysis. Should we triple the size of the database and go through all this work to benefit a small fraction of users?"

#### *Curb ramps as points: Considering needs of AccessMap users*

The AMOS team also debates the merits of different ways to visually represent curb ramps in OSM. From what they could tell, the most common way to document curb ramps is adding an annotation to a node at the intersection of two streets or to a node at the center of a crosswalk that would indicate whether or not curb ramps are present at each corner. Just like sidewalks, there is no visual cue on the map to let an OSM user know whether or not curb ramps have already been documented at any given intersection, and it requires wading through a couple layers of information to add curb ramp tag. As the team likes to say when pitching their proposal, "all this information is hidden away inside a tiny little dot."

The team would advocate for curb ramps to be visually represented in OSM, but gain, they have to decide what shape to assign them. One option is to draw ramps as polygons, which would offer the most fidelity to reality, and possibly give people with limited mobility some

important information. For example some ramps wrap around an entire corner, while others point into the intersection at a 90-degree angle, and seeing that level of detail might be valuable to certain people with limited mobility. Ultimately, though, the team ends up deciding that curb ramps shouldn't be polygons but rather nodes, which look like little points or dots. They make that decision mostly for the sake of convenience; even though polygons might provide more information, they would require a lot of precision when mapping, which would likely be a barrier to getting people to add curb ramps to the map at all. In contrast, Nick points out, a node is the easiest thing to add to OSM, making this solution simple and intuitive for map contributors. So the team suggests that instead of documenting curb ramps as attributes of other nodes or as polygons, they would be assigned their own nodes. Even still, there were several different ways this could be done, and they had to decide which one they would advocate for.

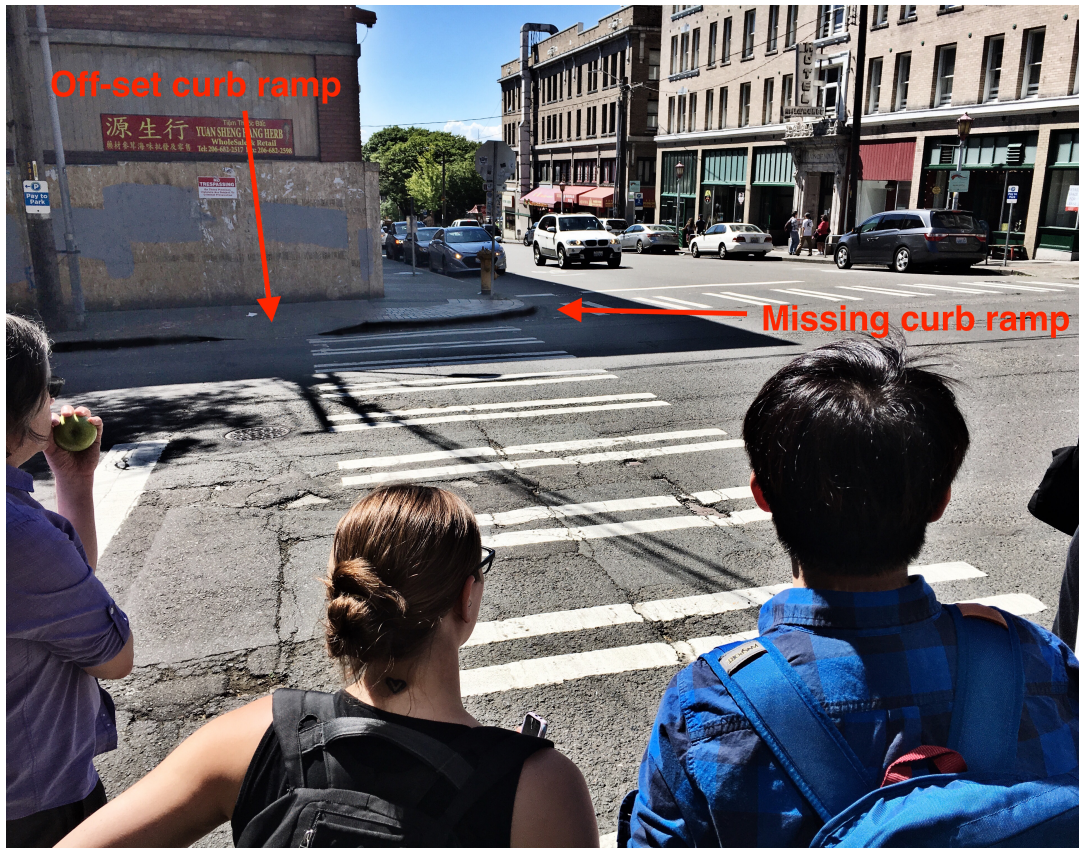


**Image 4-3.** The AMOS team's possible representations of curb ramps.

During a meeting toward the beginning of the program, the AMOS team gathers around a whiteboard to draw diagrams of several different possibilities as they talk, weighing the affordances, pros and cons of each (Figure 4-3). The first option they discuss (Figure 4-3, A) simply places a node at the junction of two sidewalk segments to indicate the presence of a curb ramp there. The data set of sidewalks created by the previous year's DSSG team already consists of sidewalk segments that have been cleaned up and joined computationally, so it would be trivial to add a node at sidewalk junctures where a ramp was present. But, someone asks, what if there are two ramps on the same corner, and they have different characteristics from each other? For example, what if one curb has a tactile surface to assist with vision-impaired navigation, while the other does not, or if one ramp has a higher lip than another? To capture this information, it would be important to add each ramp as a separate node, and they play around with several different options to do that (Figure 4-3, B, C, D). In Option B (Figure 4-3, B), each ramp is represented individually as a node on a sidewalk segment, and a line is drawn between them for the routing algorithm to traverse the corner. In Option C (Image 4-3, C), each ramp is represented as its own line segment that starts where two sidewalks meet, and extends out to meet the crosswalk. And in Option D (Image 4-3, D), two sidewalk segments meet at 90 degree angles, and nodes are placed anywhere along them to indicate the location of a curb ramp. They weigh the costs and benefits of these options. Option B would require writing an algorithm that truncates sidewalk segments and connects ramps to retain a connected sidewalk graph, which seems computationally complicated and doesn't really have any benefits they can think of. Option C, on the other hand, has similar issues to the polygon option, as it places a burden on map contributors to accurately document each ramp as a separate segment. Option D seems to be the most straightforward and efficient solution; it wouldn't require altering the sidewalk

segments from their cleaned municipal data set, and it wouldn't be cumbersome for manual map contributors either. So if they're going to represent each ramp as a separate node, this seems to make the most sense.

A few days later, the issue of curb ramp representation comes up while the AMOS team is on a field trip to learn about how a local public transportation agency goes about determining which routes are accessible to their disabled customers. The team is walking through a neighborhood near downtown Seattle with a couple of the contractors who do accessibility evaluations on behalf of the transit agency. They are explaining to the DSSG team what kind of features they look for in the built environment, how they measure obstacles, and how they document their data. In Image 4-4, the group has paused to discuss whether a particular intersection is accessible or not. Across the street from where they stand, in the shadow of an abandoned building, is a corner with irregular curb cuts. The side of the street facing the group has a curb ramp, but it is offset some distance from the marked crosswalk on the street. The perpendicular side of the block has no curb cut leading into the crosswalk at all. Nick says that among the wheelchair users they've recently interviewed, he's noticed that there are different levels of "adventurousness." One set would be okay with this situation—as long as there is a curb cut somewhere along the block so they can get off the sidewalk without toppling over, they don't mind traveling in the street for short distances. Other people need the curb ramps to be "optimally placed on crosswalks" so they don't end up traveling in the street among traffic where motorists might not see them.



**Image 4-4. The AMOS team contemplates irregular curb ramps.**

The team realizes that for some people, it would be useful to see precisely where the curb ramps are located because, in a case like this, they might not be comfortable with how far the curb ramp is from the crosswalks—especially the further crosswalk that doesn't have its own ramp. This is another reason that it makes sense to document each curb ramp as its own node—so that it can be accurately positioned to give people with limited mobility a sense of how far the ramp is from the crosswalk and determine for themselves whether or not they're comfortable with the situation. This reinforces their thinking that each curb ramp should be represented as a separate node that can be placed as anywhere on the sidewalk segment to allow for more accurate representation of curb ramp locations.

### *Selling the proposal*

The team also seeks advice from local leaders of the OSM community. Over time, they develop a close relationship with a man I'll call Roger, who is particularly active in organizing mapping meetups and participating in online discussion forums, which is where the team first encountered him. On a July day in 2016, they are meeting Roger face-to-face for the first time. They have invited him to the Data Science Studio on the University of Washington campus to discuss their proposal to OSM so they can get feedback on its feasibility, as well as advice on how to best frame their request to the community. The annual conference for US-based OSM mappers, called State of the Map United States (SOTMUS), is going to be held in Seattle in just a couple weeks, and the AMOS team is slated to present their proposal on the main stage. So they're doing a run-through of that presentation for Roger.

Eric starts the presentation off, providing the motivation for the work and the nuts and bolts of the proposal. "We can all agree that digital maps have been transformative," he begins, "but we want to challenge the notion that it's a solved problem." He then goes on to discuss how people with limited mobility are not adequately served by current mapping technologies, and offers a quote from a wheelchair user they've interviewed, who expresses frustration with Google maps for directing him up streets that are too steep to navigate. Eric then appeals to the values that OSM stands for, as a community founded on inclusive engagement and openness. In doing so, he sets up their proposal, not as something completely new and different, but as a corrective that is more in line with OSM's own values than the current way of handling sidewalk data.

At one point, Roger interrupts the presentation to point out a small, but significant problem with the slides. They've written OSM's full name as "Open Street Maps" and Roger lets

them know that it's actually just one word in camel case, and that it's not plural:

“OpenStreetMap.” There's a reason it's written that way, he says, to represent one community with many capitals. He warns, only half jokingly, that if they make that mistake at SOTMUS, everyone will just focus on the *faux pas* and dismiss their argument.

Eric thanks him for bringing this to their attention and moves on to introduce the first part of the specific recommendations they're making: to change the way the pedestrian network is represented in the map by documenting sidewalks as lines, curb ramps as points, and crosswalks as lines.

Then he hands the floor over to his teammate, Mary (a pseudonym), who will present the second part of their proposal, the plan to do a mass import of municipal sidewalk data. She begins by recounting all the AMOS team has done thus far to understand and engage with the OSM community, from attending local meetups to corresponding internationally with mappers on listservs and discussion forums. They see municipal data sets as presenting a great opportunity to put sidewalks on the map, but from their engagement with OSM, they've come to realize that the community has reservations about doing bulk imports. At this point, Roger interrupts again, this time to clarify, “they're a concern for a *segment* of the community.” Mary responds that they want to keep that segment in mind as they proceed. They understand that for people to feel comfortable with the mass import they're proposing, there needs to be a layer of human curation and verification added to the process. So what they're proposing is to import data from municipalities, but crowdsource verification of that data to make sure it's accurate. In a subsequent chapter on infrastructure, I take up the issue of the mass import and how the team approached this aspect of the proposal. But here, I continue to focus on the proposed data

schema, and how the team negotiated the different meanings, values, and priorities that are reflected in choices about data representation.

It's clear that Roger himself likes their proposal, especially because it's so "intuitive." He recounts a time that he set out to map the curb ramps in his own community, which was accomplished by annotating the intersections of roads to indicate if and where ramps were present. It was a trivial task for him because he's an expert user, but he could see that the cumbersome process would be confusing for someone who is new to OSM, without having a visual indication of whether or not a curb ramp was present. Their proposal to represent curb ramps as points on a sidewalk would provide a much more straightforward way to document ramps. Treating sidewalks as lines instead of attributes of roads is also intuitive, he says. But one issue people are likely to raise is the impact on routing, which has always been the primary concern of the community. If sidewalks are no longer attached to roads, how will you provide turn-by-turn directions along named streets? "You can route them," he says, "but how do you give them a piece of paper that says turn left here, turn right here?"

Anat and Nick argue that this issue doesn't need to be solved within OSM, which isn't itself a routing application. OSM is just a base layer that developers use to build third party applications, so turn-by-turn directions are really an interface issue that can easily be addressed by programmatically inferring the street name based on proximity and directionality. Now that they know this is likely to be a concern, though, they'll preempt it by addressing turn-by-turn directions in their proposal.

After Roger has finished giving the AMOS team feedback on the content and style of their presentation, Eric directs the conversation toward political strategy. Who do we tell this story to, he asks? Who are the influential people? Roger suggests a couple different topical

mailing lists they could engage with; but the team has already been doing this, and it's not the kind of intel Eric is after. He wants to figure out which buttons to push in order to get their proposal accepted. Does OSM as an organization ever puts its weight behind a proposal, he asks? Roger shakes his head emphatically. Do we need to engage the board, presses Eric? Roger is now even more insistent with his response. "It's not the board," he says. "Understand that. The board has no influence. It's just the users."

Roger is trying to impress upon Eric the non-hierarchical, deliberative, distributed nature of OSM as an open source community. There aren't even truly "standards" for adding features to the map, just norms that become "functional standards" if enough people adopt an approach. In other words, there is no shortcut to making things happen in OSM, and no power levers to push. But a little while later, when the team asks why some proposals have failed in the past, Roger says proposals fail to be adopted when they're not supported by developers, those who build software applications based on OSM data. This indicates that while "it's just the users" who control the community, some users do wield more influence than others.

The team takes Roger's advice when they present at the State of the Map conference a week later, including seeking out certain developers who are likely to be sympathetic to their proposals. Generally, their ideas are well received, and they are approached by mappers from other parts of the US who are interested in working with them to get sidewalks in their own cities on the map. Since there is no such thing as a true standard in OSM, they are free to start documenting the pedestrian network in the way they've proposed, with sidewalks as lines, crosswalks as lines, and curb ramps as points. Their challenge will be to get people to adopt this schema in use, which is something that will happen over time.

## **Analysis: Implications for organizing in data science as ethical innovation**

Just as the ORCA team's efforts to address bias in their work yields important insights into the processes and structures that can support data science as ethical convention, so does the AMOS team's story provide insights into the processes and structures that can support data science as ethical innovation. Below, I highlight three processes that were integral to their work: balancing the needs of various stakeholders; fractalizing the articulation of the problem by connecting the work to larger existing social patterns; and matching well-scoped problems with appropriate solutions.

### *Balancing: Weighing the values and needs of different stakeholders*

I have documented how the AMOS team labored over developing a proposed data schema for documenting the pedestrian network in OpenStreetMap, and I've introduced their proposal to import municipal sidewalk data, which I address more fully in Chapter 6. Each decision the team made entailed an exploration of alternative options, outreach to relevant stakeholder groups, and intensive deliberations about the values, judgments, and affordances that would ultimately be encoded in a programmatic representation of the pedestrian transportation network. This group's forthright acknowledgment of the value-laden and ethically-implicated nature of data runs counter to common depictions in critical data studies literature of technologists and data scientists naively assuming the inherent objectivity and neutrality of data. While the AMOS team's experience alone does not necessarily mean that such reflexivity and sensitivity is the norm in data-intensive work, it does imply that models for reflexive, ethical data science practice exist, and that critical data scholars and data science practitioners alike have much to learn from such examples.

Critical data studies scholarship has amply demonstrated that digital data, code, and algorithmic systems have the potential to reify and amplify social biases and subjective judgments while giving an aura of objectivity (Gitelman, 2013). But one thing to be learned from the AMOS experience is that data-intensive work can, in the right hands and under the right circumstances, provide a site not for obscuring biases and subjective judgments, but for foregrounding and grappling with them. For example, when discussing how to account for the “cost” of street furniture in their routing algorithm, the team noted that a bench could be an amenity to some, and an obstruction to others. The act of encoding these priorities forced the team to be explicit about what is valued by different stakeholder communities, throwing into relief the inherently political nature of what is otherwise usually taken as a perfectly innocuous object intended only for rest and repose. So while a casual pedestrian can walk past a bench without thinking about what that object means to different stakeholders with different embodied experiences of the world, the AMOS team was forced to contemplate such a question when deciding if it should be represented in the data as a barrier or as an amenity. And while optimization is often assumed in critical data studies literature to be geared toward efficiency and cost savings (e.g. Caplan & boyd, 2018; Collier, 2009; Powell, 2014; Söderström et al., 2014), the work of the AMOS team reveals how data-intensive computational technologies can be designed to optimize for many different values and concerns.

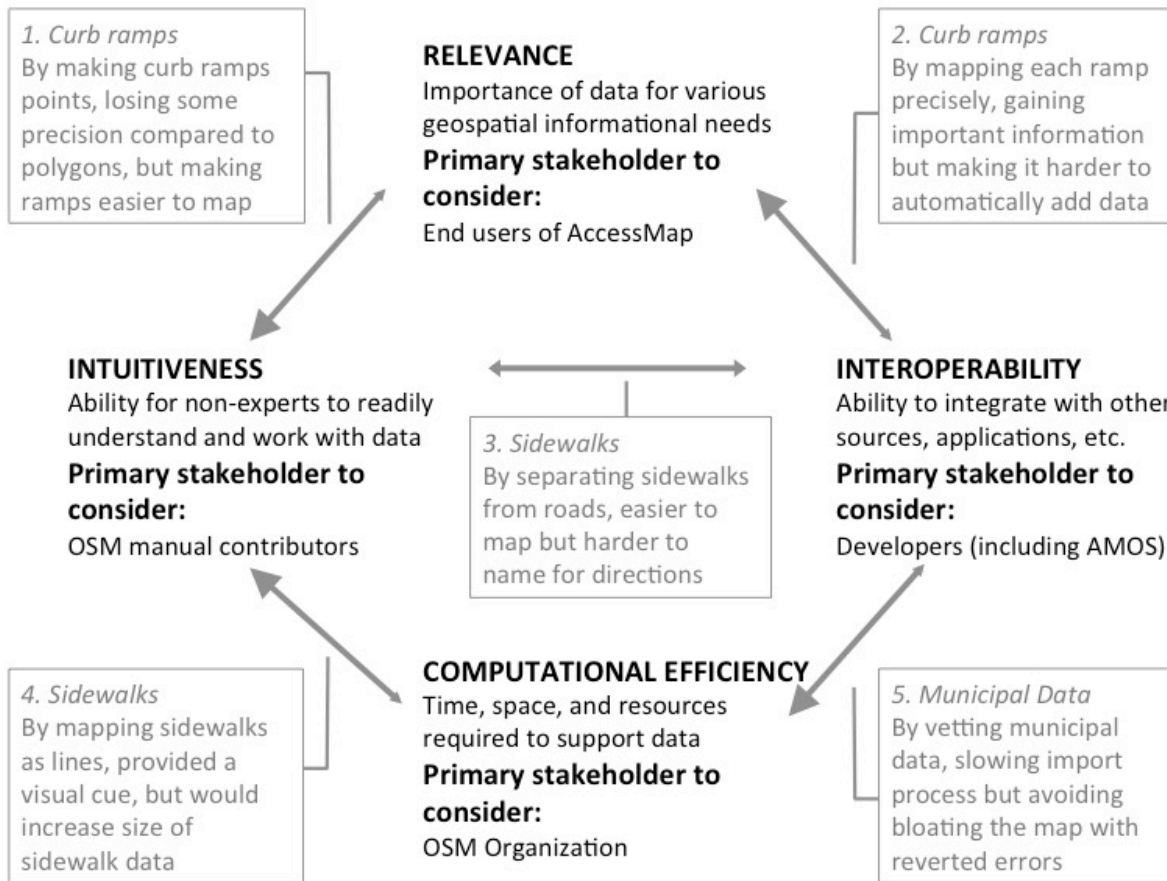
Whereas the data science as ethical convention approach seeks to correct for the subjectivities of value-laden data, data science as ethical innovation seeks to leverage those subjectivities to achieve desired ethical ends. In seeing data as a site for surfacing and embracing subjectivities, data science as ethical innovation can offer what Davide Nicolini (2012) calls an “articulated view” of the world. The point of inquiry is to make the world “more complex, not

simpler,” he writes (p. 215). “Good science, no matter from which discipline, enriches the ingredients that make up the multi-faceted universe in which we live and makes us more articulate and capable of perceiving differences (and thus meaning)” (Nicolini, 2012, p. 216). Certainly, if differentiated stakeholder positions are not considered in the design of data-intensive systems, then those systems can become an opaque veil behind which the cultural assumptions of a privileged technorati get reified and amplified, just as critical data scholars have rightly pointed out. But, if diverse stakeholders are appropriately included and considered, then the design of data-intensive technologies can actually become an occasion for surfacing the always political and contested nature of sociotechnical systems. Data may be neither neutral nor objective, but this is because the world they represent is neither neutral nor objective; the work of the AMOS team shows us that doing data science of the social need not obscure this point, and in fact can actually help us to confront the reality that a bench is never just a bench.

While AMOS leadership was already predisposed to be thinking about stakeholders and weighing the ethical implications of their work, the deliberative nature of the OSM community itself also prompted and facilitated such engagement. As Roger impressed upon Eric when they met, there is no enforced standard for adding data in OSM; to get your suggested practice to be adopted, you have to muster support from the community. This meant the AMOS team would have to develop an argument that demonstrated they had done their homework and researched previous and current proposals, provide a rationale for why the proposed changes were important, and address the concerns of various contingencies in the OSM community. This included groups who were concurrently crafting proposals for mapping norms to facilitate informational needs of people with vision impairments, a category of disability that the AMOS team was less familiar with. After interacting with these groups on the OSM forums, the team

started taking vision considerations into account, trying to ensure that nothing they proposed would discount the needs of people with visual impairments or undermine the efforts of advocates in the OSM community who were working to represent them. The point I wish to make here is that, even if the AMOS team was not already inclined to take stakeholders into account, in the world of OSM, they would have been forced to do so in order to be successful. This indicates that if stakeholder engagement is to be thought of as integral to ethical thinking, decision-making, and design in data science of the social, then working with deliberative, open-source platforms and communities offers a way forward.

Of course, scholarship on deliberative, peer-produced and open-source communities has demonstrated that they are neither perfectly democratic nor perfectly inclusive (Shaw & Hill, 2014), and large diversity gaps exist in many participatory online communities (Hargittai & Shaw, 2014; Shaw & Hargittai, 2018). Cultural norms of deliberation and adjudication can be off-putting to the uninitiated, and participation is often predicated on some degree of technical literacy. As such, diversity in the range of opinions and priorities may be limited to those individuals and stakeholders who are able to surmount these barriers to entry by being thick-skinned and demonstrating technical proficiency. It follows, then, that such communities would favor those who can assertively articulate technical rationale for community norms, resulting in a privileging of those priorities over others. And in fact, in their meeting with Roger, when Eric was pressing him to find out which stakeholders really held the most sway and Roger was insisting on the non-hierarchical nature of the organization, he eventually conceded that the third-party developers who create applications from OSM data would be the most important people to win over, indicating that the stakeholder group with the most technical proficiency holds sway. But this is not how things actually played out in the AMOS project, as I show below.



**Figure 4-3. AMOS’s tradeoffs.** This diagram represents a number of salient tradeoffs that the AMOS team had to consider in their work. Values and stakeholders are depicted in black, while the technical choices they had to make appear in numbered gray boxes.

Throughout their deliberations, the AMOS team came to see each of their choices in representing the pedestrian sidewalk network as a set of trade-offs that privileged the priorities of some stakeholder communities and some values over others. In Figure 4-3, I have summarized these values, stakeholders, and trade-offs. The AMOS team juggled four main values in their work, which are depicted in bold black letters: intuitiveness, relevance, interoperability, and computational efficiency. By *intuitiveness*, I mean the ability for non-expert users to readily understand and work with the data schema they proposed. The team felt the main reasons OSM contained so little pedestrian-related information was that there was no visual representation of sidewalks on the map, and it was cumbersome to add this information as metadata about roads.

Intuitiveness was primarily a concern for individuals who would be manually contributing data to OSM, as this could influence the degree to which they would add pedestrian data to the map. By *relevance*, I mean the importance of pedestrian data for various informational needs. For example, information about sidewalk steepness seemed to be more relevant to manual wheelchair users than powered wheelchair users. The AMOS team's considerations of relevance, then, were primarily related to the end-users of AccessMap, which would be built with data from OSM. By *computational efficiency*, I mean the time, storage space, labor, or other resources required to support pedestrian data computationally. The primary stakeholder the team considered with regard to this value was the OSM organization, as they would be storing data on OSM servers. By *interoperability*, I mean the ability to integrate sidewalk data with and from other sources, applications, tools, etc. This was a consideration made primarily with developers in mind, including the AMOS team itself as the builders of AccessMap, for they wanted to import municipal sidewalk data into OSM and in turn use OSM as the base layer for AccessMap.

In Figure 4-3, I've drawn arrows representing salient trade-offs between values that were considered by the AMOS team; the larger end of each arrow indicates which value ultimately took precedence in each case. In Trade-off 1, the team had to balance the values of *intuition* and *relevance* when deciding whether to represent curb ramps as points or polygons. Polygons would allow for documentation of the precise shape and width of curb ramps, which might be useful information for some AccessMap users. On the other hand, points (or nodes, in OSM parlance) were the simplest features for map contributors to add to OSM, making this a more intuitive choice in many ways; in the end, it was intuition that won out.

But the team still had to decide if they would represent curb ramps with one single dot in a case when a street corner had multiple curb ramps on it, or if they would assign each ramp its

own point—a dilemma I’ve labeled Trade-off 2. This choice involved a trade-off between relevance and interoperability. Adding a single point to the intersection of two sidewalk segments to indicate that one or more ramps were present would have been simple to do automatically by adding data from the municipal curb ramp data set they had. But as we saw, sometimes the precise location of a curb ramp and its distance from a crosswalk makes a difference to certain wheelchair users. If individual contributors placed the location of each ramp individually and precisely, this would provide the more accurate information those users needed. In the end, this concern for relevance to the end users of AccessMap took precedence over the ease of integrating with the municipal data sets they had.

In Trade-off 3, the AMOS team had to consider interoperability again, and how it would be affected by their idea to intuitively represent sidewalks as lines. As they learned, this change could affect the ability for developers of routing application to provide turn-by-turn walking directions because sidewalks would now be separated from named streets. Ultimately, the team didn’t have to choose between these values, but they did realize that they would need to provide a technical specification explaining how street names could be easily inferred from adjacent streets in order to accommodate turn-by-turn directions. Similarly, regarding the tradeoff depicted in #4 between intuitiveness and computational efficiency, the team didn’t necessarily need to make a decision that changed the nature of their data schema proposal, but they did have to be prepared to provide a justification that the benefit of representing sidewalks as lines outweighed the cost of the extra server space this data format would require.

Finally, in Trade-off 5, the team had to consider the values of interoperability and computational efficiency. If they were to rely on OSM as the base layer for the AccessMap routing application, the team needed sidewalk data in OSM to be complete, so they hoped to

populate the map with the municipal data sets they had at their disposal. As I discuss at greater length in Chapter 6, OSM keeps a history of every edit ever made to the map, so even if those additions were reverted, the organization would maintain a copy of them in perpetuity; this meant that the organization frowned upon mass data imports because they wanted to avoid bloating the map with errors that would reside on their servers forever. Ultimately, the AMOS team conceded to this perspective on computational efficiency, and agreed to import the data in small chunks that would be independently verified by a human, a decision that is discussed at greater length in Chapter 6.

The deliberations over these trade-offs may have largely taken place sitting in front of a whiteboard in the Data Science Studio at the University of Washington, but the AMOS team's discussions were informed by intentional and prolonged engagement with relevant stakeholder communities. Team members did several rounds of user research to understand the concerns and preferences of different types of wheelchair users, and drew deeply from their own experiences as caretakers and family members of people with limited mobility. They also took the time to understand the procedural norms and cultural values of the OpenStreetMap community by doing archival research, working with a data science mentor who had a history of participating in the OSM community, contributing to discussions on OSM's listservs and wikis, building relationships with local advisors from the OSM community, attending local mapping meetups, and presenting at the US community's annual in-person gathering.

In the course of these activities, they were able to get a sense for the cases in which they simply needed to acknowledge the trade-offs at play and justify the value of their proposal, and the cases in which those considerations of trade-offs needed to impact their own decisions and design choices. And the way these decisions and choices played out are not haphazard; mapping

them in the way that I have in Figure 4-3 shows something of a pattern: the value of interoperability yielded to the values of relevance and computational efficiency, and both of those values yielded to the value of intuitiveness. And since those values are associated with the needs of distinct user groups, this also means that there was a bit of a hierarchy to the prioritization of different stakeholder needs. When it came to their own technical priorities as software developers of a routing application, and their desire for interoperability between OSM and municipal data sets, the team deferred to the informational needs of AccessMap users and to OSM's concerns over data storage. And the needs of these stakeholders in some ways deferred to the need for an intuitive sidewalk data schema that non-expert manual contributors could easily follow and use. It may be tempting to interpret this as the team valuing the needs of the OSM contributor community over the needs of the marginalized community that they were trying to serve with AccessMap. But given the way that the AMOS teams understands the sociomaterial nature of the problem they are addressing, this compromise can also be seen as a necessary move in furthering their ethical agenda, as explained below.

*Fractalizing: Connecting the work to larger systemic issues and patterns*

In conversations I had with several members of the AMOS team while we were preparing a practitioner-oriented manuscript about the ethical issues that arose in their project (Tanweer et al., 2017), they felt strongly about not portraying their work as a perfect exemplar of ethical data science. From their perspective, there was no such thing as an ideal solution to the ethical questions they faced, just a set of trade-offs between competing priorities and a series of compromises around the digital infrastructures with which they were integrating. As I've put forward here, though, the very acknowledgment and deliberation of these trade-offs and

compromises, and the recognition of divergent implications for real and imagined stakeholders, is an act of ethical consequence that should be integrated into all data science of the social.

But I began this exploration of the AccessMap/OpenSidewalk project with the premise that their approach to ethics is informed by an underlying theory of sociomateriality, and that this is consequential for our understanding of sociotechnical systems. I return to that argument now. We have seen how the group's decision-making consisted of a series of trade-offs and compromises, and that they were fully cognizant of the ethical import of those decisions. In the previous section I discussed how those compromises can be understood as negotiations between the priorities of different stakeholder communities, an interpretation that is close to how the AMOS team itself tends to see those decisions. But, it is also worth viewing those compromises in light of the sociomaterial worldview put forth by AMOS leadership—a worldview that sees disability as a social construct arising from interactions with a narrowly conceived built environment, one that is designed for only a small range of experiences and abilities because we view difference as a deviation from “normal” rather than viewing difference as being the “normal” state of affairs. This explicit recognition of how their project fit into larger systemic patterns in society is what I mean by “fractalizing” their work. A fractal is a series of geometric figures, each with the same proportions or statistical character as every other figure, regardless of scale; they are patterns within patterns within patterns within patterns.

As I have alluded to in the previous section, the overarching theme of these compromises can be thought of under the banner of a grand compromise between the specific needs of a target population and the needs of broader swaths of society. The decision to map curb ramps as points rather than polygons because points are easier to add to OpenStreetMap might be thought of as sacrificing the needs of AccessMap users for the needs of contributors to OSM. But it also can be

understood as part and parcel of the overall ethical goal of the group, which is normalizing the needs of people with limited mobility as one among a range of options—not a special category, but part of a spectrum of abilities, desires, and needs in a pedestrian-centered transportation network and information system. Rather than the informational needs of people with limited mobility being a special case, a deviation from normal, the AMOS approach sees their informational needs as part of diverse array, and in doing so, fundamentally challenges the social construction of disability by designing a system that accommodates difference and diversity, rather than one that assumes that the “normal” mode of travel is to get from A to B by the shortest time and distance. So even more important than building AccessMap itself, their objective of designing of an informational environment that could support multiple and varied needs was central to their ethical perspective.

As such, it was important that sidewalks be recognized as important and valuable resources to wide swaths of society, not just to people with limited mobility. Only then would people care enough to put sidewalks on the map, and only if that were intuitive and easy to do. In other words, because the AMOS team’s leadership recognized how social constructs and technological artifacts mutually shape each other, they could see how the design of the informational built environment wouldn’t just yield the next greatest mapping app, but actually had the potential to influence the social construct of disability more broadly. In this sense, it was their underlying vernacular theory of sociomateriality that informed the trajectory of their work, allowed them to recognize the value-laden nature of all their decisions, and to be intentional and conscientious in recognizing the trade-offs they made.

### *Matching: Aligning problems and solutions*

Some time after the Hack the Commute challenge won by Nick and his colleagues, one of the judges of that event told me that too often in this space, people start by assuming that data can be part of the solution to any given social problem, even when many of those problems are political in nature. In other words, many social problems exist not because we don't have enough data to understand them, and not because we don't know how to fix them, but because the requisite political will to address them doesn't exist. Data can do little to help in situations like these, she said. What impressed her about the AccessMap idea was that the team was proposing an informational solution to an informational gap. Another way of saying this is that the AMOS team is trying its best to avoid technological solutionism (Morozov, 2013), the dangerously naive assumption that technology can solve all our problems. Although, as I argued above, this project is conceived of as having a broader impact on the social construction of disability, the leadership of the AMOS team scoped a specific problem and solution that are well aligned with each other.

Unfortunately, in data science for good-type projects, social problems and data-based solutions are often mismatched, or at the very least, the relationship between them goes unarticulated. A case in point is a recent competition run by the largest telecommunications company in Turkey, Turk Telekom. Called "Data for Refugees Turkey," the competition invites data science teams to analyze mobile phone records of Syrian refugees in Turkey in order to address a set of issue areas including education, safety and security, health, etc. Within each of those broad areas, the company provides brief background on some of the main challenges facing Syrian refugees in the country. For example, they highlight the difficulty in obtaining the appropriate documentation for enrolling children in school, and acquiring permits for legal employment. The project assumes that an understanding of the spatio-temporal patterns of

refugees can somehow help rectify the problems they identify, regardless of the legal, cultural, or bureaucratic reasons refugees may have a hard time securing the requisite documents.

Moreover, while the Turk Telekom project is promoted as data *for* refugees, it is important to acknowledge that the point is not to put data into the hands of refugees to empower them to solve their own problems. Rather, the data in question is actually data *about* refugees, and highly intrusive at that. The organizing committee for this project includes some of the foremost thinkers in computational privacy (Data for Refugees Turkey, 2018), who clearly put effort into ensuring that individuals would not be identifiable in this data set. But this preoccupation with an individualistic notion of privacy ignores the damage that can be done by identifying patterns in vulnerable populations. Setting aside that this particular project is taking place in a country led by an increasingly authoritarian regime that has jailed political opposition en masse, silenced digital privacy advocates, and persecuted ethnic minorities, it is questionable in any case to add a further layer of surveillance to a traumatized community that has already traded some of their independence and privacy for a semblance of security. In other words, even if the organizers of Data for Refugees Turkey in good faith desire to help refugees, there is yet another fundamental mismatch between the stated goal of empowering an already-marginalized population, and a solution that wields a disproportionate power of surveillance over them.

I have chosen to discuss the Data for Refugees Turkey project at some length here to point out the ways that the AMOS project is different. Instead of starting by asking how data *about* a marginalized population can inform policies *toward* them, they started by asking what this population needs to know in order to thrive, and worked toward solutions that would put the power of data into their hands. This is the key to the data science as ethical innovation approach: It assumes the competence and agency of a marginalized community of people, and it starts by

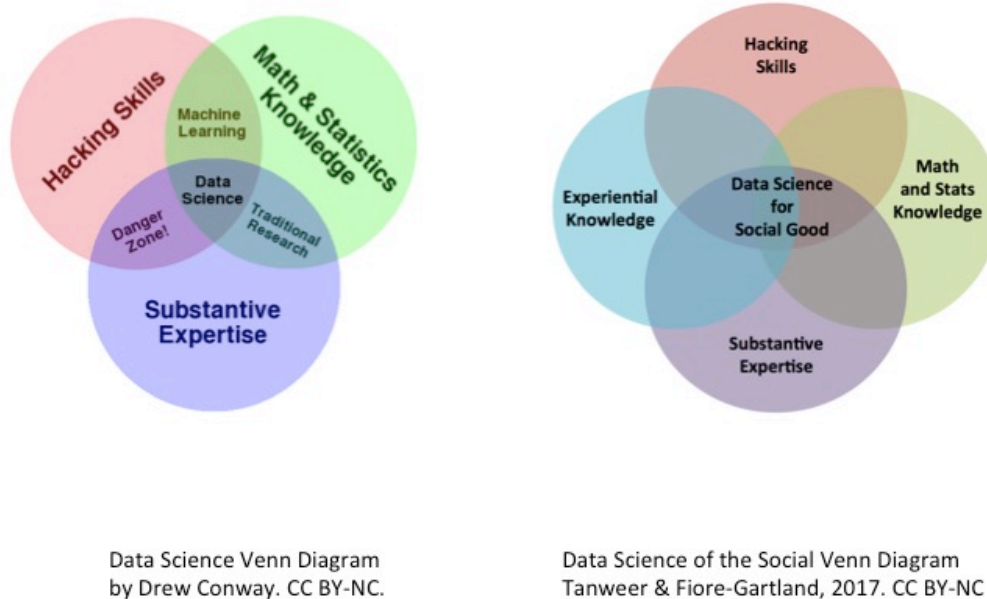
questioning what people need rather than what can be known about them. In other words, it is an effort to build new data-intensive configurations that are oriented to the aspirations of marginalized populations, rather than using data to scrutinize those populations.

## CONCLUSION

I have argued elsewhere with my colleagues that data science practitioners are often fully aware of the ways in which their data is limited and subjective, even if this doesn't always come across in the triumphalist and superficial ways data science is discussed in popular discourse (Neff et al., 2017). It's not that celebratory rhetoric cannot be found among practitioners as well. Mark, in his opening presentation, emphasized that the ORCA data provides the opportunity to see what people *really* do, even while understanding full well the caveats that statement required, and having every intention of directly addressing the question of biased data in his work. The AMOS team offered the provocation that mapping isn't a solved problem despite the ubiquity of applications like Google maps, and claimed that they had a solution. It may sound like they're a group of starry-eyed social entrepreneurs who believe in a quick technological fix. One wouldn't necessarily know from their presentations that they're informed and motivated by a nuanced understanding of the relationship between the social and the technological, and that this worldview influences everything they do as a team. This mismatch between public discourse and behind-the-scenes work means that we need to pay attention to what people say and do in the course of their practice. When we do, we may find more stories like the ones I've presented here, accounts of data science teams taking Bowker's advice and making sure their data is "cooked with care" (Bowker, 2005, p. 184).

This doesn't mean that the processes supporting ethical data science practice were always happily embraced, however. On both teams, members at times were frustrated and resentful of

the time and energy it took to “cook with care.” In part, this is because the processes I’ve highlighted above are not typical or expected aspects of data science work. To support an ethical data science of the social, we should make these processes the rule, rather than the exception. This requires integrating those processes into our expectations for data science of the social, considering them to be constitutive of, not supplementary to, the practice. To that end, I make a final proposition to integrate a meta-process into data science of the social that can support iterations of the more specific processes I’ve highlighted above: *integrating experiential knowledge* into data science of the social.



**Figure 4-4. Experiential knowledge in data science of the social.** I have suggested that the oft-cited Data Science Venn Diagram by Drew Conway should be amended for data science of the social to include a fourth area of expertise, what I’ve called, “experiential knowledge.”

This means rethinking the set of skills and expertise that we associate with data science. Drew Conway’s Data Science Venn Diagram (Conway, 2010) is an oft-cited definition of data science that identifies its constitutive skills and knowledge as “hacking” (i.e. programming), statistics and math, and “substantive expertise,” which is often operationalized in terms of what

my community of study would call “domain knowledge.” But as we’ve seen, that triumvirate falls short of what is needed to evolve robustly ethical practices in data science of the social. I suggest, then, that a Venn diagram for data science of the social should include a fourth circle, an arena I have called “experiential knowledge” (Tanweer & Fiore-Gartland, 2017). Experiential knowledge has two intertwined meanings: it is *about* the experiences of people who are involved in and affected by data science of the social, and it is knowledge that is *gained* experientially, by talking, interacting, and learning from those individuals, organizations, and communities.

Fortunately, we don’t have to reinvent the wheel in trying to think about how to include this kind of expertise in data science of the social. Across an array of disciplines, a number of research approaches and methods have already been developed and refined that systematically facilitate collaboration among heterogeneous actors, take stakeholders into earnest consideration, integrate processes of reflection, and account for subjective values. For example, participatory design (Robertson & Simonsen, 2013), action research (Reason & Bradbury, 2001), and user studies (Baxter, Courage, & Caine, 2015) to name a few. These are all approaches that systematically put subjective human experience at the center of research and design. Data science of the social can borrow from these traditions in order to become more “human-centered” (Aragon et al., 2016) by incorporating experiential knowledge as a meta-process that is integrated with the other processes I’ve identified here as integral to various ethical approaches in data science of the social. Only when we have accounted for experiential knowledge can we understand the issues and problem space well enough to successfully and meaningfully translate ethical concerns into methodological challenges, or match problems with solutions. Without experiential knowledge, we can’t begin to balance the values of important stakeholders or articulate how the work is situated within broader and repeating patterns of inequity. And in order to foster experiential

knowledge, we have to incentivize that process by recognizing its value and importance, and creating protected time and space to let it flourish.

## CHAPTER 5 INFRASTRUCTURE AND EXOSTRUCTURE: SCALING “DATA SCIENCE OF THE SOCIAL” ACROSS DOMAINS

### INTRODUCTION

The rapid growth of data in the last two decades has been referred to alternately as a data deluge (Borgman, 2006), information overload (Edmunds & Morris, 2000), and a data bonanza (M. Atkinson, Baxter, Brezany, Corcho, & Galea, 2013). Popular sources of news and commentary herald the promises of “Big Data” and marvel at imagination-defying numbers representing just how much data we’re swimming in. Humans are expected to be producing 163 zettabytes of digital data per year by 2025 (Cave, 2017), and with a single zettabyte of data being comparable to the amount of information contained in 5 quadrillion books (Computer Hope, n.d.), it would take 50 billion Libraries of Congress to contain it. But, of course, this data won’t be contained in books. Next to those bulky masses of organic pulp that are subject to rips and molds and insect infestations, bits and bytes seem pleasantly and conveniently immaterial, zipping around at light speed, flickering on and off computer screens, duplicating and deleting *ad infinitum*.

Scholars of technology, however, have taken on the task of dispelling this illusion of immateriality. Kirschenbaum’s (2008) forensic exploration of digital materiality, for example, details the physical, observable traces left behind by data on the substrates that store them. Others have elucidated the vast assemblage hardware, software, capital, organizational structures, and human labor it takes to make - and make useful - digital data (Edwards, Jackson, Bowker, & Knobel, 2007; Kitchin, 2014a). What this work shows us is that data require extensive investment in materials, tools, systems, processes, people, and institutions.

There is a widespread sense, however, that such an investment has not been sufficiently made in the public sector, and that governmental data, therefore, remains an underexploited

resource. In the three plus years I've spent observing data-intensive collaborations between academic institutions, commercial business, and government agencies, my interlocutors have frequently expressed the sentiment that while business has unlocked the secrets of big data for economic gain and researchers are making profound data-intensive discoveries, government is largely missing out on transformative opportunities to use big data for public benefit.

In this chapter, I begin by discussing a first generation effort to build an infrastructure that would allow the public to benefit from government data—the open data movement and the resulting open data portals that many cities in US municipalities have adopted in the last decade. I portray these as infrastructures for *making data public*, for simply providing the public with access to governmental data in the hopes that the private sector and civil society will step in and tap it as a resource. After discussing the shortcomings of this model, I discuss alternative models of infrastructure development that I have observed in my ethnographic fieldwork, models that I characterize as infrastructures not for *making data public*, but for *making public data*. Unlike the open data model that focuses simply on access, these approaches are distinctive in that they are folded into efforts to build holistic *knowledge infrastructures* for data science, and revolve around project-based collaborations that are designed to develop use cases upon which more stable *data infrastructures* will ultimately be built. I conceptualize such temporary project-based collaborations with grander infrastructural ambitions as *exostructures*, temporary and modular arrangements that provide platforms for infrastructural elements to jump contexts into new social spheres, and occasion the emergence of new roles and relationships for the social sectors involved.

## UNDERSTANDING INFRASTRUCTURE

Infrastructures are material and organizational configurations that serve as enablers of action. They figuratively reside in the background to support the smooth interaction and operation of objects and activities in the foreground. This makes infrastructure an inherently relational concept, in that what is backgrounded as infrastructure from the perspective of one may be foregrounded as the primary object of attention from the perspective of another (Jewett & Kling, 1991; Star & Ruhleder, 1996). Repositioning infrastructural elements, bringing them from the background into the foreground in order to make them explicit objects of attention, is what Geof Bowker and others have called infrastructural inversions (Bowker, 1994).

Given the relational nature of infrastructure, rather than offering a static definition of what infrastructure is, Star and Ruhleder (1996) suggest that it is more helpful to identify *when* a sociotechnical assemblage is serving as an infrastructure. According to their seminal explication, infrastructures come into being when: they are embedded in other structures; they have an extended reach and scope that crosses over particular situations and contexts; they embody agreed-upon standards; they are built on installed bases that are often pre-existing or legacy infrastructures; they become visible when they breakdown; they are linked to conventions of practice; they are transparent in that they remain invisibly ready-at-hand to enable activity without needing to be reinvented; and they are learned so as to become taken for granted by their users (Star & Ruhleder, 1996).

In the decades since Star and Ruhleder (1996) developed this relational definition of infrastructure, STS scholars have clarified and elaborated upon it many times over. Although the term readily brings to mind tubes and pipes and wires, physical matter does not alone constitute an infrastructure. Rather, the physical technologies of infrastructure are supported by particular

organizational arrangements (Lee, Dourish, & Mark, 2006), are made functional through standards and protocols (Edwards, 2010), and are enacted by people in skilled roles (Bowker, Baker, Millerand, & Ribes, 2010). In other words, technology and social organizing are entwined, and “artifactual infrastructures” of physical things are inseparable from the “human infrastructures” that support them (Lee et al., 2006). The social configurations of human infrastructure organize the labor that lies at the heart of infrastructure: the work of development, coordination, articulation, translation, maintenance, and repair (Baker & Millerand, 2007; Downey, 2014; Edwards et al., 2007; Star, 1999).

In keeping with this holistic view of infrastructure, Paul Edwards has defined knowledge infrastructures as “robust networks of people, artifacts, and institutions that generate, share, and maintain specific knowledge about the human and natural worlds” (Edwards, 2010, p. 17). Knowledge is not contained or developed within individuals, but rather is an accomplishment distributed across people, organizations, and technologies (Hutchins, 1995).

Get rid of the infrastructure and you are left with claims you can't back up, facts you can't verify, comprehension you can't share, and data you can't trust. Without the infrastructure, knowledge can decay or even disappear. Build up a knowledge infrastructure, maintain it well, and you get stable, reliable, widely shared understanding.  
Edwards, 2010, p. 19

In other words, without infrastructure, the pursuit of knowledge would be unsustainable. Although, from this perspective, infrastructure is implicated in the production of *all* knowledge, a large body of scholarship residing at the intersection of STS and computer supported cooperative work focuses specifically on efforts to develop large-scale infrastructures in support of geographically distributed scientific collaborations. This includes studies of “collaboratories” (Finholt, 2002; Kouzes, Myers, & Wulf, 1996; Olson, Zimmerman, & Bos, 2008),

“cyberinfrastructure” (Edwards et al., 2007; Ribes & Finholt, 2009), “eScience” (Bowker et al., 2010), “digital libraries” (Borgman, Wallis, & Enyedy, 2007), and “information infrastructure” (Baker & Millerand, 2007).

This body of work shares a central concern for infrastructure-in-the-making. In broad strokes, Edwards et al (Edwards, Bowker, Jackson, & Williams, 2009) lay out the phases of information infrastructure development thus: it begins with a technical system centrally designed and built to solve a particular problem, the success of which spawns competition from alternative solutions, which is sometimes resolved either when one system prevails over the alternatives, or—more frequently—when a set of practices and “gateway” technologies is devised to facilitate the synthesis and interoperation of multiple technological systems.

Lest that process sound too neat and linear, much of the work on infrastructure in STS reveals the imbrications, negotiations, iterations, and improvisations that occur in the process of funding, designing, adopting and adapting large-scale information infrastructures for the production of knowledge. Infrastructures are assembled, not born wholly formed. They typically are pieced together in a modular fashion from pre-existing structures rendered compatible and interoperable. For this reason, Edwards et al. suggest that infrastructural development is better understood as a process of “growing” rather than “building” (Edwards et al., 2007). While infrastructures have long been identified in part by nature of being “built on an installed base” (Star & Ruhleder, 1996), this characterization sparks an imagination of infrastructures as being layered “on top” of pre-existing infrastructures, and it may be more accurate to think instead of information infrastructures as emerging from the intersections of other infrastructures. Janet Vertesi (2014) uses the metaphor of “seams” to describe how actors “make connections and bring disparate elements together” at these complex junctures (p. 268), stitching an

improvisational assemblage that produces “fleeting moments of alignment suited to particular tasks with materials ready-to-hand” (p. 268). Through these local, situated actions, technological systems are rendered operable and interoperable. In other words, it is at these seams that infrastructure is able to function as infrastructure at all.

Along the way, actors grapple with numerous tensions and contradictions. Ribes and Finholt (2009) highlight “conflicting goals, purposes, and motivations of participants” (p. 376) in infrastructure development, noting that these were not hidden below the surface in their field sites, but rather were openly addressed as a part of community sense-making. The authors identify a number of tensions arising from a central set of developmental concerns that play out across various scales of action. For example, at the scale of the technical work involved in enacting technology, there is a tension between what is required by today’s users, and what will be expected by tomorrow’s users. At the scale of organizing and managing the design process, there is a tension between the need to invest time in tool development, and the perception that the incentive structure of science doesn’t reward such activities in the same way that it rewards the activities of research. And at the scale of institution building, there is a tension between the broader academic community the infrastructure is meant to support, and the narrower constituencies that are positioned to actually influence the design.

Each of these more specific tensions speaks to an overarching tension between particular, local, immediate needs on the one hand, and more general, global, long-term needs on the other (Edwards et al., 2007; Ribes & Finholt, 2009). At its core, infrastructure is an inherent attempt to address the latter, but it requires close attention to the former (Edwards et al., 2007; Ribes & Lee, 2010). As such, infrastructure is thought to come into being only when this tension between global and local is resolved: “an infrastructure occurs when local practices are afforded by a

larger-scale technology which can then be used in a natural, ready-to-hand fashion” (Star & Ruhleder, 1996, p. 114).

On the way to becoming “ubiquitous, accessible, reliable, and transparent,” (Edwards et al., 2007, p. i), design decisions made during the development stage create path dependencies that lock individuals and organizations into certain sociotechnical arrangements (Bowker et al., 2010; Edwards et al., 2007). This process “invariably creates winners and losers” (Edwards, 2010). As Paul Edwards notes:

If they are really infrastructures, they eventually make older ways of life extremely difficult to maintain: think of family farms against industrial agriculture, or newspapers against the internet. Every choice involves tradeoffs and consequences. Infrastructures have victims and 'orphans' (people and groups who are unable to use them or to reap their benefits because of their circumstances)—for example, people with rare diseases ignored by pharmaceutical research, blind people unable to navigate graphics-based websites, and the 5 billion people still without access to the Internet.

Edwards, 2010, p. 12

In other words, infrastructures are inherently political and power-laden. Literature on infrastructure studies has much to say, then, about the extent to which infrastructure development is socially mediated and rife with tensions. It provides numerous ways to characterize the work entailed in infrastructure development, and to understand the inevitable contradictions that arise during that work. There has been less conceptual development of the *structural mechanisms* by which such tensions are resolved or the way infrastructures are adapted to new uses and contexts, with a few notable exceptions. Ribes (2014) introduces the concept of *scalar devices*, “an assembly of techniques, tools and representational conventions that are used to know and manage scale” in infrastructure development work (p. 160), such as meetings, surveys, and metrics. Such scalar devices smooth the development of infrastructure by helping participants coordinate their distributed efforts. And in theorizing how infrastructure supports emergent and

changing objects of research, Ribes and Polk (2015) develop the concept of a research “kernel”—a set of core resources and services that are maintained to allow for “technoscientific flexibility.” Such flexibility is key not only for adjusting to changing contextual conditions locally, as Ribes and Polk (2015) discuss, but also for transferring infrastructure to new applications in different contexts.

Context means different things to different people (Seaver, 2015). Paul Dourish (2004) advocates for an interactional perspective, which approaches context as perpetually shifting, relational properties rather than static qualities, as a set of relationships that arise from action rather than a container in which they unfold. That latter perspective is what Dourish calls a “representational” perspective, which treats context as a setting with stable characteristics. While I am appreciative of the generativity, nuance, and attention to activity that are invited by an interactional perspective on context, it is nonetheless sometimes useful to be able to call attention to salient circumstances and qualities that make the distinctive spheres of action recognizable and demarcatable. And so, in conjuring context for the sake of the argument that follows, I use it more so in the representational sense following the information scholar Helen Nissenbaum (2018), who understands “contexts as social spheres, as constituents of a differentiated social space” (p. 838.).

This is also closer to the meaning employed by Greg Downey (2014) when he discusses the ability for infrastructure to “jump contexts” and support different kinds of uses. Downey documents how machine-aided transcription of speech originated in the defense industry for deployment in intelligence gathering, jumped to the legal field for use in courtroom stenography, then to the media industry for closed-captioning, and finally to the classroom as an assistive device for learners with disabilities. This phenomenon of jumping social contexts and being

adapted for wholly new uses is something that is scant accounted for in the corpus of STS and CSCW literature concerned with knowledge infrastructures and large-scale scientific research endeavors. Although there is certainly a degree of heterogeneity in the locales across which such infrastructures are intended to be distributed, there is also a fair amount of homogeneity as well: such efforts often involve centralized sources of funding, formalized relationships between relatively isomorphic institutions with similar incentive structures, a common mission of producing scientific knowledge, and an objective of establishing shared infrastructural resources. The purpose is to build "laboratories without walls" (Finholt, 2002), to connect spatially and temporally distant contexts with common features in a way that facilitates long-term scientific collaboration.

This is quite different from the phenomenon I have in my field sites over the last several years, which can be understood as a movement to develop a knowledge infrastructure for data science across heterogeneous social sectors. In these efforts, funding is decentralized, collaborating entities tend to be anisomorphic with dramatically different incentives structures and work cultures, and stakeholders often enter collaborations with markedly differing missions. The purpose is not to build "laboratories without walls" (Finholt, 2002), but to create a knowledge infrastructure in a new social sphere for the sake of new applications. Although in the cases I'm studying, this infrastructure development does involve the participation of scientific institutions, the phenomenon may have less in common with the large-scale scientific infrastructure development that has been so well documented and studied in STS and CSCW, and more in common with the infrastructural context jumping that Downey (2014) explores. Similar to the way scalar devices help explain how participants manage the scale of their distributed infrastructural collaborations (Ribes, 2014) and the way kernels help us understand

how infrastructures are reoriented within an institution (Ribes and Polk, 2015), so do we need concepts that allow us to explain the mechanisms and structures with which participants manage the disjointed transition of a knowledge infrastructure from one distinct social context to another. Base on my observation and analysis of DSSG efforts, I propose the concept of “exostructures” as one such mechanism, using it to explain a key approach by which infrastructures for public data are emerging.

In the remainder of this chapter, I first trace the recent history of public data infrastructures by looking at efforts to develop open data platforms. I discuss some of the shortcomings of this approach, which is focused exclusively on data accessibility and distribution, and then outline a newer mode of infrastructure development for public data—one that is more collaborative in nature, built around particular datasets and uses, and coupled with efforts to develop a knowledge infrastructure for data science in the government sector. I characterize this shift as a transition from data dispensaries and data reservoirs to data vaults and data commons. And I offer the concept of exostructures to explain these infrastructures-in-the-making.

## MAKING DATA PUBLIC: DATA DISPENSARIES AND DATA RESERVOIRS AS EARLY INFRASTRUCTURES FOR GOVERNMENT DATA

### **From FOIA to open data**

In the first decade of the 21st century, governments around the US were starting to converge on “open data portals” as the infrastructure of choice for creating greater access to government data and rendering it useful. Open data is viewed as a progressive alternative to an access model based on freedom of information laws, in which governments release information to the public only upon request and only in order to remain in compliance with the law. Instead of the government acting as a *data dispensary* by releasing trickles of data upon request, “open

data” efforts involve governments proactively pushing data out to the public by making it available as a resource online (Lathrop & Ruma, 2010). This essentially creates a *data reservoir*, a pooled resource that any member of the public is entitled to access.

The origins of the open data movement are often traced back to 2007, when a group of activists calling themselves the Open Government Working Group convened in Sebastopol, CA and penned a manifesto calling on governments to make their data openly available by default (Chignard, 2013). The working group, which included prominent figures in the open source and free culture movements such as Tim O’Reilly, Carl Malamud, Lawrence Lessig, and Aaron Swartz (Malamud, 2007), drafted a set of principles that designate government data as “open” when it meets the following eight criteria: it is complete, primary, timely, accessible, machine-processable, non-discriminatory, non-proprietary, and license-free (Open Government Working Group, 2007). In other words, open data is about making information collected by the government publicly available in a format that is both easy to access and easy to use.

Two years after the Sebastopol meeting, in 2009, the newly inducted Obama administration launched data.gov, the first online portal for open government data in the country. That same year, a group of chief information officers from seven major US cities committed to creating web interfaces for opening their municipal data (Douglas, 2010), and many other municipalities soon followed suit. As of 2018, over 100 US cities have open data policies (Stone, 2018), and at least 85 have online portals (Brown, 2017). These web interfaces, most often referred to as “open data portals” are commonly designed and maintained by private, for-profit vendors. Undoubtedly the most prevalent among such vendors is the company Socrata, which services more than 60 percent of the American cities that have online open data portals (Thorsby, Stowers, Wolslegel, & Tumbuan, 2017). In part because of this domination of the market by a

single company, most cities organize their data in a similar way and have a similar “look and feel” (Thorsby et al., 2017).

Over time, as more and more governments have adopted open data policies and platforms, dominant discourses have largely shifted from the rights- and accountability-based arguments made at Sebastopol to a more economic rationale (Janssen, 2012). As The Data Foundation (Gill, Hollister, & Hughes, 2016) puts it in their publication, “The State of the Union of Open Data, 2016”:

Open government data is a powerful resource that our society has only just begun to harness. Access to public-sector information as open data can of course tell us more about what government is doing—how money is spent, how programs are performing, whether progress is being made to address persistent societal issues—but this is just the smallest fraction of the immeasurable economic value of open data.... Within government, open data greatly reduces the costs of sharing and using information.... In the private sector, open data can help investors better understand risk and opportunity and provide communities with information to advocate for change and improve their lives.

Gill, Hollister, & Hughes, 2016, p. 4

Open data, then, is often justified not only as a transparency measure to help hold democratic governmental bodies accountable, but as a resource to be exploited for economic gain and social innovation. In a recent survey of participants in open data efforts conducted by Socrata, the beneficial impacts of open data are placed into the following categories: economic development, operational efficiency, quality of life, and public safety (“2016 Socrata Open Data Benchmark Study,” n.d.). It is widely believed that in order to reap these rewards, there must be “vigorous third party activity” (Robinson, Yu, Zeller, & Felten, 2008). In fact, the staunchest of open data advocates see the open data movement as fundamental to the transformation of the public sector, whereby the private sector fulfills many of government’s historical responsibilities. Open data advocates have characterized this as moving away from government acting as a

“vending machine” (Kettl, 2008) and toward what tech guru Tim O’Reilly (2010) has called “government as platform”:

Government information and services can be provided to citizens where and when they need them. Citizens are empowered to spark the innovation that will result in an improved approach to governance. In this model, government is a convener and an enabler rather than the first mover of civic action. This is a radical departure from the existing model of government, which Donald Kettl so aptly named “vending machine government.” We pay our taxes, we expect services. And when we don’t get what we expect, our “participation” is limited to protest—essentially, shaking the vending machine.

O’Reilly, 2010, p. 14-15

The non-governmental third party activity articulated in this vision is often attributed to both civil society and high tech firms, as evidenced by The Data Foundation’s observation that “the U.S. open data movement has no leader, but is invigorated by the nation’s government, nonprofit, and tech-industry sectors” (Gill et al., 2016). Such third party activity includes the work of advocacy and philanthropic organizations such as the Sunlight Foundation and Open Knowledge Foundation (McNutt et al., 2016), private companies like Zillow that build business models on open data, technology vendors like Socrata and Amazon Web Services that provide the backend software services supporting open data platforms, and “civic technologists” or “civic hackers” working either with organizations like Code for America (Goldstein & Dyson, 2013) or as volunteers in grassroots community groups such as OpenSF in San Francisco or BetaNYC in New York City (McNutt et al., 2016; Thorsby et al., 2017).

### **Failures of open data**

In spite of this expanding organizational ecosystem, there is a widespread sense that the reservoir infrastructure model of open data, so far, has largely failed to materialize as the boon that was promised, with critiques coming from all directions. In some academic circles, open

data has been cast as an elitist venture that places undue faith in the ability of markets to develop social remedies while providing a subsidized public resource for profit-seeking firms (Bates, 2012; Gurstein, 2011; Janssen, 2012). Meanwhile, governments and civic technologists alike are struggling to measure both the costs and successes of open data, beyond simply counting the number of datasets available through online web portals (Stone, 2018). Users of open data have been quick to point out the limitations of the current generation of government data portals, lamenting how slow, cumbersome, incomplete, static, and insufficiently documented they can be (Headd, 2015). Looking at the number of clicks on their own open data web portals, many government executives are finding that traffic has been underwhelming (Stone, 2018), and that their user interfaces are not friendly to people who lack sophisticated technology skills; as one chief data officer told me while discussing open data in an interview, “my mom can’t use it yet.” Recognition of these and other problems recently prompted the Civic Analytics Network—a peer-to-peer network of chief data officers from municipalities across the US—to draft an appeal to the open data community, urging vendors of data portals to improve usability for a wider audience, support geospatial data, make it easier to join related data sets, improve metadata and version history, and revamp cost structures (Civic Analytics Network, 2017). One of the chief data officers who contributed to drafting that open letter told me that vendors need this nudging because the market for creating and maintaining open data portals is so niche that there is not enough competition to spawn improvement and innovation.

But while governments may point the finger at vendors to explain the shortcomings of open data, users of open data often see government itself as part of the problem. Although there is much variation in how governmental bodies implement open data policies and programs, active members of the civic technology community often complain that governments should be

more active and involved participants in leveraging open data—not just as providers of data but partners in collective action (O’Reilly, 2010). One metaphor used to illustrate this critique is that of “eating your own dog food.” The expression is thought to reference either a commercial from the 1980’s in which the actor Lorne Greene endorses Alpo dog food by declaring that he feeds it to his own dogs, or the lore that an executive from Kal Kan Pet Food would eat a can of his company’s dog food at annual shareholder meetings (Harrison, 2006). Regardless of its true origins, in the technology industry, “eating your own dog food” (or simply, “dogfooding”) is invoked widely to mean using your own product—both to demonstrate that you have faith in its superiority, and to understand its glitches so they can be fixed for your customers (Caplan-Bricker, 2013). In an essay that identifies the open data movement as having “stalled out” and needing to “move beyond releasing data for data’s sake,” a professional technologist, civic activist, and blogger named Anthea Watson Strong (Strong, 2014) chides the government for not eating its own dog food.

The real problem behind our data quality issues, is that the people who have the power to fix the data, don’t have an incentive to understand the problem or improve it. Government officials are lovely people who work hard in under-resourced offices. Although many of them believe deeply in transparency and citizen engagement, these portals tend to generate additional burdens that get in the way of their primary functions. When data is stale or data is inaccurate, someone has to take the time to update it or fix it. It is difficult for any one group to see beyond the limits of their own projects. The real trick is to align incentives. What we actually need, is for Uncle Sam to start dogfooding his own open data.

Strong, 2014, n.p.

According to this perspective, it is unsustainable and inadequate for governments to maintain their own private stream of data for internal purposes, while pushing a separate stream of data externally for public access. If governments were to use public repositories as their sole data source and eliminate any back channels or siloed stashes, Strong argues, they would be

incentivized to continually maintain and improve this resource for both internal *and* external use. Scholars of infrastructure would, of course, recognize in these critiques and debates about open data portals a number of perennial issues in infrastructure development. We know that infrastructure must be grown in use, not conceived in the abstract for some vague prospective use; the “if you build it, they will come” approach is all but doomed. When infrastructures are centrally planned and implemented while divorced from real-world applications, there is no opportunity to configure them for the needs of those who use it (Edwards et al., 2007).

## MAKING PUBLIC DATA: DATA VAULTS AND DATA COMMONS AS SECOND-GENERATION INFRASTRUCTURES FOR GOVERNMENT DATA

### **Making public data versus making data public**

There is a growing sense, then, that in order for government data to be used to its full potential, governments must not just provide access to data for the public, but learn to make better use of data themselves. In recent years, approaches have been cropping up that share the goal of rendering value from data generated by public agencies, but, unlike the open data model, these approaches are based on use cases and close cross-sector collaborations between some combination of government, industry, academia, and civil society. A key difference between both the FOIA-based dispensary model and the open data reservoir model of infrastructure, on the one hand, and these other project-based collaborative models on the other hand, can be characterized as the difference between *making data public* and *making public data*. This distinction is inspired by Paul Edwards’ (2010) discussion of “making data global” versus “making global data” in the context of earth-wide climate modeling infrastructures. In Edwards’ (2010) study, “making global data” entailed the collection of data according to centrally-determined standards, while “making data global” involved building coherent data sets from heterogeneous data in a sort of *ex post facto* process of standardization. The distinction I’m

drawing is similar but not analogous, and should not be thought of as a straightforward transposition of those concepts to a new sphere of inquiry. In the context of governmental data, infrastructures for *making data public* support providing the public with access to governmental data (i.e. taking government data as it is and making it publicly available), while infrastructures for *making public data* support rendering governmental data useful to public institutions themselves as a way of benefitting the larger public. Put another way, making data public is about the government giving out dog food, and making public data is about the government eating its own dog food.

I have already discussed *making data public* at some length above. The infrastructures supporting the dispensary model of FOIA and the reservoir model of open data exist to facilitate the public in accessing governmental data that is thought to be inherently valuable. The development of these infrastructures undoubtedly involve many common issues we've come to understand as inevitable: contested politics, interoperability challenges, invisible labor, latent values, local-global tensions, competing interests, etc. As such, these phenomena are worthy objects of attention for infrastructure studies in their own right. However, the infrastructures supporting FOIA and open data have not been the focus of my empirical work, so I employ them here not as a primary object of study, but as point of departure and comparison for situating the importance of alternative models of infrastructure development for government data, those that I've categorized as *making public data*. In contrast to the data dispensary and data reservoir models exemplified by FOIA and open data portals respectively, this category of infrastructure is geared not toward merely *facilitating access* to governmental data, but toward *transforming* governmental data into something of public value. This doesn't entail indiscriminately opening governmental data to the public writ large; rather it means working collaboratively and

selectively to simultaneously make governmental data useful to public agencies themselves *and* non-governmental actors, such as private firms, educational institutions, nonprofit organizations, etc. Importantly, this involves these organizations working together to demonstrate the public usefulness of government data and to build an infrastructure that allows this usefulness to be replicated.

These attempts at *making public data* are different from *making data public* in a few key ways. First, they are wrapped up in broader efforts to build an entire knowledge infrastructure to support data intensive work in the public sector. As noted earlier, knowledge infrastructures are “robust networks of people, artifacts, and institutions that generate, share, and maintain specific knowledge about the human and natural worlds” (Edwards, 2010). STS scholars understand all technical systems to be social in nature, and often feel compelled to make this point to builders of technical systems who are thought to be blind to the imbrication of the social and the technological (c.f. Neff et al., 2017). But in my observations of efforts to make public data useful, the actors involved are often self-consciously aware that they are engaging in a deeply social process. Second, the efforts I’m concerned with in this chapter are project-based collaborations designed to develop a proof of concept with the intention that they will eventually lead to the establishment of a stable data infrastructure. These temporary configurations aren’t yet true infrastructures, but are intended to catalyze them. As such, I characterize these temporary attempts to demonstrate proof of concept not as infrastructures, but *exostructures*, a concept I will later explicate further in order to help us understand formative stages of infrastructure development.

## **Not information technology, but knowledge infrastructure**

Initiatives I've observed that are involving efforts to *make public data* recognize that they are not just developing technical capacity, but also reconfiguring social networks and organizational culture to support data-intensive knowledge production and decision-making with government data. In other words, they are not concerned solely with the adoption of a particular platform or technology, but are simultaneously and intentionally working toward a holistic knowledge infrastructure that includes the organizational arrangements, norms, and practices needed to support data intensive work. For example, the National Science Foundation's Big Data Regional Innovation Hubs were "established to foster multi-sector collaborations among academia, industry, and government" ("Big Data Regional Innovation Hubs: Establishing spokes to advance big data applications [solicitation]," 2017) to work on applied, data-intensive research that addresses the needs of various geographic regions in the US. Similarly, the MetroLab Network, launched in 2015 as part of the White House Smart Cities Initiative, has the explicit goal of building a network of city-university partnerships focused on data-driven urban innovation. Specifically, MetroLab hopes to foster the kind of urban innovation that "requires an emerging cross-disciplinary academic field, partnered with local government, to explore the ways that data, technology, and analytics can address urban challenges" ("MetroLab Network," n.d.). Importantly, what is being primarily supported in these initiatives are new social arrangements in the form of collaborations across sectors, as opposed to particular technologies or individuals.

Infrastructure, by definition, "has reach beyond a single event or one-site practice" (Star & Ruhleder, 1996). As such, infrastructure development is inherently about the ambition of scaling, about expanding the scope of an activity, about enlarging the reach of a technology. But

as Ribes (2014) points out, this scaling can be measured in many different ways, such as the number of participants or users, the geographic distribution of work, the amount of computational resources, and the range of disciplinary diversity (168). It is the latter sense that comes closest to capturing the knowledge infrastructure ambitions of the eScience Institute, whose mission is captured in its tagline, “advancing data-intensive discovery in all fields.” Importantly, “all fields” operationally has come to mean not only academic disciplines, but also non-academic spheres of activity. Over the course of the three years I’ve been embedded there, the organization has become increasingly involved in efforts to make data-intensive decision-making central to the work of governmental institutions and nonprofit organizations.

eScience leadership is deeply involved in both the NSF Big Data Hubs and the MetroLab network. They have also spun out complementary efforts including the UrbAnalytics Lab and the Cascadia Urban Analytics Corridor, entities focused on conducting research projects that have applied social impact in collaboration with local municipalities and regional agencies. Additionally, each year, eScience has hosted the Data Science for Social Good program, a 10-week-long intensive summer program that assigns teams of students to work on data science projects with social impact. The endeavors I’ve described—the MetroLab Network, the NSF Big Data Hubs, UrbAnalytics, Cascadia Urban Analytics Corridor, and Data Science for Social Good—are not easily compartmentalized in my study, but rather have overlapping membership and entwined objectives. Many of the same people are involved in leadership roles across these efforts, and several projects have been showcased in various venues across these distinct, but related, initiatives. What allows for such cross-pollination is that each of the efforts described above is oriented toward a common goal of advancing data-intensive computational methods for public benefit.

eScience has become deeply involved in this cross-sectoral work because it aligns with their mission of enabling what is called alternately “the fourth paradigm,” “e-science,” “data-driven discovery,” and “data science.” During the time that I was embedded at the eScience Institute, its work was largely supported through an influx of private foundation funds establishing a “Data Science Environment” (DSE) across three major research universities. The DSE, funded by the Gordon and Betty Moore Foundation and Alfred P. Sloan Foundation, is a partnership across New York University, the University of California Berkeley, and the University of Washington, with the goal of advancing data-intensive knowledge production. The DSE seeks to “catalyze a new era of research that enables interdisciplinary approaches to data-intensive discovery” by creating “new types of institutional environments in which these discoveries can take place” (MSDSE, n.d.-b). At each university, DSE funds and activities are directed by a lead organization—NYU’s Center for Data Science, the Berkeley Institute of Data Science, and UW’s eScience Institute. Affiliation with the Data Science Environment and its lead organizations is generally open to anyone from the host institution, and includes people from a wide range of academic domains and career stages. Although DSE participants at each of the three universities administer the DSE autonomously on their own campuses, they convene annually for an “all hands” summit to discuss their efforts and plans for the future. Each lead organization has a physical space on campus that serves as a point of convergence for DSE activities that address the challenges of advancing data science. Across campuses, those activities are organized around six thematic “working groups,” which, as will see, are each doing their part to develop a knowledge infrastructure for data science.

Paul Edwards reminds us that knowledge infrastructures are a sociotechnical phenomenon comprised of all things that make knowledge durable, sharable, and extensible, and

yet can easily be taken for granted (Edwards, 2010). This includes: social networks such as those described above; material resources such as physical places, tools, and media; social constructs such as community norms and values; designated roles with attendant systems for incentive, reward, and censure; specialized vocabularies; processes for establishing validity; and canonical methods, theories, and models. In many ways, the working groups of the DSE are engaged in efforts to instantiate each of these infrastructural elements of knowledge production. For example, there is a “physical and intellectual spaces” working group to foster places of convergence for data science activities; a “tools and software” working group to support the development of computational resources; a “reproducibility and open science” working group to normalize those eponymous values and practices and establish robust processes for verification; an “education and training” working group to develop curricula for propagating the vocabulary, languages, methods, theories, and models of data science; and a “careers” working group to support emergent roles in academic data science with funding and scholarly recognition. In addition, the DSE includes a “data science studies” working group led by a team of ethnographers like myself, which is tasked with reflexively interrogating the practices of data science and the efforts of the DSE community. The inclusion of the data science studies group reflects the community’s awareness that what they are doing is not purely a technical venture, but a sociotechnical one. In fact, leadership at the eScience Institute frequently refer to their efforts as an exercise in “social engineering” in an implicit acknowledgment of what Ribes and Finholt call the “multiple scales of action” involved in infrastructure development: not just the deployment of technical resources, but also the local work of organization and maintenance, and the work of institutionalization within the broader social milieu (Ribes & Finholt, 2007).

## **Project-based use case approach**

Aside from the goal of creating a holistic knowledge infrastructure, another characteristic that distinguishes *making public data* from *making data public* is that *making public data* involves the development of use-cases in project-based collaborations. Definitionally, infrastructure only becomes infrastructure once it has moved beyond particular use cases, after “transitioning effectively from one-off applications, demos, and prototypes to stable and usable informational facilities” (Ribes & Finholt, 2009, p. 376). But while use cases may not constitute infrastructure on their own, it is also true that under most circumstances, infrastructures can’t come into being without them (Edwards et al., 2013). According to Suchman, Trigg, and Blomberg (2002), the work of prototyping is to be constantly asking, “What have we got at this point, and what can we say about it and do with it, vis à vis the circumstances at hand? This is not to say that there is no constancy to the artefact. Rather, it is the reiteration of these questions and the construction of satisfactory answers to them that sustains its continuity” (p. 174). Thus, in the process of reconfiguring and reorienting to situated, localized circumstances, the prototype becomes “a reflexive probe into the practical materializations that configure new technological objects” (Lucy Suchman, Trigg, & Blomberg, 2002, p. 175) so that technologies can eventually be stabilized.

Open data portals seem to have skipped over the phase of use-case development, where contestation, improvisation, and iteration eventually lead to a reconciliation between local needs and the demands of scale. As a result, the open data infrastructure that currently exists for *making data public* has largely failed to produce the robust usage, added value, and collective action that open data advocates like Tim O’Reilly had envisioned. In contrast, the project-based collaborations that I’ve observed throughout my time at the eScience Institute are rarely seen as

ends in and of themselves, but rather are framed as proofs-of-concept that have the potential to spawn replication and eventually lead to an knowledge infrastructure for data-intensive work in the public sector. Participants in coalitions like the Big Data Hubs and MetroLab often talk about their aim to move beyond “boutique” solutions for specific, locally situated problems and find projects that are “scalable,” in that they can be replicated for new instantiations of those problems. Additionally, some of them are also explicitly geared toward developing data infrastructures for specific kinds of data.

#### EXPLICATING THE EXOSTRUCTURE CONCEPT: UPDATING A VENERABLE CONCEPT FOR THE AGE OF DATA SCIENCE

As we have seen, participants in this space are concerned with scaling their work, but in a different sense from the way scaling has typically been discussed in the infrastructure literature. Unlike large-scale scientific collaborations that have dominated the attention of infrastructure scholars in STS and CSCW, the efforts I’ve observed are not solely, or even primarily, concerned with developing shared computational resources that facilitate large-scale distributed collaboration. Rather, these are explicit efforts to spread the epistemological underpinnings of data science, guided by a belief that data-intensive inquiry and decision-making are inherently superior ways of knowing and deciding. As such, scaling here is not about developing shared infrastructural resources, but about the extension of data-intensive approaches to new applications or new contexts. Data science in the academy is envisioned as an epistemologically distinct approach that cuts across “domains”—an emic member term that captures a range of contextual distinctions, including disciplines, subject matters, problem spaces, and sectors. As such, the goal is not to build a one-size-fits-all, universal infrastructure. Rather, the goal is to produce data science artifacts that can be customized and reconfigured for new use cases by swapping in novel questions, unique data, and modified algorithms.

It is my contention that while this mode of scaling the data science endeavor shares certain characteristics of infrastructure, it is distinctive enough to require a fresh perspective and new vocabulary for describing and understanding the phenomenon. As such, I make two moves: I focus on short-term, project-based collaborations as a primary *modus operandi* for extending the scope and scale of data science, and I introduced the concept of exostructure as the vehicle by which data science is spread to new contexts.

As discussed earlier, the eScience Institute has several approaches for enacting its mission of “advancing data-intensive discovery in all fields.” This includes the development of formal educational programs such as a new masters’ degree and doctoral certificate, informal pedagogical opportunities such as peer-to-peer trainings, and the development of generalized software tools. But a large part of their work involves engaging in project-based collaborations, and it is this project-based, collaborative mode of propagating data science that I am concerned with here. The elements that I am considering to make up a data science project include: labor; articulated objectives and methods; and a suite of digital artifacts including some configuration of data, software tools, code, documentation. Sometimes, these projects support primary objectives that are ends in themselves: a report, publication, presentation, or tool, for example. In many cases, however, the hope is that, in addition to such primary objectives, the project’s digital artifacts will be later “scaled” by spawning replication or extension in another application. In still other cases, there is an explicit attempt to use these exostructures to catalyze the development of a stable information infrastructure in the classic sense. In the latter two instances, when project-based collaborations are meant to spawn extension of data-intensive computational approaches, either through replication or through the establishment of a stable data infrastructure, I consider those projects to be examples of *exostructure*. Exostructures are scaling mechanisms

in two senses then: then can be replicated in new contexts, or they can be iterated upon until achieving infrastructure status. Exostructures can be thought of in contrast to Latour's (1986) "immutable mobile", the term he uses for material artefacts such as printed books and maps that enabled the flourishing of science because they allowed knowledge to be transferred across space and time without being altered along the way. One of the ways data science flourishes, on the other hand, is through alteration and modular customization. It is characterized by the ability to adopt and adapt project-based applications, often by what data science practitioners would refer to as "cloning," "branching," and "forking" repositories of data, programming scripts, and software tools. Exostructure, then, is a concept that helps explain the rapid spread of data science as a paradigmatic approach to knowledge production.

Taking cues from Star and Ruhleder (1996), I find it to be more generative to ask not *what* is an exostructure, but *when* is an exostructure. Like infrastructure, exostructures have expanded scope or scale, in that they are able to "reach beyond a single event or one-site practice." A hallmark of data science is the opportunity for data, tools, and methods to be repurposed in a variety of contexts and applications. What is being scaled through these projects is data science itself—exostructures are a vehicle for expanding the desirability and capacity of data-intensive computational methods. Also, like infrastructures, they are embedded in other structures, they embody agreed-upon standards (although they also help new standards to emerge), they are built on installed bases, and they are linked to conventions of practice.

But in other regards, exostructure is quite different from infrastructure (Figure 5-1). According to Star and Ruhleder (1996), infrastructure is characterized by its "transparency," by which they mean that "it does not have to be reinvented each time or assembled for each task, but invisibly supports those tasks." In contrast, a key feature of exostructure is its *transience*, in

that it is intended to be remade for each new use case. This is the characteristic that inspired the use of exostructure as a metaphor, for, like the exoskeleton of certain insects, exostructures have a transient materiality that is supposed to be outgrown, rebuilt, or replaced. Any number of the components that makes up an exostructure—labor, software tools, code, documentation—is intended to be replaced or reconfigured in new contexts and for new uses. As such, there is no “taken-for-grantedness” as there is with infrastructure once it is “learned as part of membership.” Instead, exostructure is a site for customization and experimentation. People must learn how to be useful *with* infrastructure in course of their work; in contrast, people have to learn how to *make* exostructure useful as part of its development. Therefore, exostructures do not just become visible upon breakdown, as is understood to be the case with infrastructure; rather they are consistent objects of attention and iteration until and unless they evolve into an infrastructure. Infrastructure is also said to be “embedded,” or “'sunk' into, inside of, other structures, social arrangements and technologies.” Exostructure, on the other hand, is notable for its *portability*. It figuratively sits on top of infrastructure and connects action not as a stable, embedded base, but by jumping contexts. In sum, exostructures enable distributed action across contexts, time, and location much in the same way that infrastructure does, but they are not “ready-to-hand” as infrastructure is. Instead, they offer the occasion and site for a customization, replication, or iteration.

<b>INFRASTRUCTURE (Star &amp; Ruhleder)</b>	<b>EXOSTRUCTURE</b>
<i>Embeddedness.</i> Infrastructure is 'sunk' into, inside of, other structures, social arrangements and technologies. . .	<i>Portability.</i> Exostructures sits “on top” of infrastructure. They are not stable and sunken, but able to jump across contexts.
<i>Transparency.</i> Infrastructure is transparent to use, in the sense that it does not have to be reinvented each time or assembled for each task, but invisibly supports those tasks;	<i>Transience.</i> Exostructures are not stable and transparent to use, but rather, are meant to be customized and reconfigured for new use cases.
<i>Learned as part of membership.</i> The taken-for-grantedness of artifacts and organizational arrangements is a sine qua non of membership in a community of practice. . .	<i>Learned as part of development.</i> With infrastructure, people have to learn how to be useful with infrastructure, whereas people have to learn how to make extrastructure useful as part of development.
<i>Becomes visible upon breakdown.</i> The normally invisible quality of working infrastructure becomes visible when it breaks. . .	<i>Breakdown is expected part of iteration.</i> Unlike infrastructure, exostructures do not need to break in order to become the object of attention, but are meant to be iterated upon.
<i>Reach or scope.</i> This may be either spatial or temporal - infrastructure has reach beyond a single event or one-site practice. . .	Same
<i>Links with conventions of practice.</i> Infrastructure both shapes and is shaped by the conventions of a community of practice. . .	Same
<i>Embodiment of standards.</i> Modified by scope and often by conflicting conventions, infrastructure takes on transparency by plugging into other infrastructures and tools in a standardized fashion . . .	Same
<i>Built on an installed base.</i> Infrastructure does not grow de novo; it wrestles with the 'inertia of the installed base' and inherits strengths and limitations from that base. . .	Same

Figure 5-1. Infrastructure v. Exostructure.

## CONCLUSION

So far, I have introduced exostructure as a theoretical concept that explains a key mechanism by which data science and data infrastructures are being “scaled” across disciplines, problem spaces, and social sectors. In the following chapter, I return to the ORCA and AMOS projects that were introduced in Chapter 4, and tell the story of how these exostructural arrangements are supporting the ambitions for creating two very different types of public data infrastructures. I then use these empirical cases to explore the broader consequentiality of exostructures, interrogating their emergence alongside processes that are reshaping roles and relationships across social sectors.

The first case I discuss is the ORCA project, which seeks to make data from an electronic transit payment system useful for analysis, and in turn leverage that data to develop a vault-like data infrastructure called the Transportation Data Collaborative which will be used for sharing transportation network data with stakeholders across multiple sectors. The second example is the AccessMap/OpenSidwalks (AMOS) project, which seeks to build a commute routing application for people with limited mobility, and simultaneously leverage that work to develop a Pedestrian Data Commons, in which the government and the public would share and mutually maintain data about the pedestrian network. In supporting these two project-based exostructures, the eScience Institute is working toward its ambition of building a knowledge infrastructure for data science across all domains. And the project leads themselves have other ambitions to create durable sociotechnical arrangements that are undeniably infrastructural in nature.

Both the ORCA project and the AMOS project are centered on public data in the sense that their primary sources of data are representing public resources and are owned by public agencies. But the infrastructures that those projects are supposed to spawn are markedly different

from each other. As we will see, the defining value of the Transportation Data Collaborative is trust, and the aspirational infrastructure is conceived of as maximizing safeguards and assurances for stakeholders who would otherwise have strong incentives to keep their data to themselves. In contrast, the defining value of the Pedestrian Data Commons is openness, and the aspirational infrastructure is conceived of as maximizing participation and flexibility for stakeholders. The way these projects approach public data, and envision an infrastructure to support its use, differ not only from each other, but also depart markedly from the prevailing paradigm for making government data useful, the *making data public* model of online open data platforms. As such, I consider these nascent efforts to be alternatives to that reigning infrastructural paradigm, and posit that their emergence has implications for how we theorize and develop infrastructure.

## **CHAPTER 6 EXOSTRUCTURES IN ACTION: CASE STUDIES OF EXOSTRUCTURAL PROJECTS IN DATA SCIENCE FOR SOCIAL GOOD**

### INTRODUCTION

In 2015, the eScience Institute hosted in their space a one-day hackathon-style event convened by Data Champions (a pseudonym), an organization that specializes in matching non-profits and governments with data scientist volunteers. For this event, Data Champions had recruited about 20 volunteers, most of them with day jobs at technology companies, to spend a day running exploratory analyses on reams of traffic data, police incident reports, morphological features of the city, and even historical weather data. The idea was that the analysis of these data sets could inform the design and engineering of a transportation system that would result in fewer traffic fatalities, and several engineers from local government agencies were on hand to observe the work and answer questions about the data. When I spoke with the organizer of the event prior to its start, he told me that he sees Data Champions' project-based collaborations like this one as "Trojan horses"—they serve as vehicles for getting organizations excited about data, and then once they're involved, those organizations realize they need to make a significant commitment of time and resources to develop the infrastructure that will transform them into a data-driven organization.

This mindset is typical of the phenomenon that I explored in Chapter 5. There, I described how one of the important ways that proponents of data science are facilitating the growth of data-intensive computational methods in the public sector is through the development of project-based cross-sector collaborations. These projects are defined by particular configurations of labor, objectives, methods, and digital artifacts including data, code, and tools. I put forth that such project structures serve as vehicles for scaling the reach of data science and its epistemological underpinnings to new contexts, and—sometimes—also serve as an iterative

step toward a more stable data infrastructure. The term I have coined for this phenomenon is “exostructure.” Exostructures are a complement to the venerable concept of infrastructure, long recognized as an important mechanism for enabling the distribution and coordination of action across contexts. Exostructures, I have argued, shared a number of characteristics with infrastructure: they have expanded scope or scale, they are embedded in other structures, they are built on installed bases, and they are linked to conventions of practice (Star & Ruhleder, 1996). But they are quite different from infrastructures in other regards. While infrastructures are ready-to-hand, taken for granted, and invisible (Star & Ruhleder, 1996), exostructures are transient sites for learning and experimentation that get made, unmade, and remade in iterative steps. Sometimes, these steps lead toward their replication and customization in new contexts, and sometimes these steps lead toward a more stable infrastructure. In Chapter 5, I posited that exostructures are not only a key way in which data science is being spread to new social contexts, but also that they are an important mechanism by which a new generation of public data infrastructures are being developed.

As we saw in the last chapter, there is a widely held belief that making public data work for the benefit of society requires the engagement of both academia and private industry, where knowledge infrastructures for data science are thought to be already further along. At the same time that this message is being pushed from the bottom up by nonprofit and grassroots organizations like Data Champions, it is also being encouraged from the top down, through federal government initiatives like MetroLab and Big Data Hubs. What we are seeing, then, is a widespread belief that governmental bodies are largely missing a knowledge infrastructure for data science, accompanied by diffuse efforts to fill that gap and bring those sectors more in line with data science capabilities in industry and the academy. In other words, this infrastructural

development endeavor consists of concerted efforts to take a data science knowledge infrastructure and apply it to a new social context.

Data science is often celebrated for being agnostic to discipline and transferable across contexts. For example, when one Data Science for Social Good team was looking for a way to identify family units in data from social service agencies, they applied a hierarchical clustering technique that one of the astrophysicists on their team routinely used for identifying the sources of fragmented radio signals from outer space. When the team presented this analysis to their partners from social service agencies, one of them started applauding. “They love the concept that we’re using astrophysics algorithms in this sort of science,” said the astrophysicist. “That is a great story. They love that. They love that [one of the other data scientists] comes from neuroscience and that I come out of astro[physics].” Moments like these, then, are celebrated as the fulfillment of one of the promises of data science—that its methods are portable across contexts, applicable to a wide range of datasets, and relevant to research questions about diverse phenomena. Importantly, though, the code for the clustering algorithm could not have simply been shared with the public agencies for them to use it on their own. The transference across contexts required an exostructure consisting of focused questions and objectives to orient the work, an assembled team with multiple types of expertise, a collaboration between stakeholders in different sectors, the appropriate selection of methods, and the translation of specialized languages, tools, and values.

Having previously established that exostructures are a key way that data science is being spread to new contexts—and in particular, to government entities—in this chapter, I turn my attention to focus on the consequentiality of these exostructural arrangements. Coming from a perspective on sociomateriality that sees action and structure as being imbricated, emergent, and

co-constituted, I argue that new sectoral roles and relationships are emerging through a set of transformative processes enabled by the combination of exostructural configurations and the adaptive qualities of the modern research university.

I have characterized exostructures as vehicles for the methods, tools, and techniques of data science to jump contexts from the academic and industry spheres into the governmental sphere. Importantly, this context jumping is dependent upon the labor of coordination, articulation, and translation by collaborators from across these different contexts. As such, the data science for social good exostructures I've described above can be thought of as special cases of cross-sector collaboration; it is important, therefore, to situate exostructural arrangements in DSSG within the historical context of increasing collaboration across sectors in recent decades.

David Siegel (2010) identifies several antecedents to this trend. First is a long-term shift in the U.S. toward the privatization of public services that is driven by two distinct but non-mutually exclusive notions: the widespread distaste among the American electorate for a “big government” social welfare state, and the belief that non-governmental actors can outperform the public sector in efficiency and competence. Second, there is a growing awareness of the complex and multi-faceted nature of social problems, resulting in mounting pressure for actors to address their own complicity in the perpetuation of those problems. This is evidenced by phenomena such as the “engagement movement” in higher education and the “corporate social responsibility” movement in business (Siegel, 2010, p. 1-2). Third, there is also a belief that collaboration sparks innovation by bringing together varied perspectives and skill sets, allowing social actors to “think outside the box” and develop here-to-for unimagined solutions to social problems (Siegel, 2010, p. 6). Bryson and Crosby (2016), meanwhile, put forward their own premise, that sectors are likely to collaborate when they realize they have failed at fulfilling their

own mandates (p. 45). But if cross-sector collaboration is fundamentally driven by failure, as they maintain, this begs the question of who has failed. Whereas Siegel (2010) sees cross-sector collaboration as part of a privatization movement in which government is ceding responsibilities to the private sector, Bryson and Crosby (2016) consider the historic role of government to be stepping in only under circumstances in which the private sector has failed.

For Selsky and Parker (2005, 2010), however, cross-sector collaboration is not a monolithic phenomenon with a single or simple antecedent. They see different types of collaborations resting on distinct “platforms,” each with their own set of logics, drivers, and relationships. First, a cross-sector collaboration based on a *resource dependence platform* is informed by a logic of resource acquisition or possession, in which the participating organizations obtain some resource through the collaboration that allows them to improve the performance of their own roles and the attainment of their own goals. Each organization, in essence, is participating to address its own needs. The collaboration is mutually beneficial, organizations retain their autonomy, and each sector maintains clearly delineated functions and boundaries. A second type of cross-sector collaboration is based on a *social issue platform* that is informed by the logic of contribution, in which the participating organizations work together to fulfill their own social responsibilities, as they share a common definition of the problem they are trying to solve. Their collaboration is marked by segmented interdependencies, in which functions are distributed or shared, and task boundaries may overlap. Third, a cross-sector collaboration based on a *societal sector platform* is based on the logic of inclusion or identity, in which the participating organizations are working to reshape the norms by which various sectors operate in response to an environment of turbulence or complexity. The definition of the problem they are working on is emergent and in the process of being constructed. The collaboration is

marked by integration, with the functions and boundaries of various sectors being in flux. In these cases, cross sector collaborations are not about addressing failure or compensating for inadequacies, but may serve as “harbingers” of greater social change, “designed to experiment with new sectoral roles and functions” (Selsky & Parker, 2010, p. 22). I argue that the exostructural arrangements I explore below through the ORCA and AMOS projects should be understood as this latter type of cross-sector collaboration, in which sectoral roles are blending, evolving, and emerging.

Loet Leydesdorff and Henry Etzkowitz (1996, 1998), two scholars of science and technology policy, have discussed the shifting roles and relationships between universities, governments, and industrial firms in terms of a “triple helix” metaphor. According to Etzkowitz (2008), a triple helix arrangement “typically begins as university, industry, and government enter into a reciprocal relationship with each other” (p. 8), and through “processes of mutual adjustment” (Leydesdorff & Etzkowitz, 1996, p. 284), their collaboration evolves into a “regime of transition” in which each sector ends up “playing both their own traditional roles and each other’s, in various combinations” (p. 147). This recombination forms “the basis of societal creativity” (Etzkowitz, 2008) and drives innovation that, from a Schumpeterian perspective, stimulates economic growth (Leydesdorff & Etzkowitz, 1996; Schumpeter, 2017/1983).

The triple helix literature is concerned in particular with the evolving role of universities, which has undergone a number of transformations in recent decades. Among those was the shift from a near-exclusive focus on liberal arts education to an emphasis on basic scientific research, following the recommendations made in Vannevar Bush’s (1945) watershed “Endless Frontier” report, which launched what would become the National Science Foundation. This transformation was followed several decades later by a growing emphasis on applied research,

hastened by the passage of the Bayh-Dole Act in 1980, which ensured intellectual property rights for academic researchers and institutions funded by the federal government. These developments have led to what Etzkowitz calls “the entrepreneurial university” (Etzkowitz, 1983) that now plays an important role in transferring technology to the private sector, spinning off new firms, and spawning regional investment (Etzkowitz, 2008). Not only are universities becoming more like businesses, according to Leydesdorff and Etzkowitz, but businesses are becoming more like universities in an economy where technological innovation requires significant investment in research and development (Leydesdorff & Etzkowitz, 1998). For Etzkowitz, all of this means that universities are essentially “the predominant organizational format of a knowledge-based society” (Etzkowitz, 2008, p. 147). The triple helix formulation encourages examination of the evolving relationships between institutional helices (what I call “sectors”) rather than a focus on what is happening within institutions, warning that “an economic and science policy analysis that fails to consider these potentials for recombination of elements among the helices will miss the lessons of several decades of experience in knowledge-based economic developments” (Leydesdorff & Etzkowitz, 1996, p. 285).

The triple helix model offers useful provocations, but is limited in several important ways. First and foremost, it is concerned exclusively with questions of economic growth. Although Leydesdorff and Etzkowitz’s (1996, 1998) original formulations emphasize the many possible recombinations and reconfigurations of roles and relationships among universities, governments and businesses, the authors have focused on these institutional roles only in so far as they relate to economic growth and development. As such, the triple helix literature ends up casting respective sectors into limited and relatively stable roles: universities innovate and spawn

business, business creates profit from research and development, and government referees the relationship between them.

A second limitation of the triple helix concept is that it falls short of providing equal treatment to every level of analysis identified in Leydesdorff and Etzkowitz's original formulation, which include: "the economic dynamics of the market; the internal dynamics of knowledge production; and governance of the interface" of the helices (1996, p. 279). While the authors spend time elucidating macro-economic market dynamics and historical developments in the governance of cross-sector relationships that have facilitated the emergence of the triple helix model, they have little to say about "the internal dynamics of knowledge production" (Leydesdorff & Etzkowitz, 1996, p. 279). Although they acknowledge that "global developments induce local dynamics, and local recombinations constitute the variation for higher-order systems" (Leydesdorff & Etzkowitz, 1998, p. 198-199), the foundational formulations of the triple helix model are not based on empirical observations in the local contexts of knowledge production, so this aspect of the model goes under explicated.

A third limitation of the triple helix model is that it doesn't account for the presence of civil society or nonprofit organizations. This exclusion was critiqued from the outset by participants in one of the original conferences that spawned the triple helix idea in 1998 (Leydesdorff & Etzkowitz, 1998), who wanted to see the inclusion of nongovernmental organizations involved with economic development efforts in lesser-developed countries. Leydesdorff and Etzkowitz's response was that nonprofits and NGOs didn't have a place in the triple helix model because its purpose was "for analyzing innovation in a knowledge-based economy" (1998, p. 198). This implies that innovation occurs only in highly economically and technologically developed societies, a notion that scholars of decolonized science and technology

studies have contested (Philip, Irani, & Dourish, 2012). But also, in the highly technologically advanced western societies that Leydesdorff and Etzkowitz are primarily concerned with, nonprofit open source communities are quite frequently responsible for innovations that have enormous impact, economically and otherwise. For example, the mother of all community-driven open source projects, the Linux operating system, runs all 500 of the world's most powerful supercomputers (Vaughan-Nichols, 2017), and the nonprofit WordPress Foundation supports the open source website content management platform that is used by more than 25 percent of the world's websites (Munford, 2016). This makes Leydesdorff and Etzkowitz's dismissal of NGO's seem shortsighted. Accordingly, since the original formulation of the triple helix, authors have suggested amending the concept to accommodate other helices. For example, Carayannis and Campbell proposed a quadruple helix that includes "the media-based and culture-based public" (Carayannis & Campbell, 2009), then added on a fifth helix for "natural environments" (Carayannis & Campbell, 2010). And Leydesdorff (2012) himself has suggested that the model might be extended to accommodate any number ("n-tuple") of helices.

Here, based on my observations in the field, I offer a modification of the triple helix concept that addresses the limitations described above. I retain several of the broad provocations suggested by Leydesdorff and Etzkowitz's model: 1) a focus on interactions between sectors rather than actions within sectors 2) an assumption of recursiveness in the way participants in cross-sector collaborations shape and are shaped by their participation 3) the emerging preeminence of the university in a knowledge-based society. But while building on these provocations, I offer a perspective that diverges from the original triple helix formulation in three ways. First, I ask what can be learned about the emergent relationships across helices (or sectors, as I prefer to call them) by looking beyond questions related to economic growth. The

phenomenon I've outlined in the previous chapter—efforts to make public data useful for society through exostructural collaborations—does not seek innovation first and foremost for the sake of the economic growth, but for the sake of public good. Therefore, I do not take up arguments about the economic impact of the triple helix, and instead am concerned with cultural and institutional changes. Second, rather than focusing on the macro-economic and regulatory contexts of the triple helix, I focus on the context of knowledge production, attending to the practices, processes, and artifacts enrolled in cross-sector collaborations. Third, I do not constrain my analysis to the relationships between universities, businesses, and governments, but also include the role of a distributed open-source community.

Below, I present further depictions of the projects I introduced in Chapter 4, the ORCA project and the AMOS project, this time illuminating their role as catalysts for longer term plans to develop data infrastructures in support of stable and sustained cross-sector collaboration. I argue that in the process of working toward such infrastructural ambitions through exostructural collaboration across sectors, the participants are engaging in process of realigning sectoral roles. I use this structural configuration as a starting point to understand the actions that are supported by and imbricated within it. As Paul Dourish (2004) has said, we must treat “the stable features of everyday interaction not as underlying structures to be captured and modelled, but as the outcomes of practical action. We can support the emergence and use of these structures, but we cannot separate them, analytically or technically, from the circumstances and occasions of their production” (p. 29). In that spirit, I turn to the processes that are imbricated with exostructures, and explore their consequentiality for the role of the university. Through the stories of ORCA and AMOS, I surface four interrelated processes that are enabled by and enmeshed within the characteristics of exostructure: how the portable nature of exostructure facilitates the translation

of data-intensive methods across contexts and spawns infrastructural investment; how the transient nature of exostructure allows for experimentation with roles and relationships; how the iterative nature of exostructure and concomitant anticipation of breakdown and repair provides for the mitigation of risk; and how the customizability of exostructure that requires it be learned as part of its development prompts the mobilization of intellectual skills. I argue that through these processes, the university is emerging as a key player in the datafication of governance, taking on the role of developer, trusted mediator, entrepreneur, and source of intellectual labor.

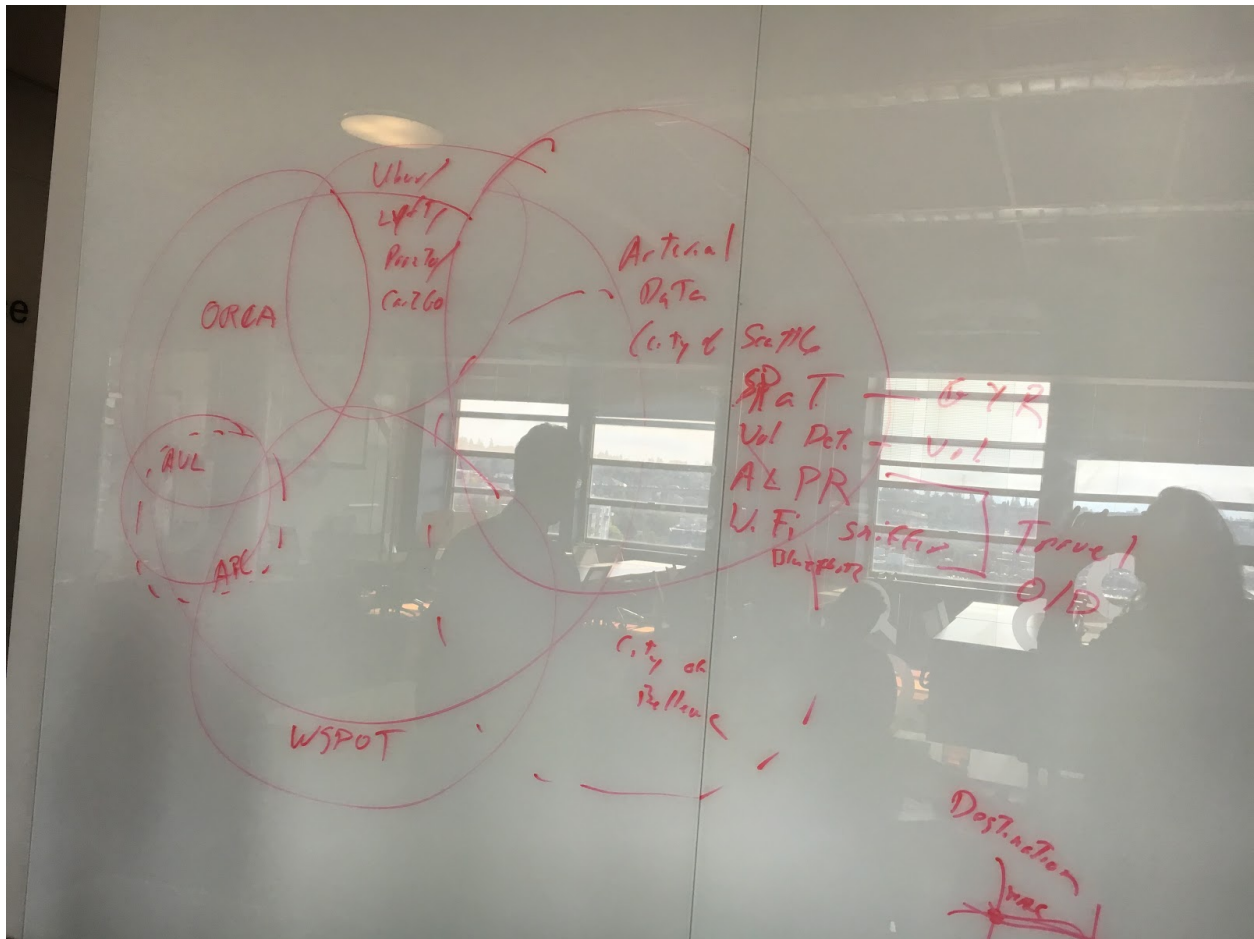
#### FIELDWORK STORY: THE ORCA PROJECT AND VISIONS FOR A TRANSPORTATION DATA COLLABORATIVE

The first case I turn to is the ORCA project. As noted in Chapter 4, this is an effort led by Mark Hallenbeck, a research scientist at the University of Washington, which seeks to analyze data generated by the electronic payment system for public transportation in the Seattle region. For seven years since the system was introduced, this data was used only for transactional purposes like maintaining riders' account balances and for operational purposes like performance evaluation and management. But Mark hoped to prove the ORCA data's usefulness for making predictions and doing strategic planning. With 30 years of experience collaborating with transit bodies, he knew they were hesitant to analyze this transaction data because of its sensitivity: it contained records of riders' transit use that could be cross referenced with the location of transit vehicles they boarded in order to reveal patterns of movement around the city. Mark was able to convince the agencies that the university had the expertise, resources, and regulatory structures in place to safeguard the data and make it useful. After receiving permission to access the data from the ORCA governing board, he hired a graduate student to structure and clean the data, and also applied to participate in the eScience Institute's Data Science for Social Good program so that a team of four other students could spend a summer analyzing the data. His goal was

seemingly simple: to demonstrate that the ORCA data could be useful for planning purposes and to convince the transit boards that it would be worthwhile to further invest in an infrastructure to support it.

Mark's infrastructural ambitions for this project are two-fold. First, he wants to develop an infrastructure for the ORCA data itself that renders it usable for analysis and planning. This entails developing a package of algorithms for joining the ORCA data with other relevant datasets, cleaning the data of errors and anomalies, modeling the biases in the data, doing transformations to create variables that are relevant to planners, and storing this transformed data in a secure, efficient, and stable database structure on the cloud. With such an infrastructure in place, new batches of ORCA data can be automatically cleaned, transformed, and organized as they're added to the database, so that analysts and planners from multiple transit agencies will not have to recreate this labor every time they wish to use the ORCA data. Second, Mark envisions the ORCA data eventually being folded into a larger information infrastructure that combines transportation data from a number of sources, allowing for analysis and control of the entire transportation system.

A few days after the DSSG program begins, I ask Mark to tell me about the stakeholders in his project. He rattles off which of the transit bodies in the region are essential for getting access to the ORCA data, which ones are involved in directly informing the analyses he runs, which ones will be most interested in preliminary results, etc. But those are just the organizations that currently have a stake in this phase of the project, he says. He has much bigger plans for this work.



**Image 6-1. Mark’s vision for a Trusted Data Platform**, depicting data from different entities to be included.

Eventually, he wants to see the ORCA data combined with data about other modes of transportation, including the city’s traffic counts on arterial roads, the state’s traffic counts on highways, and data from private transportation companies like Uber and Lyft. To get all these entities to share their data, this would have to be a trusted network with robust privacy protections and restricted permissions. The idea is that the university would maintain the data, and other stakeholders could query it based on the explicit permissions they’re granted by the network, so that they “can do the math without ever seeing the data.” He gets up and walks over to the wall, which, in the fashion of modern open-plan offices, is plated in glass so that the surface can be used as a whiteboard. Mark selects a red marker and starts drawing a messy Venn

diagram on steroids, with big, overlapping circles representing different stakeholder organizations and the types of transportation data he imagines each of them contributing to a joint data repository. With all these data sources integrated, he continues, the entire transportation network can be monitored in real time and smoothly orchestrated by timing stop lights, changing lane access, and directing travelers for the most efficient flow of traffic. What he's describing is a common pursuit in utopic smart cities visions: the city as a smoothly functioning system that can be monitored and controlled in real-time.

### **Getting provisional answers**

But the students who are working with the ORCA data in the DSSG program this first summer aren't involved in working on this infrastructure. As I discussed in Chapter 4, after lengthy discussions and deliberations, the team decided that their primary focus would be on identifying and correcting biases in the data. Suffice to say here that once the students began working with the data, they realized how full of errors, inconsistencies, and anomalies it was, and they spent the majority of their summer cleaning and wrangling it. Toward the end of the program, however, the students wanted to have some more tangible results to show for their efforts, and so they turned their attention away from the bias problem and cleaning tasks, and focused more so on conducting analyses and creating visualization tools, in spite of the fact that bias was still not a solved problem. Everyone on the team knew that these products weren't bulletproof and couldn't be used for planning or evaluation of the transit system due to the fact that the underlying data was still highly problematic. But the students nonetheless presented their preliminary analyses at presentations attended by members of the transit agencies, and Mark also started circulating their work in his own presentations to his stakeholders. This is because, even if they were tentative and temporary, the artifacts the students produced did have the power to

demonstrate what might be possible with further investment in the ORCA data. And this was really all that Mark needed for the moment.

And so, six months after the students' final presentation to the public, Mark is back at eScience, discussing the possibility of working with another DSSG team the following summer. He tells the staff how well the students' work from the previous year had been received by his stakeholders. "Those analyses they did last year," he says, "they were jerry-rigged at the last minute, but man does it make an impressive visualization. It makes people go –," finishing his thought by raising his hands to his temples and spreading open his fingers to mime eyelids widening in wonder.

The eScience staff, for their part, remain excited about the potential of the ORCA data, but they're concerned about the possibility of students spending the entirety of another summer on data cleaning and engineering without having solid analytical results to show for it, so they ask Mark to articulate what the "deliverables" would be for the summer. The key deliverable, he responds, is standing in front of the transit bodies and showing them all the cool stuff we did. His main goal is still simply getting the data into a condition in which it can be used for analysis, and demonstrating its value to the transit bodies. To do this, he knows that they still need to figure out the bias question, and a few other things that would help make the data useful as well; as he has noted on other occasions, the ORCA card was designed as a payment system, not as a data collection system, and as such, a number of transformations must be performed on the data to create categories that will be meaningful and useful to transit planners.

One such transformation is the generation of origins and destinations that can give planners a sense of where people are going when they use public transit. For public trains, this is a straightforward process. Because fares are based on the distance traveled, riders "tap" their

card on a scanner to make a payment when they start their trip, and they tap again when they get off the train. This doesn't happen on buses, however, as the standard fare doesn't vary with distance. For bus trips, the ORCA system only records what time and on which bus a passenger tapped their card to make a payment upon boarding. To determine where in space the tap took place, they have to figure out the location of that vehicle at that particular time, which they can do because all transit vehicles are equipped with GPS transponders that produce an automatic vehicle location (AVL). By joining the ORCA data with the AVL data, they can determine the exact bus stop where a passenger boarded. But they would also like to know where that person got off the bus. And since bus riders don't tap off to end their trip like they do on the passenger trains, Mark would like to figure out a way to infer that information. So an important goal for this summer is to generate a table of origins and destinations for each ORCA transaction.

But Mark has learned some lessons from his experience as a project lead last year. This time around, he plans to have concrete research questions in place so the students can work on the bias, transfer, and origin-destination analyses while answering substantive questions about the transit system. He plans to have the team focus on the University District, the neighborhood surrounding the University of Washington campus, and explore how the recent opening of a new light rail station had impacted bus use in the area.

### **Building to rebuild**

This seems to assuage eScience's concerns, and they turn to discussing the data pipeline, including issues such as where the data will be stored and how the students will access it. As Mark starts describing the current components of the data pipeline, one of the data scientists who has volunteered to serve as a mentor on the project becomes increasingly concerned. In the course of the conversation, Charlotte (a pseudonym) learns that data files are created in

LabView, then loaded into an SQL database for pre-processing, and then copied over to a Postgres database for analysis purposes. And then sometimes, people are pulling data from Postgres, doing transformations locally, and writing those files back into SQL tables.

Charlotte is horrified at how inefficient this circular process is, working back and forth between two different databases. She would prefer that everything be in one Postgres database. She's okay with doing the preprocessing in SQL—since that should, in theory at least, be done just once—and then transferring the data over to Postgres for analysis, as long as no one ever touches the SQL database again and all the analysis is done within Postgres. But constantly moving back and forth between them is computationally inefficient and makes version control a nightmare. “I think you need to make a management decision to have people working for you do their analysis in Postgres,” she says. “And that’s a strong recommendation.”

Mark, however, is concerned about making such an injunction because most of the people who work on the project are already comfortable with the SQL database query language. He jokes about how he’s an old man who hasn’t kept up with advances in computing over the last several decades, so he relies on students to do the heavy lifting computationally while he provides the subject matter knowledge to inform their work: I hand them tasks, he says, and they either hand me questions and I answer them, or they hand me results. A rotating cast of undergraduate and graduate students have cycled through this project in the last couple years, often working in short-term stints dictated by the 11-week long quarters of the academic calendar. If he demanded that everyone who came through his lab learn new tools, they would spend all their time getting up to speed and not producing results. Therefore, he says, “I never argue with students or staff using the tools they know.”

Charlotte is sympathetic to this argument. She's run into similar issues in her own work on international collaborations. Her team is working with people in four different countries who are paid from different sources, and there's no way to dictate that they all use the same tools. "But it creates a management problem," she says, and the one thing they have been able to agree upon is that they should all be working from a single, central database. If Mark can do the same, he should. She understands that people are coming into the project with different backgrounds and skillsets, but it shouldn't be difficult for someone with SQL skills to pick up Postgres.

Mark replies that if he viewed the students' work as a long-term solution to managing the ORCA data, he would agree. But that's not the plan. All he needs is for the students to provide a proof of concept that can be built upon in the future. "The reason you hire the university to do this exploratory stuff is because we'll get it wrong the first three times, but the fourth time it will work," he says. "And it's much cheaper to work with us than start some millions-of-dollars IT project that's not going to work." The students' work need not be perfect because someone else is going to come along and iterate upon it. "I'm hoping the whole thing gets rewritten from scratch next year," he says.

Mark is referring to a budding relationship with Microsoft, which has been in conversations with the regional transit agencies and municipalities to build the architecture for the trusted data network Mark described to me the year before, which is now being called the Transportation Data Collaborative (TDC). In recent months, this idea has been gaining traction, and Mark is angling for the ORCA data to be the first data set to be added to the repository that is eventually supposed to include other data from the transit agencies, departments of transportation, and commercial transportation companies.

## **Highlighting the promise and peril of the TDC**

About a month after this planning conversation between Mark and eScience, and a month before the DSSG program actually begins, I get a better sense of what the Transportation Data Collaborative is and how it will work at a public workshop convened by the Northwest Institute for Advanced Computing (NIAC), a partnership between the University of Washington and the Department of Energy's Pacific Northwest National Laboratory to "take on the most pressing problems facing science and society" (Pacific Northwest National Laboratory, 2013). NIAC has hosted a series of workshops since 2013, and this one is focused on transportation and smart mobility. As such, the proposed Transportation Data Collaborative is at the forefront of people's minds.

For example, one speaker from the City of Seattle discusses the goal of providing the region's population with a mobile based application in the model of "mobility as a service," a system that aggregates and coordinates real-time data from multiple modes of transportation into a single platform so that users can be presented with options for different ways to link segments of their journey. For example, they might see that the quickest option is to take a train from downtown to a transit center in the suburbs and then hire an Uber to travel the last mile to their destination—but the most affordable option is to take two buses to a stop a third of a mile from their destination and then walk the rest of the way. In order for this vision of real-time, integrated transportation data to work, though, they need systems in place that uphold the privacy of individuals and protect the proprietary claims of all entities contributing their data. So the idea is to "tether" the mobility as a service platform to the Trusted Data Collaborative that's in the works.

After this, a speaker from Microsoft addresses the audience to talk about the company's vision for the TDC and their role in making it happen. First, he explains why the issue of trust is so important. If you want private transportation companies like Uber and Lyft to contribute their data, he says, you have to understand why they're so reticent to share it in the first place. One is that they're afraid the government will "pull out the regulatory hammer and hit them with it" if, for example, the government can see from the data that companies aren't serving low-income communities. But the even bigger concern, he says, is that their data will be leaked to competitors, allowing them to reverse engineer proprietary algorithms that give them an advantage in the market. What they need to build is a "vault," in which vested and vetted parties can query the data without ever accessing the raw files, governed by data sharing agreements that determine which queries each party can perform based on their membership and security credentials. Microsoft's role in the proposed infrastructure would be to host the data on their Azure cloud platform and build the architecture for "role-based access control" that will protect the data. This includes credentialing systems, layers of encryption, and algorithms that assess whether any given query meets the relevant data sharing agreements.

Next, a professor from the University of Washington who has been working on the policy framework for the TDC gets up to talk about the university's role in the collaboration. While the last speaker from Microsoft focused on the need to protect the data from competing interests of data co-contributors, the UW professor's primary concern is on protecting the privacy of individual transportation users. She reminds the audience of how trivial it can be to re-identify naively anonymized data, citing research out of MIT showing how, with just four spatio-temporal points, 90 percent of individuals in a set of mobile phone call data records could be identified (de Montjoye et al., 2013). Washington State has one of the most expansive public

records laws in the entire country, she explains, which mandates that if a public agency uses data to make a decision, it has to be made public unless an exemption has been secured on an *ad hoc* basis. She's concerned that a massive database with linked travel records could potentially be subject to public release, which would compromise the safety and security of individuals who are represented in the data. This is where the university's role is key, she says. She's working with the Attorney General of the University of Washington to confirm that if the TDC is hosted at UW as research data, it will automatically gain privileged protected status that exempts it from public records requests. Researchers can then use computational techniques to derive a privacy-protecting version of the data for public release.

Nearly every speaker at the NIAC conference had something to say about the Transportation Data Collaborative. A number of projects, like the proposed Mobility as a Service application, would rely on this infrastructure if and when it got built. It was clearly the star of the show, generating ample interest, excitement, and support. What drew less attention at the meeting was a brief presentation given by Anat Caspi, who offered a vision for a very different kind of a transportation data infrastructure, a pedestrian data commons. And with that, I return my attention to Anat's AccessMap/OpenSidewalks project.

#### FIELDWORK STORY: THE ACCESSMAP/OPENSIDEWALKS PROJECT AND AMBITIONS FOR A PEDESTRIAN DATA COMMONS

In Chapter 4, I introduced the AccessMap/Open Sidewalks (AMOS) project. To recap, the project began with the goal of building a routing application that would account for aspects of the built environment influencing travel decisions for people who use wheelchairs or have other limitations in navigating the built environment. This includes information such as the location of sidewalk curb cuts, the presence of crosswalks, the steepness of an incline, and the surface quality of a pedestrian path. While static maps displaying certain accessibility features

were already available through the City of Seattle, such information about the built environment was not available in dynamic digital form comparable to popular routing application such as Google Maps or Waze. The AccessMap project was originally conceived of during a “hackathon” event sponsored by the City of Seattle called “Hack the Commute” that was designed to prompt the use of open datasets published by the city. At this event, UW graduate student Nick Bolten met UW computer scientist Anat Caspi, and they came up with a plan to use the city’s sidewalk data to create a routing application called AccessMap. The idea received top honors at the hackathon, which won their team free resources from business sponsors to support their work. Nick and Anat have been working closely together as the leaders of the project ever since, with a rotating cast of team members and contributors cycling through the project.

In a previous chapter devoted to ethics, I detailed how, in addition to building AccessMap for the City of Seattle, Nick and Anat were simultaneously working toward a more expansive vision. They hoped that their efforts in Seattle could be duplicated across cities around the world, and even more broadly, sought to elevate the status and availability of pedestrian network data to spawn further imagination of a more inclusive pedestrian-centric society, and innovation in pedestrian-centered technologies. These complementary efforts they called the OpenSidewalks project, and I have referred to the intertwined AccessMap and OpenSidewalks teams and projects as AccessMap/OpenSidewalks, or AMOS.

Nick and Anat’s work was supported by the eScience Institute’s DSSG program for two years in a row, which provided them with a team of four students each summer who were assigned to work full time on the OpenSidewalks initiative. The team came into the second summer of the DSSG program with a live, public (though beta) version of AccessMap. If their only goal was to create a tool to help people with limited mobility navigate Seattle, they could

have simply continued updating their application as changes were introduced to the municipal data set. But they needed a reliable mapping infrastructure that could support their broader ambitions of replicating AccessMap and shifting the paradigm in how the pedestrian network is prioritized. To these ends, AMOS decided they would eventually replace the base layer of AccessMap and build it on top of OpenStreetMap (OSM), an open-source mapping platform that is widely used around the world. OSM could serve as a repository with global reach, with which they could both contribute and retrieve sidewalk data.

Essentially, the team wished to catalyze the development of a robust layer of pedestrian network data in OSM, a data infrastructure to support pedestrian-centric thinking and technology design similar to the way the map already contains a cycling layer, a transit layer, and a humanitarian layer to support different modes of mapping and planning. But the commonly accepted practices in OSM for mapping pedestrian features of the built environment—such as sidewalks, crossings, and curb ramps—were sub-optimal for pedestrian-centric routing applications like AccessMap. And so the AMOS set out to change the way things were done.

In Chapter 4, I highlighted the ethical dimensions and implications of the data schema they proposed to the OSM community—what they hoped would come to be accepted as a “functional standard” in mapping the pedestrian network in OSM. In the process, the team made a number of trade-offs and compromises when balancing the priorities and values of their target beneficiary community for the AccessMap project, and other groups with stake in the OpenSidewalks work, including OSM.

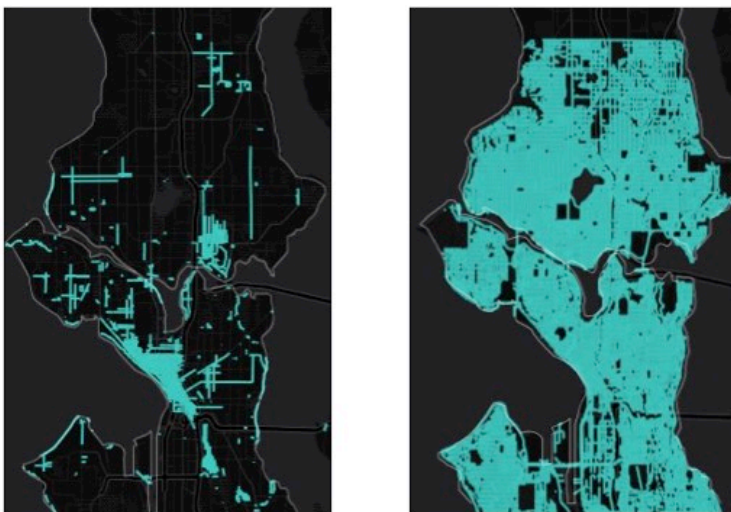
Here, in order to draw out the infrastructural ambitions and implications of the AMOS work, I turn to a second major proposal the team put forth to OSM, a proposal to import municipal sidewalk data into the map *en masse*. In separating the treatment of these two issues,

in no way do I mean to imply that their proposed data schema did not have infrastructural implications, or that their proposed data import does not have ethical implications, as both issues are very much entwined. I only mean to highlight different aspects of their work as occasions for exploring distinct theoretical constructs and practical implications. Giving the data schema and data import separate analytical treatments also makes sense because of the way the AMOS team themselves bifurcated these two goals by making them separate proposals to the OSM community. In part, this was a strategic move, as they realized that the community might embrace one proposal while opposing the other.

In Chapter 5, I set up a theoretical argument that informs my treatment of AMOS's infrastructural ambitions and their plan to import municipal data into OSM. Previously, I put forth that project-based approaches in data science motivated by ambitions of spawning replication or infrastructural investment can be understood as "exostructures," a concept that complements and builds upon our understanding of information infrastructures. Like infrastructure, exostructure enables the scaling of action across context, time, and location much in the same way that infrastructure does, but they are not stabilized and "ready-to-hand" as infrastructure is. Instead, they offer the occasion and site for transportation, iteration, replication, and customization. In what follows, I dive into the case of the AMOS project to draw out the ways in which the project can be understood as an exostructure supporting their larger infrastructural ambitions. Following this detailed account, I explore the implications of such an exostructural arrangement, calling attention to the ways in which processes of transformation are imbricated with the structure of exostructure, and how these processes are resulting in shifting and emergent roles for the university.

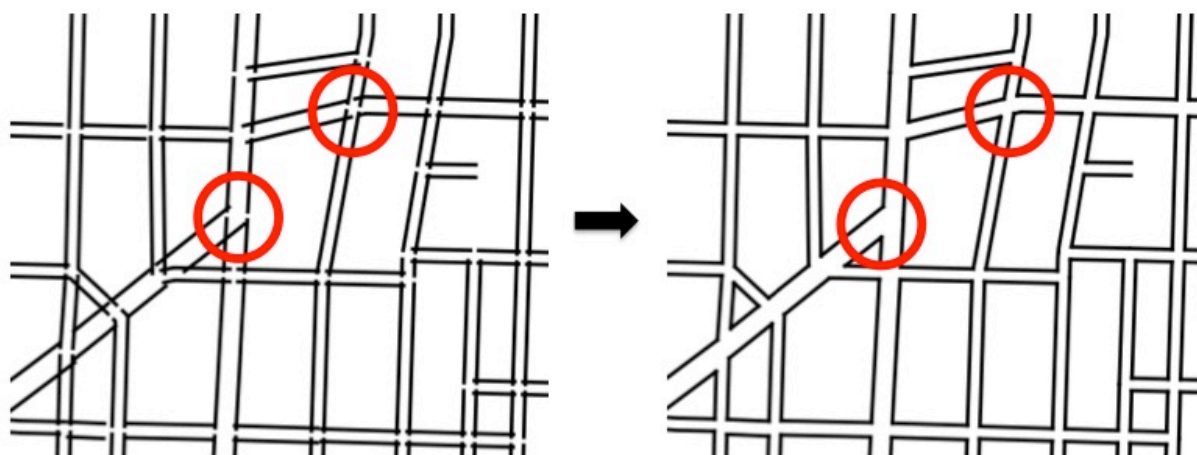
## Iterating to a universal solution

A key ambition of the AMOS team was to put sidewalks on the map, not just in Seattle, but across the country and around the globe. As discussed in detail in Chapter 4, it was already possible to add sidewalk data to OSM, but the dominant practice was to record sidewalks as metadata, as attributes of streets rather than as primary features. Not only was that form of data collection and representation sub-optimal for pedestrian-centric applications, sidewalk data was also quite sparse. Figure 6-1 shows the limited documentation of Seattle’s sidewalks and curb ramps in OSM when the team started their work, in the image on the left. The AMOS team felt that, in part, this sparseness was due to the unintuitive way sidewalks were documented, and that their proposed data schema could help rectify the situation by making it easier to contribute data about the pedestrian network. But relying on individual users to add sidewalks one at a time would take forever and likely would lead to gaps in coverage. If the team added municipal data, however, they could quickly get nearly comprehensive sidewalk coverage for an entire city at one time, as illustrated in the right-hand image of Figure 6-1.



**Figure 6-1. Actual v. potential sidewalk coverage in OSM.** The image on the left depicts sidewalk coverage of Seattle in OSM in 2016 during the DSSG program. The image on the right depicts possible sidewalk coverage in OSM if the AMOS team were to import municipal sidewalk data. Images courtesy of the AMOS team.

Before the team decided to adopt the OSM platform, they had already developed a set of algorithms for preparing municipal data for mapping purposes. The problem they encountered with open government sidewalk data in the city of Seattle was that the individual sidewalk segments didn't connect neatly with each other, but rather had thousands of little gaps and overlaps between them, a situation that made it impossible for a routing algorithm to traverse (Figure 6-2). So the AMOS team, including the four DSSG students and data scientists from the first year of the DSSG program, set about deriving methods to programmatically clean this data and generate a connected sidewalk graph. The process they came up with by the end of the summer involved finding the endpoints of existing sidewalk segments, measuring the angle between each of those endpoints and the center of an intersection, using the difference between those angles to determine when the endpoints of two segments that should have touched did not, and then extending or trimming the segments until their endpoints met each other. This process used the original sidewalk data provided by the City of Seattle, and algorithmically cleaned it up until they had connected sidewalk graph (Figure 6-2).



**Figure 6-2. AMOS team's original cleaning process for sidewalk data.** This diagram represents the cleaning process that the AMOS team in 2015 created. It was subsequently replaced by a method that could be replicated across different formats of municipal sidewalk data. Images courtesy of the AMOS team.

This process worked just fine for the City of Seattle, and if the team's ambitions were only to create a routing application for that locale, then this technique would have been sufficient. But the AMOS team wanted to be able to generate AccessMap for cities anywhere in the world, and they found that different municipalities recorded their sidewalk data in very different ways. In places where sidewalks weren't documented as line segments with precise geospatial coordinates as they were in Seattle, but rather as a record of whether or not a particular block contained sidewalks, the technique the DSSG created that first summer wouldn't work. So over the course of the academic year following the DSSG program, the team looked for solutions to generating a connected sidewalk graph under those other circumstances as well. They ultimately settled on a technique that involved drawing sidewalk segments by estimating their distance from street centerlines based on the width of the street. Because this method required only knowing if a sidewalk existed, and an estimate of how far the sidewalk should be from a street's centerline based on its width, the algorithm could be used in cities where sidewalks were not recorded as segments, but as metadata—which was the vast majority of US cities. And this same technique could be applied to redraw the messy, unconnected segments of sidewalk data in places like Seattle, instead of the computationally intensive method of cleaning the data that the DSSG team had developed. This meant they could use just one solution to generate a clean, connected sidewalk graph virtually anywhere in the world. In other words, this was an important step in the desired scaling of their work; they now had a method for cleaning and preparing municipal sidewalk data in a format that could be imported into OSM according to the schema they had proposed, and this would dramatically and rapidly increase the coverage of sidewalk data.

## Acknowledging risks to OSM

But as they engaged with the OSM community, they anticipated that this would be a big ask; in some ways a bigger ask than the data schema discussed at length in Chapter 4. In the course of engaging with OSM, they realized that certain vocal segments of that community had major concerns with mass imports. For some, they were concerned with betraying what they saw as the founding premise of OSM—that it would be a democratic, crowd-sourced project based on individual contributors’ physical observations of the built environment. But for others, their concerns were strictly pragmatic. OSM saves every version of the map that is ever created; if an erroneous data point is added and later edited, both versions will be stored in perpetuity. Because OpenStreetMap is a nonprofit, volunteer-run organization, their biggest expense is the cost of servers to store their data. And so the community has historically been particularly cautious about adding a lot of data at one time in a mass import; because if something goes wrong, and it needs to be reverted or corrected, this will quickly balloon the size of the database. So while creating a way to add sidewalks to the map was not likely to raise anyone’s hackles, there would be resistance in some pockets to the idea of importing municipal sidewalk data *en masse* due to a concern that data which hasn’t been vetted by human judgment could bloat the map with errors that drove up their operating costs.

But this wasn’t an insurmountable issue. When the AMOS team proposed a mass import of sidewalk data, they were already fully aware of these concerns from reading through the histories of discussion board posts related to previous proposals for mass imports, and so they decided to follow the example of successful previous imports. In spite of the concerns described above, several important mass imports of data into OSM had been completed in the past. For example, in 2007 and 2008, the entire road network across the US was added to OSM from the

“Topologically Integrated Geographic Encoding and Referencing” system data collected by the US Census Bureau. Commonly referred to in the community as “the TIGER import,” this project dramatically improved the coverage of roads in OSM, allowing for the platform to be adopted by companies and organizations developing routing applications for vehicles.

A more recent import, the one that the AMOS team chose to emulate, was the import of municipal building data in Los Angeles, including addresses. The organizers of that effort recognized the community’s concerns related to bloating the map with errors, and developed an elegant solution. They would prepare all the data for import, but break it up into smaller segments instead of importing all the addresses in the entire city at once. They organized what they called “work parties”—short, intensive, hackathon style events—to get volunteers to manually verify the accuracy of the data before each of these smaller segments was imported. When the AMOS team attended the State of the Map US conference in the summer of 2016 to pitch their proposals, the LA building import project was well underway, and a much-discussed topic, as other cities around the country considered replicating that effort. The AMOS team, too, decided to follow this approach, proposing that instead of importing municipal sidewalk data all at once, they would organize events for humans to validate and correct the algorithmically altered municipal data before adding it to OSM. But this added yet another layer of organization and mobilization to their work. It would mean adapting a suite of contribution and map editing tools for these tasks of human validation, and organizing events where the validation would take place. To this end, they decided they would adapt tools that had previously been used in humanitarian mapping projects, and to organize a series of hackathon-inspired “mapathons.”

## **Acknowledging risks to government**

In addition to gaining the support of the OSM community and volunteers for the import, the AMOS team also hoped to engage and mobilize public agencies with a vested interest in pedestrian network geodata. The team had secured open data sets about sidewalks, curb ramps, and crossings from the City of Seattle Department of Transportation. These were maintained as inventories of assets in separate, unconnected data sets. But they hoped that, if they did succeed in importing municipal sidewalk data in a connected pedestrian layer, those agencies would take ownership over maintaining the data.

Rather than simply acquiring data from the city and transforming it to make it suitable for routing, Anat and Nick hoped that transportation-related agencies and departments in Seattle—and other cities in the future—would become partners in maintaining an open-source connected graph of the pedestrian network. Their vision, spelled out in detail in a paper (Bolten, Mukherjee, Sipeeva, Tanweer, & Caspi, 2017) published by the IBM Journal (on which I am a co-author), involves governments contributing data collected in the course of inventorying pedestrian network assets, and the public updating, enriching, and annotating that network data with details that are salient to a diverse range of interests and needs. That crowd-sourced data would in turn be shared with the government agencies, which could be used for any number of planning and service delivery purposes. The AMOS team imagined that government wouldn't just periodically publish their data in a csv file through an online open data portal, but rather, they would use the data commons as their own primary location for maintaining the data they collected, and retrieving data that has been enhanced and amended by the public.

At a planning event attended by a number of government transportation agencies, as well as non-governmental organizations involved with transportation advocacy, the AMOS team

made a pitch for this vision. As Anat introduced their team, she noted that they were there “to ask you as agencies to subscribe to a data commons.” In a city being choked by traffic congestion generated by its rapid population growth and constrained geography, the AMOS team argued that high quality pedestrian network geodata would catalyze civic engagement around pedestrian issues and spark innovation in the development of tools that facilitate pedestrian travel.

They argue that the infrastructure for this proposed commons already exists in OpenStreetMap, making it a logical choice for a commons platform. To illustrate the robustness of OSM, Anat plays a time-lapse video of edits made to the global map over the years (for a contemporary version of this video see Gruschko, 2018), with new edits showing up in red, then fading to blue or green. “You see whole areas popping up in red at once,” Anat says, “because you can organize events to add a large amount of data at one time.” Moreover, she argues, OSM is richer in detail than something like Google maps.

Anat says she realizes that government agencies need to be worried about the trustworthiness of data, and concedes that this could be a concern preventing agencies from relying on a commons approach as their primary data source. But, she offers the group, the data commons could be designed and organized in such a way that allows stakeholders to customize control over which data is shared and synced. A city transportation agency could maintain its own data layer for example, only syncing updates provided by the public after those contributions have been vetted and verified by an employee. To indicate the feasibility of this approach, Anat provides the example of Portland, OR, whose regional metropolitan transit agency has adopted OSM as the baselayer map for their online trip planner application. They have someone responsible for verifying updated contributions to the map before pushing those

changes to their trip planner app, a job that a single person can easily do because there aren't actually very many edits in a given week, she says.

Not long after this presentation, though, the concern for data reliability in OSM comes up in real life. The AMOS team is having a weekly meeting when Roger, the active OSM organizer I introduced in Chapter 3, stops by to say hello and see how the project is progressing. He tells them that recently, some OSM contributors have noticed an apparent uptick in the mislabeling of certain features in the built environment. For example, they're finding private swimming pools labeled as public ponds, and front yards of people's homes labeled as public parks. They suspect, but don't know for sure, that the virally popular Pokémon Go game for mobile phones is using OSM for the location of certain landmarks, and so some players have started gaming the system by falsifying features that would allow them to set up a "lure" for Pokémon at their own house and accrue more points. This is exactly the kind of behavior that would make government agencies hesitant to invest in, contribute to, or rely on the kind of data commons model that the AMOS team is proposing.

As of the time of writing, the AMOS project is still thick in the stage of development. They continue to run AccessMap in Seattle on their own base layer they have built with municipal data, and have formally put their proposal to import municipal pedestrian data into OSM on hold while they take the time to design, build, and refine a number of user-friendly tools for viewing, verifying, editing, and contributing sidewalk data. They began working with groups of computer science students at the University of Washington to develop interfaces for various age groups and use cases, some of which had educational purposes, some of which gamified the collection of data, etc., and have been testing iterative versions of contribution tools in a series of mapathon events held to document pedestrian data on the University of Washington

campus. After the initial meeting I described in which Anat and Nick presented the case for a pedestrian data commons to one of the regional transportation coordinating bodies, that organization agreed to work with member agencies to contribute data to the proposed commons, and a couple of those agencies are actively working toward that goal.

#### FIELDWORK STORIES ANALYSIS: HOW EXOSTRUCTURES ENABLE THE EMERGENCE OF INFRASTRUCTURE

In the fieldwork stories presented above, the two projects under discussion are what I have called exostructures—temporary project-based collaborations that are being used to scale data-intensive approaches and technologies across new contexts, and as stepping-stones toward more stable data infrastructures. Both projects have been used as justification for further government embrace and adoption of data-intensive approaches, and to argue for public investment in robust *data infrastructures*—computational platforms consisting of particular arrangements of hardware, software, and policies that enable the secure sharing of specific data among select parties. The ORCA project has been discussed as a catalyst for a vault-like information infrastructure known as the Transportation Data Collaborative, and the AccessMap/OpenSidewalks project has been discussed as a justification for a Pedestrian Data Commons. Both projects are also supported by initiatives that are focused on developing a more holistic *knowledge infrastructure*—the expertise, methods, languages, tools, roles, norms, and organizational cultures that support the creation, maintenance, and use of public data more generally.

What is the consequentiality of such exostructural arrangements? From a sociomaterial perspective, the imbrication of structure and action constitute the social world. So here I explore how the qualities of exostructure enable certain kinds of processes to unfold, how those processes play out given the characteristics of the university, and how this is resulting in new

roles being carved out for the academy. Earlier, I discussed the triple helix model introduced by Leydesdorff and Etzkowitz (1996, 1998), a theory of cross-sectoral relationships that places a central focus on the role of the university in producing innovation and stimulating economic growth in knowledge-based societies. But the stories I've shared here show that there is more to the story than just technological invention and economic development. In exostructural collaborations designed to expand the reach and scope of data-intensive approaches and technologies, the university is coming to play key roles in the governance of a knowledge-based society.

Below, I argue that the university is emerging as a key player in the datafication of governance, taking on the roles of developer, trusted mediator, entrepreneur, and source of intellectual labor. And that it is through the imbrication of structure and process in exostructural arrangements that these roles are emerging. I argue that several different combinations of structural characteristics, processes, and roles can be distilled from the stories of the ORCA and AMOS projects: 1) the portability of exostructures allows for a process of technological translation across contexts, and that the technical acuity of the university positions it to play an important role as a developer in these translations; 2) The transient and ad hoc nature of exostructures allows for a process of temporary experimentation with sectoral relationships and roles, and that the perceived neutrality and stability of the university allows it to try on the role of trusted intermediary 3) The iterative nature of exostructure, in which breakdown and repair is expected, provides for a low-stakes environment that helps mitigate the risks involved with trying out new technologies and new roles, and that the universities culture of research positions it to take on that risk in an almost entrepreneurial role 4) The customized nature of exostructure, which means that it must be learned as part of its development, requires the mobilization of

intellective skills; and that the university because of its educational mandate is positioned to provide the labor pool for this intellective work.

### **Portability and technological translation across contexts**

One of the salient features of an exostructure is its portability, the quality of “sitting on top of” infrastructure rather than being “sunken” or “embedded” as infrastructures are (sometimes literally and often metaphorically) thought to be. I argue that this portability allows for a process of sociotechnical translations across infrastructural contexts, and that in exostructural arrangements involving academic partners, the technical acuity of the university positions it to play an important role as a technology developer in these translations.

We have seen how both the ORCA project and the AMOS project in effect “sit on top of infrastructure.” The AccessMap application could be supported by a base layer map that the team created themselves from municipal data, or—under the right circumstances—it could rely on OpenStreetMap as its baselayer. The data, databases, and algorithms of the ORCA project could be housed on local servers on campus, or in a specialized cloud architecture built by Microsoft. In both cases, the goal was ultimately to move the projects from their temporary infrastructural homes and integrate them into longer-term, more stable infrastructures that would be developed in conjunction with that translation. In part, the university is in a position to develop these transportable technical configurations because it possesses the necessary technical acuity. The process of translation is neither simple nor straightforward, however. As we have seen, it required many layers of negotiation and articulation—the “front-loaded work and epistemically charged negotiation that thereafter become infrastructural” (Ribes, 2017, p. 1514). In a sense, then, this translation is a meta-process enabled by the next three processes I will discuss, including experimenting with new roles, mitigating risk, and mobilizing intellective labor.

## **Transience and experimentation with sectoral roles and relationships**

The transient, ad hoc nature of exostructure allows for small-scale experimentation before sociotechnical arrangements and roles become formalized and entrenched. And because the academy is viewed as a stable and relatively neutral actor, one of the roles that the university is experimenting with in a number of data-intensive projects is that of a trusted intermediary. One academic researcher who maintains a repository of regional transportation data told us that agencies trust her in a way they don't necessarily trust each other:

They're all worried about everybody else ... Who's got power? Who's got control? Being in a university with this neutral agenda, we don't run any roadways, we don't manage anything, we don't control any money. We really just try to educate students and do research. It means that it's a safe environment to send your data to.

This is certainly how the university's role is being framed in the Transportation Data Collaborative that the ORCA project is supposed to grow into. Regardless of whether or not ORCA actually ends up being the first data incorporated into the proposed Transportation Data Collaborative, the ORCA project has already helped advance the very idea of the TDC by establishing the university as caretakers of sensitive transportation data, with both the technical prowess to keep the data secure and the regulatory structures to safeguard it. And having no profit motive themselves, the researchers can make the argument that they will safeguard proprietary raw data of competing transportation companies, only allowing queries that abide by data sharing agreements participating parties have agreed to in advance. In a presentation to the Cascadia Urban Analytics Corridor that touched on the TDC, a Microsoft employee underscored the importance of this "neutral third party role," saying "what is needed to get sectors to share

data with one another is someone who is trusted more than the government by the private sector, and more than the private sector by government.”

In this instance, then, the university is leveraging its position as a relatively impartial and disinterested party to mediate the relationships between public and private sector entities. It is reasonable to ask, though, whether the university can maintain this stance, or if such arrangements in and of themselves pose challenges to academia’s perceived neutrality by entwining the fates and interests of the university, government, and private companies. The coziness between academics and the technology industry is something that has already sparked critique from observers who view their entanglement as a conflict of interest (Mullins & Nicas, 2017). But it is also reasonable to accept these entwinements as fundamental to and an essential path for understanding our increasingly data-mediated society (Gray, 2017). As it becomes more feasible and more commonplace for universities to serve as intermediaries between government agencies and commercial interests, we’ll have to consider closely what the appropriate boundaries of those relationships should be.

The AMOS team is also leveraging their project as a demonstration of the viability of such an arrangement, and trying spark further investment and commitment from other sectors. Realizing that the government is skeptical of crowdsourced data, and that the OSM community is skeptical of mass imports of municipal data, the AMOS team at UW is positioning itself as an intermediary that can address both of those concerns—by designing and maintaining the protocols that would govern access and versioning in the pedestrian data commons so that the government could retain control over its informational resources, and by creating tools and processes for vetting governmental data to assuage OpenStreetMaps’ concerns over importing massive amounts of data that might need to be corrected in the future. But the pedestrian data

commons may ultimately prove to be a tougher sell than the trusted data collaborative, as the very thing that mitigates risk for one, increases it for another.

### **Iteration and the mitigation risk for collaborators**

The iterative nature of exostructure, in which breakdown and repair is expected, provides for a low-stakes environment that helps mitigate the risks of ethical and financial failure involved with exploring new technologies and roles. And in this scenario, the research culture of the university positions it to take on that risk, therefore serving in an almost entrepreneurial role.

By now, thanks to much excellent journalism and scholarship, most people are aware of the many potential shortcomings and excesses of big data and data science (e.g. Angwin et al., 2016; boyd & Crawford, 2012; Hargittai, 2015; Lazer, Kennedy, King, & Vespignani, 2014). Public agencies are rightly concerned about these issues, and in many cases, reluctant to make use of datasets that raise ethical concerns. As one government employee put it to me:

There is fear from both sides—from agencies that don't want to make mistakes in handling data and from the public who don't want their private data revealed.

More and more, public entities are looking outside of government for guidance on how to make use of sensitive data in a way that both protects citizens and shields the government from liability. At a recent conference convened to help governments and nonprofits use data more effectively, one seasoned administrator gave some pragmatic advice to her counterparts who are thinking about getting into the data science game: “hire a conscience.” What she seemed to be suggesting was partnering with ethicists who can consider all the things that could go wrong, working with legal scholars who understand precedents, collaborating with social scientists who understand cultural nuance. Likewise, at a panel discussion on cross-sector collaboration in data science I convened in 2015, participants from a number of sectors recognized that when public

agencies collaborate with academia, one of the benefits to governmental actors is that they are able to defer and diffuse the ethical risks involved. A city employee told the audience that when governments collaborate with data scientists at the university, “more than the skills that data scientists bring to the table, the city also gets management of risk.”

This can sometimes make the difference between an agency sitting on its data, and putting it to use. Such was the case with the ORCA project discussed in detail throughout this dissertation. For seven years, the data was used only for transactional purposes such as maintaining riders’ account balances and for operational purposes such as performance evaluation and management. But a team of academic researchers hoped to prove its usefulness for predictions and strategic planning. The lead researcher knew the transit agencies were hesitant to analyze this transaction data because of its sensitivity. Despite this hesitation, the researcher was able to convince the agencies that the data would be in good hands. This was, in part, because of his positioning within the academy and the fact that researchers at universities are subject to ethical oversight by an institutional review board (IRB) with a mandate to ensure research participants are not incurring harm, and that both their rights and their data are being protected.

Of course, working with a university is not an ethical panacea. Having the approval of an academic IRB is not a guarantee that no harm will be done, or that the work will be widely regarded as ethically sound. And as it becomes more and more common for academics to repurpose data collected by non-researchers rather than collect primary data with their own research instruments, IRB’s face new challenges in determining the boundaries of their jurisdiction and establishing acceptable norms. For example, Cornell University’s IRB determined that the infamous emotional contagion experiment conducted on Facebook users

didn't require their review because the Cornell researchers who worked on it weren't involved in the data collection (Sullivan, 2014); clearly, the backlash from that study suggests that many people felt the university had abdicated its responsibility as an ethical conscience (Chambers, 2014).

Project-based, proof-of-concept exostructures also have the potential to mitigate the risk of failure because the financial stakes are relatively low for collaborators. With so much of data science being about exploration, trying new techniques, and using data in novel ways, success is far from given. And so the culture of iterative experimentation that is so prevalent at universities can help other sectors get their data-intensive projects off the ground. In government, for example, if a program or project fails, budgets can get cut, people can get fired, elected officials can get unelected. But in academia, failure is seen more so as an inevitable part of the research endeavor, something that happens again and again on the way to discovery. When experiments fail, researchers learn what they can from that failure, and try again. Similar to the way academic partnerships can defer some ethical risks in these project-based collaborations, if universities are shouldering most of the financial burden in exostructural collaborations, this can defer some of the risk of failure by providing the space and time to try new, untested approaches with minimal investment provided by partners from other sectors. This rationale is clearly visible in the way MetroLab projects are framed as “R&D for cities,” and “test-beds” for academics (“MetroLab Network,” n.d.).

We saw how the AMOS project was able to iterate through several different methods of cleaning sidewalks before developing a method that could be used nearly universally across a range of heterogeneous municipal data sets. That a team of four students and a research scientist spent an entire summer working on a cleaning method that ultimately was not used is nothing to

bat an eyelash at in the academic universe. A culture of research recognizes that this first approach was important for learning about the limitations of the data, eliminating insufficient approaches, and ultimately iterating upon a more universal solution. As Mark Hallenbeck, the lead researcher on the ORCA project, has put it, “you can’t design an IT process effectively when key procedures within that system are still not understood.”

This can be a double-edged sword, however. While it may relieve some of the intense pressures of accountability in other sectors, the more pedagogical take on failure in academia may at times lead university partners in data-intensive exostructural collaborations to settle for simply publishing a paper about what they’ve learned, instead of pushing as hard as possible for the implementable solution their partners in other sectors may need. Similarly, the culture of experimentation at universities is accompanied by a valuation of novelty and discovery. This, too, can sometimes be at odds with the needs of partners in other sectors, when it turns out that the solutions public sector agencies actually need are less *avant garde* and more *de rigueur*. Most academics are evaluated first and foremost on their records publishing work that furthers the knowledge base of their respective fields, which may be difficult to do if truly putting the needs of non-academic partners at the forefront of the collaboration. In other words, while the research environment defers some risk of failure, there is also a potential tension between the academy’s mandate to produce novel results and generalizable knowledge, and the mandate to produce actionable results tailored to the specific needs of partner organizations in other sectors.

An even more important concern is that while deferring risk, exostructures may bypass important accountability mechanisms. We have seen how exostructures can provide a sheltered space for experimenting with emergent sectoral roles in a rapidly shifting technological landscape. But project-based, pro-bono, proof-of-concept, collaborative projects between

governments, technology companies, and universities may also provide a shield for efforts and relationships that would otherwise, and rightfully, attract public scrutiny. Journalists have recently exposed how a predictive policing program in New Orleans flew under the radar by being cast as a philanthropic commitment by the company Palantir to develop a prototype for the city. Set up in this way, the project bypassed public debate and procurement procedures in city council that would have been triggered if the city needed to come up with a budget to fund a contract with the company (Winston, 2018). Some cities have recently started taking measures to avoid similar situations. For example, in 2017, the City of Seattle passed a Surveillance Ordinance requiring public debate prior to the acquisition of surveillance technology that would avoid a situation like the one that played out in New Orleans by defining acquisition to be inclusive of the acceptance of in-kind donations. Regardless, the potential for exostructures to fly under the radar may be an especially pressing concern if the rhetoric of “social good” is leveraged to whitewash efforts that would otherwise seem questionable or creepy to the public. After one university researcher at a MetroLab meeting presented work being done in his school’s DSSG program, a prominent politician known for being a champion of data-based decision-making took mic: “We should steal that,” he joked. “‘Data science for social good.’ It’s so much warmer and friendlier than predictive analytics, isn’t it?”

### **Customization and the mobilization of intellectual labor**

Exostructure is characterized by its customizability, which means that it must be learned as part of its development. In data science work, this customization requires the mobilization of what Shoshanna Zuboff (1988) has called intellectual skills, a combination of abstraction, explicit inference, and procedural reasoning. Importantly, these are not skills that just require *more* learning, they are actually synonymous with learning. Writing in 1980 about the changing

nature of work in highly informed environments where organizational structures and decision-making are all oriented around data, Zuboff (1988) presciently concluded that, “learning is the new form of labor” (p. 395). Learning is not a precursor to productivity, but is perpetually happening as an inextricable part of productivity.

As Zuboff (1988) points out, intellectual skills are “traditionally associated with formal education” (p. 195). This is one of the reasons, then, that we see academic institutions playing such crucial roles in the kinds of exostructural collaborations I’ve described, in which students are doing the lion’s share of the project work. Etzkowitz (2008) points to students as the key factor in his prognosticated ascendancy of the university:

The university is the generative principle of knowledge-based societies just as government and industry were the primary institutions in industrial society. Industry remains a key actor as the locus of production, government as the source of contractual relations that guarantee stable interactions and exchange. The competitive advantage of the university, over other knowledge-producing institutions, is its students.

Etzkowitz, 2008, p. 1

Because they involve student labor, the exostructural arrangements that I’ve observed have a twofold purpose: they exist not only to meet the objectives of the project, but also to provide an educational opportunity for these students. In making decisions about a project’s evolution, then, one of the challenges is striking the right balance between these two priorities. In Zuboff’s (1988) studies within commercial firms, she saw a fundamental tension between the need for constant learning on the one hand—which requires intellectual workers to be engaged in their work and relatively autonomous—and on the other hand, conventional forms of management—in which imperatives of the organization are dictated and monitored by the managerial class. When an organization depends on intellectual labor, it has to relinquish some of that control. Although I’m looking at a very different context from Zuboff (1988), this tension

can still be seen playing out in the exostructural collaborations I've observed in the DSSG program. This is why Mark told Charlotte that even though it may be best practice to utilize a single database, he was reluctant to enforce that requirement among the students and staff who worked for him. In other cases, stakeholders from government agencies have told us that they felt the students they worked with sometimes came up with ideas and solutions that were overly complicated because they wanted to learn more advanced technical analytical skills along the way. On the other hand, I have heard students express frustration when the things they were learning from or about the data seemed at odds with what the organization wanted them to do with it. Given the educational mandate of the university, exostructural arrangements that involve student labor should recognize the need to compromise between pedagogical opportunities presented by the work, and the need for results.

## CONCLUSION

Data-intensive computational methods for producing knowledge and making decisions are expanding to ever more contexts, problem spaces, and applications. This includes the governmental sector, where forces from the top down and bottom up are exerting pressure to develop the technological and organizational capacity to incorporate data more fully into planning and operations within public institutions. We cannot yet fully grasp the consequences of this datafication of governance because the transformation has only just begun. But we *can* try to understand the consequentiality of the process as it unfolds.

I have argued that one of the key ways data science technologies and methods are being applied to public data is through short-term project-based collaborations. In the context of the Data Science for Social Good program run by the eScience Institute, I have observed a number of such projects that are geared toward helping knowledge infrastructures for data science jump

contexts and take root in new sectors. Sometimes, these projects are also aimed at catalyzing and supporting the establishment of specific data infrastructures for scaling the use of public data across new purposes and new constellations of actors. I have characterized this subset of project-based collaborations as exostructures. In my discussion of the ORCA and AMOS projects, I highlighted the qualities of the projects that make them exostructural: their portability, their transience, their iterativeness, and their customizability. These are qualities that allow those projects to serve as vehicles for the emergence of infrastructures for public data. In the stories of these projects, we can see that exostructural arrangements are allowing sectors to translate technologies across contexts, to experiment with new roles, to mitigate risks, and to mobilize the intellectual labor required for data-intensive work. From a sociomaterial perspective, the social world emerges through the imbrication of process and structure. In other words, we cannot produce new technologies without simultaneously reordering the social world. And so in this chapter, I've asked how exostructures and their concomitant processes are transforming the role of the university. Previous theorizations of the academy's role when entwined with government and business have focused exclusively on the economic impact of universities. Instead, here I begin to explore the implications of exostructure for the university's role in governance. Governments need a neutral mediator that can smooth over the tensions that arise between governments and businesses or civil society in data sharing arrangements. They need an entrepreneurial actor that can shoulder the risk of new, untried technologies. They need a technically savvy actor who can help them develop the customized technologies they need. And they need a source of intellectual labor required to do this work, especially given how hard it is to retain talent with advanced programming and analysis skills. In the data-based exostructural collaborations that I have observed, the university is performing all of these roles. Whether this

is a temporary arrangement, or whether those roles become stabilized and integrated into the infrastructures emerging from the temporary exostructures that spawned them remains to be seen.

## CHAPTER 7 CONCLUSION

### SUMMARY OF PRACTICAL AND NORMATIVE CONTRIBUTIONS

As I discussed in the explanation of my methods in Chapter 2, my involvement at the eScience Institute has deepened over the course of the three plus years I've spent embedded there as a participant-observer. As time has gone on, I've shifted gradually from the observer end of that spectrum and moved closer to the participant end. In fact, following the completion of my doctoral degree, I have tentatively decided to join the eScience Institute as a full time staff member, which will include taking on a leadership position in the DSSG program about which I have written so much. This is relevant here because it means that, in many ways, the writing of this dissertation has been the ultimate application of practical research. I will not only be translating and disseminating the insights from this dissertation to my community of study, as is typical in engaged practical research (Barge & Shockley-Zalabak, 2008; K. J. Barge, 2001; Petronio, 1999); I will also be using these insights to inform my own actions in a leadership position that will directly influence the trajectory of data science practice within the community of study I have written about here. And so, as I present my concluding thoughts on the practical importance of the foregoing analyses of data ethics, these are not merely hypothetical reflections. Rather, they are comments on the very real ways in which I plan to translate my findings into practice.

#### **Implications of the framework for ethical approaches in data science of the social**

The emerging area of scholarship that has been called critical data studies has taken on the task of surfacing many concerning consequences that can result from data science of the social: the reification and magnification of inequity, the privacy challenges raised by ubiquitous digital surveillance, the privileging of the so-called *technorati* class, and the reliance on opaque

and unaccountable algorithmic systems. I have shown that many of the ethical concerns addressed in the critical data studies literature are not unknown to data science practitioners, and that there is a growing trend within the data science community to acknowledge and address various such issues. In academic computational research, there is now a burgeoning area of specialization in developing more ethical computational methods. For example, researchers are working toward advancements in privacy-preserving techniques, algorithmic audits, fairness metrics for evaluating model outputs, and approaches to making machine learning more interpretable. In industry labs, too, companies are forming research groups focused on issues of ethics and social impact. Networks of practitioners and professional associations are coming together to craft codes of ethics, or propose some version of the Hippocratic oath for data scientists. There is also a shifting legal and regulatory landscape related to the ethical challenges of data science. Perhaps the most important development is the new General Data Protection Regulation (or GDPR) that was recently adopted in the European Union to give consumers more access to and control over the data that is generated about them.

In other words, the dialogue about ethics in data science of the social is shifting quickly and dramatically. Questioning the assumptions and consequences of data-intensive computational work is clearly not just the domain of science and technology studies or critical data studies, and data ethics is clearly not considered to be a touchy-feely fringe topic. These matters have become a pressing concern for powerful institutions across many sectors of society and for many communities of data scientists as well. That means now is the time for critical data scholars to contribute generative ideas to the diffuse conversations currently taking place about responsible, ethical data science. Many are already doing just that, and this dissertation is one

part of my own contribution toward the evolution of a more humane, more reflexive, more ethical, and ultimately more powerful data science of the social.

In Chapter 3, I introduced an ethical framework for data science of the social (Figure 3-3) that captures various ways in which I've observed data scientists discussing and enacting their ethical values in practice. In particular, this framework that I advance centers around a major and recurrent ethical concern in data science of the social: its impacts on vulnerable, marginalized, or protected communities. The framework is built on two axes: the first axis portrays whether an ethical orientation emphasizes *reducing harm* or *producing empowerment*, and the second represents whether an ethical response is centered on the *process* of doing data science or on the *product* of data science. The relationship between these two axes yields four distinct approaches to ethics in data science of the social. I have characterized these four approaches as “Data Science as Ethical Convention,” “Data Science as Ethical Interrogation,” “Data Science as Ethical Innovation,” and “Data Science as Ethical Participation.” These are in no way mutually exclusive, but by surfacing the multiplicity of ethical approaches in data science of the social, I hope to feed the imagination for how the field can respond to the ethical challenges it faces. The world needs a more nuanced perspective on ethics in data science of the social, one that doesn't narrowly seek to avoid unintended consequences (Jasanoff, 2016), but seriously considers what it would take to leverage data science methods proactively as a form of ethical intervention.

The framework for ethical approaches in data science of the social is a grounded practical theory that emerged from what Adele Clarke (2003) has called situational mapping. According to Kevin Barge (2001), mapping exercises allow practical scholars to “develop the guiding concepts, normative prescriptions, and rules” of practice (p. 7). Organizing distinctive ethical approaches in this framework opens up a number of opportunities for practice-based reflection

and planning by providing a language that helps practitioners articulate their own values and positions, surface their own assumptions, and weigh their own approaches against other possibilities. In fact, I have already begun to incorporate this framework into reflection activities with data science practitioners. For example, when I was recently asked to deliver a workshop on data science ethics, I had participants work through a case study of a data science for social good project, and asked them to reflect on how different that project might look if they were to adopt each of the respective ethical approaches. Participants seemed to recognize that each of the approaches demanded different levels of commitment to the marginalized or vulnerable community in question. In fact, this caused me to reflect that the graphical representation of the framework could be amended to reflect those increasing levels of commitment, as in Figure 7-1.

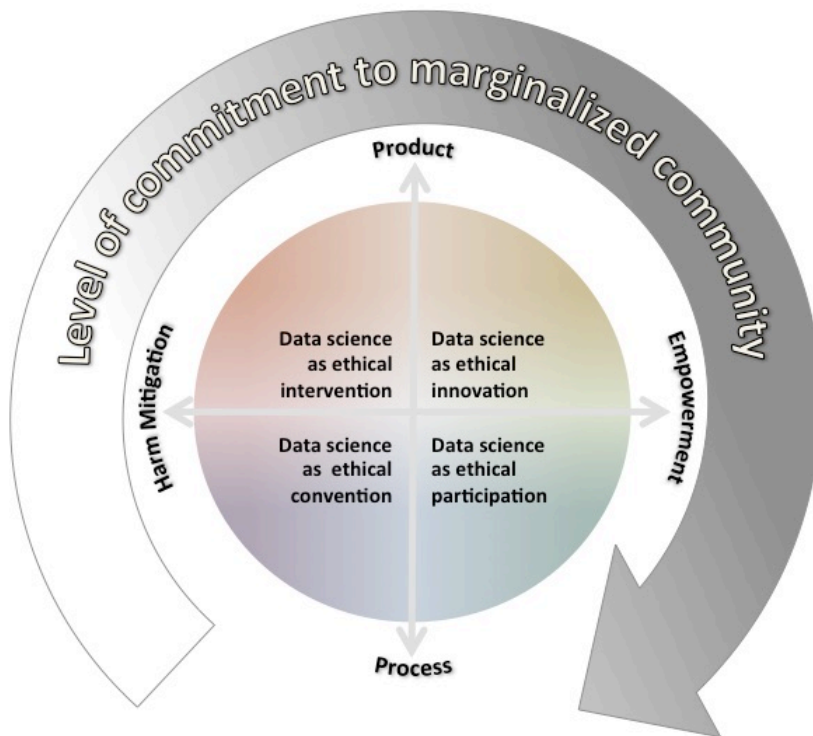


Figure 7-1. Updated framework for ethical approaches in data science of the social.

## **Leveraging academic and vernacular theories of sociomateriality**

I have suggested that these various ethical approaches are reflections of *vernacular theorizing* within the practice of data science. In making this move, I have drawn on the work of Thomas McLaughlin (1996), a literary theorist who developed the concept of vernacular theory in the context of critical cultural studies. Writing about undergraduate students in critical cultural courses, McLaughlin (1996) surfaces their own instinctive vernacular theorizing about the culture that surrounds them. Inspired by Paulo Freire's (1970) "pedagogy of the oppressed," McLaughlin (1996) promotes "a pedagogy of vernacular theory" that supports the students' own cultural critiques by creating "an opportunity for encounters with radically different subjects with radically different histories" (p. 157). The job of the educator, in this view, can be seen as expanding the horizons of vernacular theorizing and facilitating a dialogic relationship between it and more formal theorizing.

McLaughlin (1996) recognizes that vernacular theory arises across a range of communities and situations, and in particular calls attention to the vernacular theorizing of professionals that share a common practice. Many communities of practice engage in "persistent self-reflection and scrutiny" (McLaughlin, 1996, p. 102) across shared discursive spaces such as conferences and publications, through which they form notions of how their practice contributes to society, what existential questions they face, what counts as good practice, etc. I have argued that deliberations over the ethical crisis facing data science of the social constitutes an important example of such practice-based vernacular theorizing.

Viewing certain discursive moves in data science of the social as vernacular theory creates a space to think about how critical data scholars might engage in the "pedagogy of vernacular theory" that McLaughlin (1996) suggests. How might we create dialogic

opportunities to put practitioners' own vernacular theorizing into dialogue with more formal theories used by critical data scholars, scholars of science and technology studies, and communication scholars? Just as anthropologists once worked to break down the ethnocentric barriers they imagined to exist between the primitive "savage" and the expert ethnographer, so do scholars of science and technology need to deconstruct the barrier they have imagined between the credulous practitioner and the critical observer.

I have shown how the vernacular theorizing evident in various ethical approaches to data science of the social map onto distinctive strains within more formal theories of sociomateriality. Those theoretical perspectives vary in whether they focus on material mediation or material activation, and whether they focus on the co-constitution of the human-technology relationship or the mutual-shaping of that relationship. Those distinctions, I have argued, yield four strains of sociomaterial theory that share common premises with the aforementioned vernacular theories of data science ethics: practice-based approaches to sociomateriality speak to data science as ethical convention; network-based approaches to sociomateriality speak to data science as ethical interrogation; political-based approaches to sociomateriality speak to data science as ethical innovation; and identity-based approaches to sociomateriality speak to data science as ethical participation.

The implication of such a mapping is that very real connections exist between theory and practice, and that there is an opening for surfacing and integrating important ideas from science and technology studies and critical data studies into the day-to-day work of data science of the social. Such a dialogue between formal sociomaterial theories and vernacular theories has the potential to generate new ideas and directions in the community's response to the ethical crisis it currently faces. While each of the ethical approaches that I have outlined above actually exist

within different corners of data science of the social, they are not necessarily all simultaneously recognized or discussed across the community. In fact, the default and predominant ethical approach seems to be data science as ethical convention—an awareness that decisions made by analysts and designers can have rippling and multiplying effects, and a conviction that practitioners should be on guard against possible unintended consequences of their work.

Such recognition is necessary, but insufficient, if data science is to be harnessed for its transformative potential to make the world a better place. A more expansive sociomaterial outlook can open up new imaginations for how data science might ethically intervene on the world, and prompt data scientists to think beyond the reduction of harm in their own work. As Pink and Lanzetti (2018) have recently put it, we need to be “generating not an ethics process for big data analysis but instead an ethics through which big data might contribute to an emergent and possible rather than objectified and predictive future” (p. 2). In Chapter 4, I provided a detailed account of an effort to do just that. The AccessMap/OpenSidewalks project was deeply informed by the team leadership’s adoption of the social model of disability. This is a thoroughly sociomaterial worldview that sees disability not as an inherent quality of individuals, but as a social construct arising from a built environment that is not designed to accommodate difference. As I argued in Chapter 4, this perspective allowed the team to imagine how a data-intensive technological innovation might play a role in interrupting the recursive relationship between notions of “normal” and exclusionary technologies that produce disability.

The AMOS team’s experience suggests that opening up nuanced understandings about the sociomaterial nature of our world can prompt and provoke the consideration of alternative possibilities and new directions in data science of the social. STS and critical data scholars can contribute meaningfully to the ethics of data science practice by finding ways to link more

academic sociomaterial theories with the vernacular theorizing that practitioners inevitably do. One way in which my colleagues and I have tried to foster such dialogue within the data science environment at UW is by hosting a series of monthly “Data Science Studies Working Group” meetings. These meetings have become a space for critical data scholars and data scientists alike to share their work and ideas with one another. In a recent session, critical theorist and ethics scholar Anna Lauren Hoffman (2018) critiqued the way many treatments of data ethics elevate material harm to individuals over cultural harm toward groups, and the way they lay blame on bad actors rather than institutional forces. Her eloquent lecture conjured contemporary critics of data-intensive technologies like Cathy O’Neil (2016) and Virginia Eubanks (2017), and wove those together with the ideas of foundational philosophical and sociological thinkers, such as Johan Galtung’s (1990) cultural violence, Iris Marion Young’s (1990) politics of difference, John Rawls’ (1968) distributive justice, and Kimberle Crenshaw’s (1989) intersectionality. Following the session, I asked one of the self-described data scientists in the room what he thought of the talk. He responded that he had needed to parse every word and use all his focus to follow along with the lecture because he had never before been exposed to the ideas and thinkers Hoffman introduced in the presentation. Like any good intellectual, he meant this as a compliment. “It was great,” he said. “My mind was blown.”

This anecdote underscores the potential to incorporate high-level concepts and foundational ideas from the humanities and social sciences into data science practice. There is already a recognition that data science education and training programs should acknowledge “the social” in their curricula, leading to courses like an introductory “Data and Society” class for undergraduates at the University of Washington who are interested in a new interdisciplinary data science option on offer there. What I am suggesting here is that such efforts need not

exclusively focus on surfacing the concrete consequences of data science *qua* data science, but rather, could more expansively incorporate social theory into the way data science is taught and practiced. In particular, the relationship I have described between academic theories of sociomateriality and vernacular theories of data science ethics indicates that sociomaterial theories could open up expansive terrain for contemplating the relationship between technology and society more broadly, and in turn, imagining a more ethical future for data science of the social in the course of vernacular theorizing. Spaces for such constructive dialogue between data science practitioners and scholars of technology are currently emerging in interdisciplinary venues such as the journals *Big Data*, *Big Data & Society*, and *New Media & Society*. Acknowledging the vernacular sociomaterial theorizing that practitioners do in the course of their work has implications for fostering dialogic relationships not just in data science of the social, but across the study of science and technology. Although I have focused here on mapping ethical perspectives onto a framework of sociomaterial theories, those same sociomaterial perspectives are likely to implicitly inform sense-making on a whole host of issues of concern for practitioners in the work of science and technology. Through careful attention to practice and discourse, we can see the ways in which vernacular theorizing intersects, merges, or is orthogonal to more formal social theory.

### **Fostering processes and structures that support ethical thinking**

In Chapter 4, I presented two accounts of data science for social good projects addressing ethical issues and motivations in their work. Rather than focusing on cases of ethical transgressions, I have chosen to highlight examples and instances of practitioners taking ethical concerns and questions seriously. I do this because I believe that the perils and excesses of data science of the social are becoming abundantly clear, and we are at a point now where we need to

be facilitating generative dialogue. From the empirical accounts presented, I distilled several processes that were integral to each respective ethical approach, and suggested that organizers and participants in data science of the social could support ethical thinking in data science by incorporating these processes into practices and organizational structures. In drawing out the processes that were crucial to the ORCA team's data science as ethical convention approach and the AMOS team's data science as ethical innovation approach, respectively, I do not mean to imply that there is no overlap in the processes that support these different approaches (for example, incubation was important for both of these projects, as was the balancing of stakeholder priorities), but I have chosen to highlight those processes that were most pronounced in each case.

#### *Processes supporting data science as ethical convention*

In the story of the ORCA project, which sought to make transaction data from a transit fare payment system useful for analysis, I described in detail how the team went about defining various biases in their data and deciding which types of bias they would investigate. I consider their attempts to address biased data to be an exemplification of the data science as ethical convention approach, which emphasizes repairing data science practices through methodological rigor by developing ways to detect biases, protect privacy, interpret results, etc. I argued that their experience points to the importance of the following processes in supporting that the data science as ethical convention approach: *translating* ethical values into technical challenges; *incubating* the process of ethical thinking; and *incentivizing* ethical progress by recognizing it as an integral and valuable contribution to data science of the social.

In the discussion of *translating* ethical values into technical challenges, I described how the students started off hoping to work on issues related to transportation equity, while the

project lead joined the DSSG program hoping for a group of technically skilled students who could whip the ORCA data into shape so that it could be used by his stakeholders in the world of transportation planning. Ultimately, the team was able to translate across these different priorities by studying a type of bias in the data that would render it more reliable, and in turn, prevent the magnification of bias in downstream uses of the data. In a sense, then, the question of bias became an abstract boundary object (Star & Griesemer, 1989) around which the team could orient and coordinate. I have suggested that such a process of translating ethical values into technical challenges provides a fruitful way forward for bridging the concerns of critical data studies and the culture of computational work.

This process of translation has a number of limitations and risks, however. As we saw, the boundary object of bias offered the opportunity for only a partial translation of the students' ethical priorities, and constrained their impact to preventing ambiguous downstream harms rather than directly addressing existing inequities that they suspected existed. This is a fundamental limitation in the data science as ethical convention approach. It needs to be recognized that not all ethical concerns can be translated into technical challenges, and the political, cultural, and institutional complexities that swirl around data science of the social do not disappear no matter how unbiased, privacy-protecting, or interpretable our data-intensive technologies are. While it is heartening to see computational researchers working toward methodological approaches that address some very serious ethical concerns in data science of the social, we can't let technologists off the hook by saying that their job is only to fix technical problems, while someone else is left to deal with the messy realities in real-life implementations of their work. Hoffman (2018) makes this point when she reprimands a Harvard researcher who, in the face of critical questioning about how a crime prediction algorithm he helped develop would be used,

defended himself by responding, “I’m just an engineer.” Thinking of ethical challenges only in terms of technical solutions makes this kind of response all too easy. We need to tackle ethical concerns as both technical challenges and political challenges simultaneously, with computational researchers and technology developers acting as informed participants in the life cycle of technological implementation, and with critical scholars and stakeholders involved in technical development as well.

In the discussion of *incubating* ethical thinking, I pointed out that in the ORCA team’s exploratory and deliberative sense-making conversations, one of the most important points to be made is simply that these discussions took place at all. Although the team was at times frustrated with the slow pace and circuitous course that led to them to finally hone in on their priorities for the remainder of the summer, they were not under external pressure from their project lead, eScience, or the transit agencies to rush through that important stage of the work or produce unassailable final results. I have argued that this actually freed the team up to surface important ethical considerations in their work and come to a compromise with which they could all feel at ease. In the DSSG program, the ORCA project was incubated and kept at arms length from the demands of productivity in such a way that the team could take their time exploring the ethical dimensions and complications of the work. This is not to say that a program structure similar to the DSSG is necessary for incubating the process of ethical thinking; but it does mean is that anytime a new data set, project, method, or technology is introduced, it may be wise to grant a period of incubation to engage in brainstorming, speculation, experimentation, and exploration wherein ethical issues can be surfaced and grappled with in a low-stakes environment.

A challenge to implementing this process is that it may be misinterpreted to mean that ethical thinking should be shunted off as something separate and apart from doing data science.

This is by no means the point I am trying to make, though. As I argue below, ethical thinking in data science of the social cannot and should not be artificially separated from the practice of data science. In the ORCA project, the team was exploring their data, running descriptive analyses, and doing visualizations all along, and these steps were important to their understanding of the data's limitations and their sense-making around ethical issues. So rather than suggesting that ethical thinking should be sheltered from the process of doing data science, I am suggesting that the process of doing data science should be sheltered from the demands of productivity during an exploratory phase of work, and that this may create the much needed space for ethical thinking.

But in the discussion of *incentivizing* ethical progress as a valuable contribution to data science, I pointed out that even though the project was relatively sheltered from demands for immediate results, the team was not immune to their own internal (though undoubtedly culturally derived) drive to do something that felt worthwhile, and productive. Again and again in the DSSG program, I saw teams express ambivalence over the time they spent engaged in communicative labor as they made sense of the ethical issues in their work; they recognized the work was vital, and yet resented the time they spent “just talking,” as one participant put it, because this was viewed as time that was not spent producing tangible outcomes. We saw this in the ORCA team as well when, after a marathon sense-making session in which the students defined the different types of bias in ORCA data, Jordan joked that the visual representation they created would be the only thing they put on their CVs. And yet that diagram did become an important tool for guiding, explaining, and justifying their work, and it would appear in multiple public communications about the project. Their experience suggests that if we don't want ethical thinking to be something that is rushed through, resented, or treated as a checkbox to tick off, we

need to recognize it as not merely a step to be taken before the real work of data science begins, but integral to and inextricable from the work of data science.

I have already been experimenting with ways to incorporating this perspective into the DSSG program. For example, this year, instead of holding an ethics workshop for participants at the beginning of the program, I conducted a workshop that I called simply, “Introduction to Data Science for Social Good,” and within it, I framed the need to address ethical challenges as part of the evolving state of the art in data science of the social. Another thing that would help to incentivize ethical thinking is explicit acknowledgment of it as a concrete contribution to the progress of data science projects. In order to avoid practitioners thinking of this work as “just talking,” we can make aspects of that labor concrete, visible, and public-facing by documenting the process of exploration and deliberation, creating visual artifacts that summarize ethical issues, and including sections in publications that explicate the ethical issues that were identified and addressed (or not) in the project. Doing so would help teams keep ethical concerns in mind as they work, normalize ethical thinking as part of data science practice, and help external audiences of other data scientists and stakeholders think through ethical challenges in their own work.

#### *Processes supporting data science as ethical innovation*

The second story I presented in Chapter 4 concerned the AccessMap/OpenSidewalks (AMOS) project, which had dual and complementary objectives of building a routing application for the needs of people with limited mobility, and developing functional data standards and tools that could support that application. I characterized their work as an exemplar of data science as ethical innovation, an ethical approach that seeks to understand the pattern of systemic social forces that result in marginalization, and interrupt that pattern with the design of data intensive

technologies that primarily address the needs of marginalized communities. I highlighted three processes that supported this approach in the AMOS project: *balancing* priorities and values of multiple stakeholders, *matching* problems with solutions, and *fractalizing* the formulation of the social problem.

In the preceding discussion of *balancing* priorities and values of multiple stakeholders, I foregrounded how the AMOS team, rather than treating data as objective and neutral, took very seriously the value-laden, subjective nature of data. While critiques of algorithmic mediation often problematize the privileging of instrumentalized efficiency, the AMOS story shows that it is possible to consider and weigh subjective values in a conscientious way, to promote ones that are carefully considered and selected for their ethical implications. But it also shows us that doing so requires many layers of communicative labor of the type that, as I've discussed above, is sometimes dismissed in data science as "just talking." We have seen how the AMOS team spent nearly an entire summer of the DSSG program working to understand the positions, values, and needs of various stakeholders in their projects. The team interviewed users of assisted mobility devices to find out what kinds of information were useful to them in navigating the city; they studied previous attempts to change OSM standards by poring over hundreds of pages of discussion threads and listserv archives to ascertain what the concerns of the community were and what approaches could lead to acceptance; they sought out leaders in the local OSM community to get their advice on how to proceed; and they presented their ideas to national and international audiences through the community's established channels of communication. The team carefully considered the insights they gleaned from these interactions when making key decisions about how to represent data about the pedestrian network. In doing this, they called attention to the ways that choices about the representation of data had the potential to encode

judgments that privileged some perspectives and values over others. The conclusion they came to was that there is never a perfect solution, only a set of trade-offs and compromises. Their work illustrates the truism that data is never objective or neutral, but it also shows that data-intensive work can be an opportunity for surfacing values and assumptions that often go unnoticed and unmarked. In other words, data can be a site not for the obfuscation of values, but a site for their revelation and contestation. When this happens, data-intensive work is not only more likely to ultimately be embraced by targeted stakeholders, but also has the potential to build a more ethical world.

Another process that supported data science as ethical innovation in the AMOS project was the *matching* of problems and solutions. A common critique of data-intensive technologies that are intended to serve the public good is that they often lapse into what Evgeny Morozov (2013) has called technological solutionism, a phenomenon that elevates technology as an inherently beneficial tool that can be applied to any range of problems without consideration for what makes the technology appropriate, worthy, or tenable. In contrast, the organizers of the hackathon event that launched AccessMap were impressed that the team had avoided such a mistake by identifying an informational gap and matching that to the information that could fill it. It is important to acknowledge that this did not happen automatically or spontaneously, but systematically and processually. Importantly, that hackathon that seeded the project did not merely offer municipal open data as a blank slate by inviting participants to propose any and all ideas for what could be done with the data. Instead, it was organized around a particular problem space of easing commuting problems within the city, and included subject matter experts that were on hand to guide teams in tenable directions. Furthermore, once the team had honed in on the problem of missing information that would be relevant to people with limited mobility, they

engaged in an iterative process of identifying just what information would be valuable to their target users. There may be a temptation to dogmatically interpret this to mean that a problem must always be clearly articulated before seeking out the appropriate data and technology to solve that problem. That would be foreclosing many opportunities that are presented and enabled by new technologies, and it can be worthwhile—dare I say even ethical—to ask how technologies that have proven themselves useful in certain capacities may be adapted for other uses that address social problems. Such was the case with the AMOS project, which essentially asked why the mapping tools that help so many people get around aren't meeting the needs of people with limited mobility. So in actuality, the creative process of matching problems and solutions involves iteratively tacking back and forth between problems and possible solutions until the appropriate match is found.

In the discussion of *fractalizing* the formulation of the social problem, I showed how the AMOS team not only articulated a clearly scoped solution to a clearly scoped problem, but also had a vision for how their work fit into and affected broader systemic patterns in the construction of disability. As I have described, the team's leadership adhered to the social model of disability, which sees impairment as arising from a built environment that is designed for a narrowly defined range of "normal" abilities and uses, rather than for a wide range of diverse abilities and uses. Therefore, while the AMOS team wanted to design a tool that could specifically meet the unfulfilled needs of people with limited mobility, they simultaneously sought to develop a supporting informational infrastructure that could accommodate an array of diverse uses and needs; for in a world that supports such diversity, disability is no longer disability, but simply part of an array of abilities. This position goes hand in hand with a sociomaterial worldview that acknowledges how our deeply entrenched cultural norms and power structures inform the design

of our technologies, and how our technologies usually serve to perpetuate those norms and structures. The particulars of that arrangement vary from case to case and problem to problem, but understanding and being able to articulate the relationship between technology and power in the issue at hand is essential to practicing data science as ethical innovation. This is what I mean by “fractalizing” the formulation of the problem: acknowledging the broader pattern of sociomaterial relationships that play out again and again in producing and reproducing the social problem at various scales. Without this recognition, good intentions run the risk of simply reinforcing those patterns instead of interrupting them. This is something that Virginia Eubanks cautions against in “Automating Inequality.” She chides well-intentioned data scientists working on projects to improve social welfare services for not recognizing all the ways that technology has historically been wielded to punish the poor, warning that the technologies they design will ultimately have the same effect unless they acknowledge this history and flip the script by starting from an entirely different place.

#### **4. A Meta-Process Supporting Ethics in Data Science of the Social**

I have argued that to fully integrate the aforementioned processes supporting ethical thinking into data science of the social, we must adjust expectations for what skills, knowledge, and expertise are constitutive of data science. While data science is often conceived as being comprised of programming, statistics, and specific domain knowledge (Conway, 2010), data science of the social requires *integrating experiential knowledge* into practice (Figure 4-4). A number of methods and approaches can help in this regard, including participatory design (Robertson & Simonsen, 2013), action research (Reason & Bradbury, 2001), and user studies (Baxter et al., 2015). In my own role in the DSSG program, I have begun to make this shift by

advocating, for the first time, for the inclusion of a human-centered design mentor to work with the teams in conjunction with a data science mentor.

## SUMMARY OF THEORETICAL AND EXPLANATORY CONTRIBUTIONS

### **From consequences to consequentiality**

STS scholar of infrastructure, David Ribes, has noted that, “reading the scholarly literatures focused on data one may be struck by a distinct disjuncture between those that study the work of data sharing, and those that study its consequences” (Ribes, 2017, p. 1514). A way forward for bridging this gap is to focus not on consequences *or* practices, but on the consequentiality of practice—the manifold ways in which data science of the social matters to our values, our institutions, our communities, and our future. We need not only to interrogate the outcomes of data science of the social when it goes wrong, we also need to explore the significance of the day-to-day practices that produce data science of the social. The first part of this dissertation, consisting of the chapters on ethics in data science of the social, was an exercise in practical, applied, and normative practice-based research. In the second couplet of chapters, those related to infrastructuring processes in data science of the social, I continued to follow a practice-based approach, but here, my findings are less normative and more explanatory. I have attempted to understand how the practice of data science is spreading across social sectors, institutions and problem spaces by theorizing the concept of *exostructure*. I adopt a sociomaterial perspective, understanding process and structure to be the building blocks of the social world. As such, I seek to reveal the imbricated structures and processes that are supporting the spread of data science to new sectors, domains, and problem spaces—and in the process, realigning relationships and carving out new roles for established institutions. In particular, I have

examined cross-sector relationships in the context of data science for social good, paying particular attention to the evolving role of the university in such arrangements.

### **From infrastructures to exostructures**

We are currently undergoing a social transformation that some have called “datafication” (Mayer-Schönberger & Cukier, 2013; Sumartojo et al., 2016; van Dijck, 2014), a process whereby many aspects of the social world come to be represented and mediated by data-intensive technologies. Data are being ever more deeply integrated into the fabric of our social world, a process that is supported by the development of information infrastructures and knowledge infrastructures. Infrastructures are not born, they are grown, and this work has explored the process of growing knowledge infrastructures and data infrastructures that increase the value and utility of public data. I have portrayed earlier efforts to build open data portals as infrastructures for *making data public*, a model that is focused nearly exclusively on providing access to public data for those outside of government. I contrasted these with more recent efforts geared toward *making public data*—the key distinction being that making public data involves working collaboratively with governmental institutions to not only make data accessible to the public, but to make data more useful for government itself.

I suggested that a key way this is happening is through cross-sector collaborations that are built around *exostructures*—temporary, project-based arrangements that are intended to provide proof-of-concept and spawn further investment so that they can be replaced with more stable knowledge infrastructures and data infrastructures down the road. I employ the term exostructure in a metaphoric sense; like the exoskeleton of certain insects, exostructures have a transient materiality that is supposed to be outgrown, rebuilt, or replaced. Any number of the

components that makes up an exostructure—labor, objectives, software tools, code, documentation—is intended to be replaced or reconfigured in new contexts and for new uses.

Like infrastructure, exostructures have expanded scope or scale, in that they are able to “reach beyond a single event or one-site practice.” A hallmark of data science is the opportunity for data, tools, and methods to be repurposed in a variety of contexts and applications. What is being scaled through these projects is data science itself—they are a vehicle for expanding the desirability and capacity of data-intensive computational methods. Also, like infrastructures, they are embedded in other structures, they embody agreed-upon standards, they are built on installed bases, and they are linked to conventions of practice.

But in other regards, I have argued, exostructure is quite different from infrastructure (Figure 5-1). According to Star and Ruhleder, infrastructure is characterized by its “transparency,” by which they mean that “it does not have to be reinvented each time or assembled for each task, but invisibly supports those tasks.” In contrast, a key feature of exostructure is its *transience*, in that it is intended to be customized for each new use case. As such, there is no “taken-for-grantedness” as there is with infrastructure, once it is “learned as part of membership.” Instead, exostructure is a site for learning and experimentation. People have to learn how to be useful *with* infrastructure; in contrast, people have to learn how to *make* exostructure useful in their work routines. Therefore, they do not only become visible upon breakdown, as is understood to be the case with infrastructure; rather they are consistent objects of attention until and unless they evolve into an infrastructure. Infrastructure is also said to be “embedded,” or “'sunk' into, inside of, other structures, social arrangements and technologies.” In this way, it is conceived of as a stable layer. Exostructure, on the other hand, is notable for its *portability*. It figuratively sits on top of infrastructure and connects action not as a stable,

embedded base, but by jumping contexts. In other words, exostructures enable distributed action across contexts, time, and location much in the same way that infrastructure does, but they are not “ready-to-hand” as infrastructure is. Instead, they offer the occasion and site for an infrastructure to potentially emerge.

The exostructure concept offers a unit of observation and analysis with the potential to prompt further exploration into the scaling of data science methods. It emerged initially from my own need to identify and bound my object of study, and I believe that it can similarly help orient other scholars who are interested in the development of data science, the dynamics of cross-sector collaboration, the life span of temporary teams, or the material nature of organizing. It also opens up a host of questions that can further develop our understanding of infrastructures, such as how exostructures integrate with infrastructures, or when and why certain exostructures grow into infrastructures and others do not.

### **Exostructures and the emergent role of the academy**

After introducing the theoretical concept of exostructure, in Chapter 6, I returned to the ORCA and AMOS projects to discuss their infrastructural ambitions and exostructural arrangements. Through these empirical accounts, I explored the imbrication of process and structure, showing how exostructures are supporting processes that can lead to more stable information infrastructures, and how these processes are transforming the role of the university in significant ways.

I argued that the temporary nature of exostructure is allowing for short-term experimentation with shifting institutional roles. And because the university is seen as a relatively neutral actor in collaborations that involve combinations of governmental, business, and/or nonprofit actors, the academy is emerging as an important mediator in these cross-sector

collaborations. The iterative nature of exostructure, meanwhile, means that their outcomes are not expected to be definitive, final, or bulletproof, which mitigates some of the risk involved in developing new technologies and experimenting with new roles. Because the university has a research culture in which failure is viewed as having a pedagogical purpose, and ethical safeguards are institutionalized, the academy is poised to take on some of the ethical and financial risks in exostructural collaborations, acting in something of an entrepreneurial role. The customized nature of exostructures means that they have to be reconfigured or remade for new uses, and therefore, learned as part of their development. In data science projects, this customization requires the mobilization of what Shoshanna Zuboff (1988) calls “intellective skills,” a combination of abstraction, explicit inference, and procedural reasoning required for data-intensive work that renders learning “the new form of labor” (p. 395). Because universities have the mandate to educate and train students, they have an abundance of intellective labor that is being leveraged in exostructural cross-sector collaborations. And the portable nature of exostructure is what enables these other processes to play out across sectors, providing the occasion for experimentation, iteration, and sharing of intellective labor. In occasioning emergent roles for the academy, exostructure is playing an important part in bringing about Etzkowitz’s (2008) prognosis that the university “goes into the future as the predominant organizational format of a knowledge-based society” (p. 147).

Through the concept of exostructure, I have reimagined Leydesdorff and Etzkowitz’s (1996, 1998) triple helix idea by putting it into conversation with literatures on cross-sector collaboration and critical data studies in a way that I hope contributes to the ongoing conversations taking place on all of those fronts. Whereas the original formulation of the triple helix model is focused exclusively on economic outcomes, I have attempted to broaden its scope

and explore questions of values, organization, and materiality. To the literature on cross-sector collaboration, the triple helix idea introduces a rare focus on the role of universities (cf. Siegel, 2010a, 2010b), and the exostructure concept provides an analytical object for making explicit and concrete the “connective tissue” that is understood to hold interorganizational collaborations together (Gherardi, 2006) but nonetheless is often treated as ethereal. For the field of critical data studies, the emphasis on social sectors in both the triple helix model and the exostructure concept invites exploration of areas that are sometimes glossed over—the histories, cultures, and political economies of established social institutions in data-intensive practice. This opens up a number of pressing questions that could be pursued in future work. What does the further entanglement of university, government, and industry interests and activities mean for the core missions of those sectors? How do we balance the educational mandate of the university with the act of mobilizing student labor toward instrumental ends? How do we ensure that these cross-sectoral entanglements don’t end up hindering accountability?

## LIMITATIONS AND FUTURE WORK

### **Ethics meets exostructure**

Thus far, I have provided rather distinct treatments of my two research questions. In exploring how practitioners are responding to ethical crisis in their field, I introduced the notion of vernacular sociomateriality and a framework for ethical approaches in data science of the social. In my efforts to explain how data science methods are being scaled across social sectors, I introduced the concept of exostructures and renovated the triple helix model of cross-sector relationships. But ethics and exostructure are not, in practice, unrelated phenomena.

In the cases I present within this dissertation, ethical practices and perspectives are emerging in and through exostructural relationships, not extraneous to them. It is the roles and

relationships between sectoral partners that occasion many of the ethical questions with which practitioners are grappling, and provide the parameters within which those questions can be answered. For example, exostructural configurations that support data science as ethical convention might not adequately support data science as ethical interrogation, data science as ethical innovation, or data science as ethical participation. Who has a seat at the table matters for how ethics are made sense of and incorporated into data science work, and the particular configuration in an exostructural arrangement may enable some ethical responses and constrain others. This can be seen in both of the case studies examined here; the ORCA team settled on an instrumental understanding of bias in part because they were responsible for supporting the objectives of their stakeholders in government, and the AMOS team made value-laden design decisions to accommodate the values and norms of the OpenStreetMap community.

The philosopher of information, Luciano Floridi (2013), discusses the need for what he calls an “infraethics”—an infrastructure of “moral enablers” that can lead to ethical information systems. What he proposes for such an infraethics consists of principles, concepts, and ideals such as sharing, openness, and transparency. While such ideas certainly have infrastructural implications, science and technology studies have taught us that efforts to build or understand infrastructure require close attention to the material. So just as exostructures in data science of the social are being leveraged to develop robust data infrastructures in the future, we can ask how these exostructures can be leveraged to support the materiality of more robust *ethical* infrastructures in the future. Scholars of science and technology or critical data studies often talk about how values and subjectivities get baked into sociotechnical systems; but they can also sometimes slip off. The care and thoughtfulness and diligence that a team puts into their work may be lost, overturned, or unrecognizably transformed in its translation across contexts. We

need to think carefully about how to make the ethical thinking, deciding, and acting that takes place in exostructural arrangements durable and reproducible.

### **Negative examples**

In this work, I have tried to capture and make sense of two of the most important issues facing my community of study. The “scaling” of data science to new social contexts and problem spaces is core to the mission of the eScience Institute, as evidenced by its tagline, “advancing data-intensive discovery in all fields.” And the ethical issues implicated in data science of the social have become a pressing concern for practitioners, regulators, and critical data scholars alike. I hope that the ideas I’ve put forth here can contribute in some way to a better understanding of these issues, and a more intentional, reflexive, and ethical practice.

Having said that, much has been left out of these pages. I have explained my rationale for largely focusing on positive examples of ethical approaches in data science of the social, rather than negative lessons. Such positive examples are sorely needed and can help point the way forward, for one thing. But also, my very public affiliation with the program and projects I’ve studied makes it difficult for me to offer incisive critique and simultaneously maintain the confidentiality of my research participants; for this reason, I’ve chosen to write about those projects and stories that can be discussed openly without concern for compromising anyone’s reputation or peace of mind. This doesn’t mean, however, that I have not witnessed questionable practices taking place under the umbrella of data science for social good. For example, I have only gestured at the potential for the naming and claiming of “social good” to obfuscate problematic practices, and this is something that should be explored and developed in future work.

## **Multi-sector field sites**

Likewise, in the chapters related to the scaling of data science across social sectors and problem spaces, I have left many stones unturned. While I have suggested that exostructural collaborations are occasioning emergent roles and relationships between social sectors, I was only able to explore what this means for the university from my vantage point within the academy. But I caught a few glimpses of similar transformations in other sectors as well. For example, at a presentation about an upcoming university-government-business data infrastructure collaboration, an employee from a large technology company said that, “Historically, we’ve just said, here’s our product, install it. But you can’t do that with AI.” Artificial intelligence, machine learning, data science, and big data analytics require customized and flexible sociotechnical configurations to support them—“out of the box” software simply won’t cut it. And so the company is “shifting to a model of solution-based delivery.” To do that they need to work with the people on the ground who are coming up with problems and questions in the course of their work. “We’ll rely on groups like this,” the employee told the audience of academic researchers and government officials. “It has to be a collaboration.” This indicates that future work should attempt to gain equal access to the various institutions in cross-sector exostructural arrangements in order to truly understand the complexity and consequentiality of those relationships for all actors involved. And while it was beyond the scope of this dissertation, future studies should link to relevant bodies of literature such as work on collaborative governance from policy studies. Viewing exostructures and ethical approaches from the perspective of multiple sectors would build on the contributions I’ve made here, and further a pressing and worthy task: to better understand the consequentiality of emergent practices in data science of the social, and to positively impact its trajectory.

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## APPENDIX: METHODS

### FIELDWORK

<b>Dates</b>	<b>Site</b>	<b># Pages</b>
<b>Primary Fieldwork</b>		
2015, Jun 16-Aug 21	UW DSSG	*315
2016, Apr 18-Aug 18	UW DSSG	*356
2017, Feb-Aug 18	UW DSSG	*305
<b>Secondary Fieldwork</b>		
2016**	Conference on data in social sector organizations	27
2016**	Conference on university-government-industry research partnerships	15
2016**	Panel on cross-sector collaboration in data science	6
2016**	Hackathon related to government transportation data	42
2017**	Non-UW DSSG program	13
2017**	Hackathon related to using data for social impact	19
2017**	Conference on using data for social impact	24
2017**	Conference on using data for social impact	33
2017**	Conference on university-government-industry research partnerships	17
2017**	Workshop on using transportation data for public benefit	35
	<b>TOTAL</b>	<b>1207</b>

\* Includes notes taken by collaborators

\*\* Exact dates not included for the sake of maintaining confidentiality

## INTERVIEWS

<b>Subjects Interviewed</b>	<b>#</b>	<b>Interviews Conducted</b>	<b>#</b>	<b>Interviews by Site</b>	<b>#</b>
Subjects interviewed one time	72	Interviews with a single subject	88	UW DSSG	84
Subjects interviewed two times	24	Interviews with two subjects	2	Supplementary Sites	14
Subjects interviewed three times	2	Interviews with three subjects	3		
		Interviews with four subjects	5		
		Interviews with five subjects	1		
<b>TOTAL</b>	<b>98</b>		<b>99</b>		<b>99</b>

All interviews, whether solo or group interviews, tended to last 60-90 minutes.

## SAMPLE INTERVIEW PROTOCOL

### DSSG 2017 Interview Protocol—Project Leads

#### **ORIENTATION**

- What drew you to the DSSG?
- What does data science mean to you?
- Do you consider yourself to be a data scientist?
- What does social good mean to you?

#### **PROJECT REFLECTION**

##### **Vision and Context**

- How would you characterize what the social good is that this project is working toward?
- Can you tell us about the process of scoping this project for the DSSG and applying?
- What is the longer-term goal for the project, or the big picture vision it fits into?

##### **Goals and Challenges**

- How would you characterize the goals of your project this summer in the DSSG? And how do you think it is going?
- What have been the biggest challenges or constraints in your project this summer?
- What kinds of ethical questions do you think are implicated in this work?
- How does this DSSG project fit into your broader corpus of work?

##### **Roles**

- How do you see your role as the project lead? What were the challenges of your role?
- How do you see the role of the data scientists?
- How do you see the role of the fellows?
- How do you see the role of eScience as an organization?

##### **Collaboration & Stakeholder Engagement**

- What has it been like to work with a team from so many different disciplinary backgrounds and orientations?
- Can you tell us about the process of engagement across project stakeholders?

##### **Sustainability**

- What happens after this summer?
- What will it take for this work to be sustained? How do you plan to make that happen?
- If your project had not been selected for the DSSG, what would have happened to it?
- What do you think is the future of [your domain or problem space]?

#### **PROGRAM REFLECTION**

- In what ways did the program meet your expectations, or not?
- What have you learned?
- Do you have ideas about what might improve the program for next year?