Cross-sector Collaboration in Data Science for Social Good: Opportunities, Challenges, and Open Questions Raised by Working with Academic Researchers

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Abstract

Recent years have seen growing support for attempts to solve complex social problems through the use of increasingly available, increasingly combinable, and increasingly computable digital data. Sometimes referred to as "data science for social good" (DSSG), these efforts are not concentrated in the hands of any one sector of society. Rather, we see DSSG emerging as an inherently multi-sector and collaborative phenomenon, with key participants hailing from governments, nonprofit organizations, technology companies, and institutions of higher education. Based on three years of participant observation in a university-hosted DSSG program, in this paper we highlight academic contributions to multi-sector DSSG collaborations, including expertise, labor, ethics, experimentation, and neutrality. After articulating both the opportunities and challenges that accompany those contributions, we pose some key open questions that demand attention from participants in DSSG programs and projects. Given the emergent nature of the DSSG phenomenon, it is our contention that how these questions come to be answered will have profound implications for the way society is organized and governed.

Introduction

With growing interest and investment in data science for social good (DSSG) efforts comes a growing need to understand what's at stake in collaborating across sectors. That complex social problems require a multi-disciplinary and multi-sector approach is something we have known for a long time (e.g. Selsky & Parker, 2005, 2010). Yet our understanding of how to build, motivate, and maintain successful partnerships across sectors around data science for social good is still emerging as different configurations are being tested. What are the motivations and challenges that accompany working relationships among multi-sector stakeholders? How are different resources, experience, and expertise leveraged to support data science for social good efforts?

There is increasing support for cross-sector partnerships in DSSG from both the top down and the bottom up. Groups such as the grassroots Data for Democracy and non-profit startups like DataKind are fostering collaborations that often involve some combination of non-profit organizations, government agencies, academic institutions, technology companies, and tech-savvy volunteers. Meanwhile, at the highest levels of government, investment in cross-sector partnerships related to data science for social good is thought to spur innovation. For example, the National Science Foundation 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 research projects that address the needs of various geographic regions. 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 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.). What is being supported with this initiative and with the NSF Big Data Hubs are partnerships and collaborations across sectors, as opposed to particular projects, technologies, or people.

Our research focuses on understanding the sectoral relationships and roles that are emerging across such partnerships and collaborations. On its website, the MetroLab Network characterizes city-university partnerships as "mutually beneficial," such that:

> "the university is the city's R&D department and the city is a test-bed. Faculty and students get access to real-life laboratories to test advanced approaches aimed at addressing city priorities and challenges. Cities, and their residents, benefit from technologies and policies that leverage digital and information technology, data analytics, sensing, and more."

These mutually beneficial alignments are mediated by the distinct positionality, capacities, and constraints that accompany different sectors, all of which present a host of both opportunities and challenges. In this paper we take up these opportunities and challenges as they manifest for the role that academia plays within these collaborations. Based on three years of fieldwork with multi-sector collaborations in the space of data science for social good, we argue that there are five distinct contributions that motivate collaborations with academia: expertise, labor, ethics, experimentation, and neutrality. This paper organizes and articulates these contributions as a way to better understand the opportunities and challenge that surface through multi-sector collaborations in data science for social good, and the open questions that these relationships spark.

Our analysis is based on nearly three years of ethnographic fieldwork, in which we collectively have spent over a thousand hours as participant-observers of 16 different DSSG projects across two universities, attended numerous conferences and hackathon-style events related to the use of data in the service of public good, and interviewed over 40 participants in DSSG efforts. Throughout the research process, we have been embedded in a community of academic researchers with partnerships that span academia, government, technology companies, and civil society. Given this positioning, our access to various actors involved in these partnerships has not been evenly distributed across sectors, and our understanding of cross-sector collaborations in DSSG very much has been influenced by our vantage point within the academy. Therefore, in this paper, we focus primarily on the role of academic researchers, and discuss implications of DSSG for other sectors *vis-à-vis* their collaborations with academics.

Expertise

Collaborations in the DSSG space are often portrayed as filling expertise gaps in organizations that are working to address social problems. Whether public entities or nonprofit organizations, they are thought to be lacking the capacity to harness the power of data. As the founder of DataKind, an organization that matches volunteer data analysts with social change organizations, put it in an interview with *Wired* magazine, "Non-profits don't know what they don't know … They don't know what's even possible with data" (Medeiros, 2013). In the DSSG projects and programs we've observed, faculty, staff, and students at universities are often are lending their expertise to help other organizations make use of data and data science methods in their efforts to address a variety of social issues.

What kinds of expertise are sought and foregrounded in these collaborations with academics has epistemological implications for how we understand the cause of social problems and how we formulate solutions to those problems. DSSG is informed on some level by the implicit assumption that social problems exist not necessarily because there is a lack of political will or because some people with power and privilege benefit from the *status quo*, but because we simply haven't figured out how to fix them yet. And we haven't figured out how to fix them because we haven't been making optimal use of data (Brown & Duguid, 2017; Castells, 1996). It follows, then, that the most important kinds of expertise have to do with making sense of the data itself. Strong candidates for the competitive spots on DSSG teams we observe usually have command over one or more programming languages, substantial experience with canonical statistical methods, and familiarity with advanced computational techniques such as machine learning and natural language processing. These skills and methods are valued, in part, because they are thought to be agnostic to discipline and transferable across contexts. For example, when one DSSG 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.

This is not to say, however, that quantitative and computational skills are prized in DSSG to the exclusion of other forms of expertise. "Domain knowledge," or expertise in a particular subject matter, is typically considered to be an integral part of data science, depicted as "substantive expertise" by the oft-cited Data Science Venn diagram developed by Drew Conway (Fig. 1). In non-DSSG, purely academic data science collaborations we've observed, domain expertise is often contributed by a research partner with post-secondary education in a specific field who is working on a research question that is of interest within that field's intellectual community. In other words, domain knowledge is operationalized as academic expertise in a particular subject matter.

However, the types of expertise harnessed across successful DSSG projects are not limited to academic treatments of the issue. The critical types of expertise we observed emerge around: a) contextual data provenance, b) organizational structure and culture, and c) navigating multiple perspectives on the given issues. First, DSSG teams need to understand the contextual provenance of their data, which is often information that can only be shared by the data's owners or guardians. Without this knowledge, DSSG teams are in danger of misinterpreting the data and proposing inappropriate or ineffective solutions. Second, DSSG projects can be more effective when done with consideration for the structures and cultures of partner organizations. This knowledge is often tacit for those stakeholders, and therefore difficult to articulate and convey – but without it, DSSG teams run the risk of developing products and services that have little chance of being embraced by stakeholders given their respective organizational norms and constraints. Third, DSSG teams need to view social issues from multiple perspectives, realizing that different communities and interest groups have uniquely positioned, highly localized, and sometimes conflicting, stakes in the way social problems are portrayed and addressed. Without understanding the complex political landscapes and contested histories within which social problems are enmeshed, they run of the risk of alienating affected communities or producing unintended deleterious consequences.

In other words, exposing an inequity or proposing a solution to a social problem doesn't necessarily mean that social good will follow. If we ignore that warning, we are in danger of lapsing into technological solutionism (Morozov, 2013), where we propose data-informed solutions that have little chance of actually making a difference because they are contextually misconstrued, organizationally untenable, or socially unacceptable.

In the DSSG projects we've observed, where academic team members come from a wide range of disciplinary backgrounds, they often recognize their lack of knowledge about the issue to which they have been assigned, and instinctively begin their forays into these new research questions by reviewing relevant scholarly literature. This is a necessary, but probably insufficient step; the kinds of knowledge we outlined above -- understanding where data comes from and how it is collected, understanding organizational cultures and constraints, understanding the multiplicity of uniquely situated perspectives about any given social problem -- are not things that can typically be found in a literature review. These forms of knowledge are first and foremost about understanding the experiences of the people involved in and affected by the project. And they are best gained experientially as well, by talking and interacting with those individuals, organizations, and communities (Neff, Tanweer, Fiore-Gartland, & Osburn, 2017). So the triumvirate of skills and knowledge that have come to represent data science for so many practitioners – programming, statistics, and domain knowledge – falls far short of what is needed in data science for social good. We suggest, therefore, that a Venn diagram representing DSSG should include a fourth circle, an arena we are tentatively calling "experiential knowledge" (Fig. 2). An experiential perspective may draw on a range of approaches and methods, including participatory design, action research, and user experience studies – all rpractices that systematically put subjective human experience at the center of research and design (for primers on these approaches, see, respectively, Robertson & Simonsen, 2013; Reason & Bradbury, 2001; Baxter, Courage, & Caine, 2015). Organizers of DSSG programs and projects may enrich their efforts and increase their chances of success by seeking expertise in such experiential approaches and incorporating them into program and project design from their very inception.

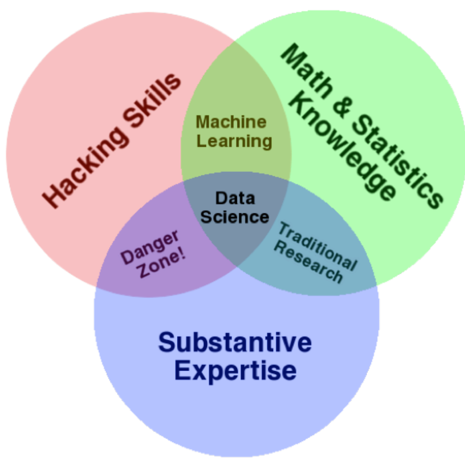

Fig. 1. Drew Conway's heavily cited depiction of the key skills that comprise data science, accessed from http://drewconway.com/zia/2013/3/26/the-data-science-venn-diagram. The Data Science Venn Diagram is Creative Commons licensed as Attribution-NonCommercial.

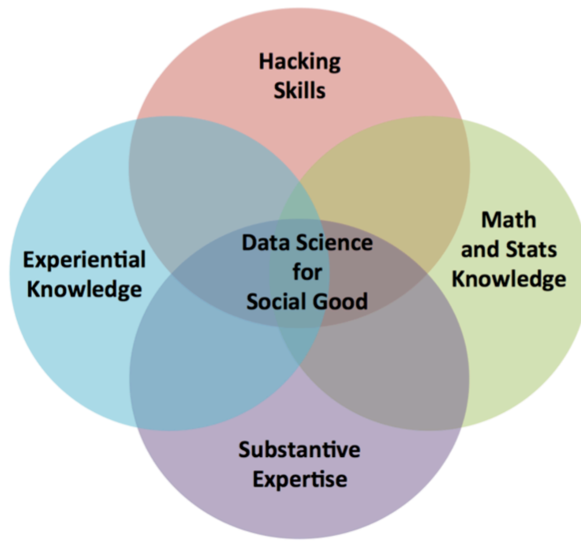

Fig. 2. Tanweer & Fiore-Gartland's modification of Drew Conway's Data Science Venn Diagram to reflect additional expertise that is critical to Data Science for Social Good. The Data Science for Social Good Venn Diagram is Creative Commons licensed as Attribution-NonCommercial.

Having said that, we have observed that even when experiential knowledge is highly valued and prioritized in DSSG projects, it is still a challenge to strike the right balance between the time and energy that goes into cultivating this knowledge, and the time and energy that is demanded by the computational work at the heart of DSSG. This was the case with one of the projects we observed, which had the ultimate goal of building a routing application for people with limited mobility. The team spent a very large part of their time not just writing code, but developing the sort of experiential knowledge we are advocating for. They interviewed users of assisted mobility devices to find out what kinds of information were useful to them in navigating the city. To get buy-in from an open-source mapping community, they pored 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 local leaders 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. All this thinking, deliberation, and communication was not treated as orthogonal to the work of data science, but as an essential component of data science for social good. Rather than rushing through deliberations and pressing team members (who were working on a short 10-week timeline) to produce a tangible outcome, the team's leadership valued the time spent in lengthy discussions among themselves and with stakeholder groups. At times, however, some of the team members expressed frustration with spending so much time "just talking" and eagerness to get to the "work" of writing code. Importantly, then, although the team's leadership prioritized and foregrounded the sort of experiential knowledge that we are advocating for here, their experience points to open questions about how to strike the right balance between the value of this work and the value of producing code for immediate use, and how to meaningfully incorporate the requisite experiential knowledge into DSSG projects that have ambitious goals and highly constrained deadlines.

Labor

Going hand-in-hand with expertise, academic researchers in DSSG also make contributions in the form of free labor, for the hours of work that university students, faculty, and staff put into DSSG projects often come at little or no cost to partner organizations who stand to benefit from the work. This is not to say that those partner organizations are not making any contributions of monetary value, as supporting and collaborating with DSSG teams takes significant time and resources; the point is simply that university affiliates themselves are usually being paid by someone else. In the DSSG programs we've observed, students are doing the lion's share of the project work, and the programs 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.

For example, one lead researcher on a DSSG project we observed felt that the students on the team were using more complicated techniques than were needed to answer questions with the degree of certainty her agency required. She also felt that they spent a long time building a data pipeline that was technically robust and computationally efficient, but that probably could not be understood by other personnel in her agency. This researcher realized that the students wanted to learn or hone these techniques, and didn't mind those choices as long as they ended up meeting all their objectives for the summer. In another project, the lead researcher suggested the team apply a particular kind of algorithm to the problem they were trying to solve, but the students didn't readily understand the way the algorithm worked, and instead went with a solution that was more intuitive to them. But by the end of the summer, the student who had pushed back the strongest against the lead researcher's suggestion said he now understood that approach, could see why it would have been the better option, and regretted steering his team toward something that seemed easier for them to learn. In both cases, what the students were interested in and were able to learn had a significant impact on the trajectory of the project. But the balance can easily tip to the side of prioritizing project objectives at the expense of students' learning opportunities as well. For example, one student talked about how he applied to the program in part because he thought he would be learning new programming languages and analytical techniques, but instead spent the whole summer writing boring database queries in the same language he had used to write his dissertation because no one else on the team had those skills, and it needed to be done.

Given the educational mandate of the university, every DSSG project that involves student labor should recognize the need to compromise between pedagogical opportunities presented by the work, and the need for results. At the DSSG program in which we are embedded, the organizers try to do this by soliciting students' expectations and goals in advance, anticipating the likely trajectory of the projects through multiple meetings with lead researchers well in advance of the program, and doing their best to assign students to projects based on the best match between interests and needs. But just how to strike the right balance remains an open and ongoing question, and one that requires revisiting and recalibrating continually throughout a project.

Another question raised by the reliance on student labor and the concomitant pedagogical obligations is, what are we training students for? If we are hoping to prime and prepare them for a lifelong career using data science skills in the service of social good while working for public institutions or non-profit organizations, then in addition to the arguments we made in the section about expertise, this is further reason to provide students with a systematic and experiential orientation to the cultures and practices of partner organizations. If we are hoping to prepare them for a career doing applied academic research, then we could be intentional about addressing the challenges and rewards along that path, and modeling for them best practices. If we are preparing them for careers in commercial data science, where profit motives can sometimes trump ethical concerns, then we could be even more diligent about emphasizing the critical thinking and communication skills for navigating ethical quandaries. Regardless, if part of the mandate of a DSSG program is to train students for their future careers, we should see the program not just as an opportunity to develop technical skills, but also as an opportunity to develop the organizational intelligence, best practices, and critical perspectives that will set them up for success in data-intensive careers across a range of contexts.

Ethics

Ethical considerations are another impetus for collaborating with universities on DSSG projects. Academic research has a sordid history of ethical transgressions that prompted universities to institutionalize practices and procedures to atone for those misdeeds and prevent future harms (Childress, Meslin, & Shapiro, 2005; National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research, 1979). For this reason, they can make attractive partners for government agencies that want to do powerful analytics or implement machine learning algorithms for automating decision-making, but are worried about not foreseeing all the possible ethical repercussions of that work. 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, Larson, Mattu, & Kirchner, 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 told us:

> 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.

This means oftentimes, datasets that could potentially yield valuable insights remain analytically untapped. But 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 non-profits 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 convened by the authors of this paper, participants from a number of sectors recognized that when public agencies collaborate with academia and other sectors, 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 data generated by the electronic payment system for public transportation in the Seattle region. For seven years, this 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: it contained records of riders' public 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. 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 a 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 (as is the case with most DSSG projects), 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).

Another question facing the venerable IRB in the digital age is whether the ethical gold standards in academic research - anonymity and informed consent - are enough to sufficiently prevent harm in this day and age. Solon Barocas and Helen Nissenbaum (2014) call for an overhaul of these concepts. Anonymity essentially means removing the ability to identify an individual by name, and they argue that this is no longer a sufficient protection. Individuals can be isolated in a dataset and labeled with a random number or pseudonym, but the absence of a name does not prevent that individual from being targeted. For example, if someone (or an algorithm) knows where a person lives, what time she goes to work, and what she buys online, it hardly matters if her name is attached to her personhood or not -- she is still vulnerable to being distinguished as an individual. For this reason, Barocas and Nissenbaum suggest that we replace the notion identifiability with the concept of *reachability*. In other words, it matters less that a person can be named, and more that their persona can be singled out. The scholars also question the suitability of informed consent in the era of ubiquitous digital data. To access common services, citizens and consumers regularly must agree to jargon-filled terms of service that relinquish control over their data without a complete understanding of all its potential downstream uses. For this reason, Barocas and Nissenbaum (2014) suggest replacing the standard of informed consent with a standard of *contextual integrity*, which would account for the reasonable expectations that users and citizens have for the flow of information about themselves. Their arguments, and similar concerns raised by other astute thinkers, raise an important open question to be considered in DSSG cross-sector collaborations: If partners from other sectors are interested in working with academics as part of their due diligence in practicing data science ethically, how do we ensure that universities never become a rubber stamp, and that these collaborations are instead leveraged as opportunities to continually develop and improve conventional ethical norms and practices?

Experimentation

With so much of data science being about exploration, trying new techniques, and using data in different ways, success in data science for social good projects is far from given. And so the culture of experimentation that is so prevalent at universities can help other sectors get their DSSG 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 an experiment fails, you learn what you can from that failure, and try again. Similarly to the way academic partnerships can defer some ethical risks, if universities are shouldering most of the financial burden for DSSG projects, 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.).

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 DSSG projects 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 are often looking for. 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 social change organizations 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, there is a potential tension between the academy's mandate to produce novel results and generalizable knowledge, and the DSSG mandate to produce actionable results tailored to the specific needs of partner organizations in other sectors. So a big, open question in DSSG cross-sector collaborations is how to balance the value of experimentation and the accompanying tolerance of failure with the value of tangible results and accountability? How can partners plan and scope projects that render their different incentive structures into strengths rather than obstacles?

Need for neutrality

Another thing stakeholders in DSSG cross-sector collaborations may value in their academic partners is the perception of their neutrality. 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.

At a recent conference convened by a national lab, speakers from universities and technology companies echoed this sentiment in presentations about another kind of data repository in the works, one that would combine not just data from public transportation agencies, but also from private transportation companies. Such a repository is envisioned as benefiting society by making possible analyses to support the planning of more efficient regional transportation systems, as well as services to provide consumers with seamless access to multimodal transportation options. But there are many obstacles to overcome before such a repository can be built. Government actors are aware that combining datasets makes it easier to de-identify anonymized data (Montjoye & Kendall, 2014), and are concerned about creating a single repository of highly sensitive data that could conceivably be subject to public records requests. And private companies refuse to share data with their competitors. The university researchers involved, however, are offering a solution to both of those concerns. If they house the datasets at the university as research data, they become exempted from public records laws, assuaging some of the government's concerns. And having no profit motive themselves, the researchers can safeguard the proprietary raw data of competing transportation companies, and only allow queries of the database that abide by data sharing agreements participating parties have agreed to in advance.

In this instance, the university is leveraging its position as a relatively impartial party to mediate the relationships between public and private sector entities. It is reasonable to ask, though, whether in similar scenarios 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 (e.g. 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 (e.g. 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.

Contributions	Opportunities	Challenges	Open Questions
Expertise	Filling gaps	Technological solutionism	What expertise counts? How to integrate experiential knowledge?
Labor	Free labor by students and faculty	Dual mandate to teach and produce results	How to strike the right balance between pedagogical aims and project objectives? How to prepare students for future careers?
Ethics	Distribution of risk	Outdated norms	How to avoid turning the academy into a rubber stamp? How to evolve existing ethical norms and standards?
Experimentation	Safe space for innovation	Different incentive structures	How to strike the right balance between the values of novelty and accountability?
Neutrality	Intermediary role	Conflicts of interest	What are the appropriate boundaries between sectors?

Fig. 3. Summary of academic contributions to DSSG, and their associated opportunities, challenges, and questions. Analysis is based on data collected through participant observation in an academic DSSG program.

Conclusion

With a number of universities replicating the University of Chicago's DSSG summer program, the federal government supporting networks such as MetroLab and Big Data Innovation Hubs, and players convening events such the Bloomberg Data for Good Exchange, Do Good Data, and the University of Chicago DSSG Conference for which this paper was written, it is clear that there is growing momentum behind efforts to use data science in the service of society. Importantly, academic researchers and institutions are playing a key role in the phenomenon by making contributions in the areas of expertise, labor, ethics, experimentation, and neutrality. We have outlined how each of these contributions is accompanied by unique opportunities and challenges that raise a number of pressing questions (Fig. 3). How do we ensure that the right mix of expertise is valued in DSSG collaborations? How do we meet both the pedagogical needs of students and the need for actionable results? How do we further the evolution of ethical norms and standards at our academic institutions in response to modern sociotechnical arrangements? How do we strike the right balance between the values of novelty and accountability? How do we determine the appropriate boundaries and relationships between sectors when sharing data and technological platforms? The DSSG community's response to these and other questions has implications not just for the outcome of individual DSSG projects or particular social issues, but for society at large. Future work, including our own, should explore how experimentation with sectoral roles and relationships in DSSG may signify profound changes in the way society is organized and governed.

References

Angwin, J., Larson, J., Mattu, S., & Kirchner, L. (2016, May 23). Machine bias: There's software used across the country to predict future criminals. And it's biased against blacks. *ProPublica*.

Barocas, S., & Nissenbaum, H. (2014). Big data's end run around anonymity and consent. In J. Lane, V. Stodden, S. Bender, & H. Nissenbaum (Eds.), *Privacy, big data and the public good: Frameworks for engagement* (pp. 44–75). Cambridge, UK: Cambridge University Press.

Baxter, K., Courage, C., & Caine, K. (2015). *Understanding your users: A practical guide to user research methods*. Waltham, MA: Morgan Kaufmann.

Big Data Regional Innovation Hubs: Establishing spokes to advance big data applications [solicitation]. (2017). Retrieved from https://www.nsf.gov/funding/pgm_summ.jsp?pims_id=505264

Boyd, D., & Crawford, K. (2012). Critical questions for big data. *Information, Communication & Society*, *15*(5), 662–679.

Brown, J. S., & Duguid, P. (2017). *The social life of information*. Boston, MA: Harvard Businees Review Press.

Castells, M. (1996). *The rise of the network society*. Malden, MA: Blackwell.

Chambers, C. (2014, July 1). Facebook fiasco: was Cornell's study of "emotional contagion" an ethics breach? *The Guardian*.

Childress, J. F., Meslin, E. M., & Shapiro, H. T. (Eds.). (2005). *Belmont revisited: Ethical principles for research with human subjects*. Washington, DC: Georgetown University Press.

Gray, M. (2017, July 24). We need more, not fewer, collaborations with tech companies. *The Chronicle of Higher Education*.

Hargittai, E. (2015). Is Bigger Always Better? Potential Biases of Big Data Derived from Social Network Sites. *The ANNALS of the American Academy of Political and Social Science*, *659*(1), 63–76.

Lazer, D., Kennedy, R., King, G., & Vespignani, A. (2014). The parable of Google flu: Traps in big data analysis. *Science*, *343*(6167), 1203–1205. http://doi.org/10.1126/science.1248506

Medeiros, J. (2013, June 4). Jake Porway wants to turn his network of scientists into a league of information champions. *Wired*.

MetroLab Network. (n.d.). Retrieved July 28, 2017, from https://metrolabnetwork.org/

Montjoye, Y.-A. de, & Kendall, J. (2014). Enabling Humanitarian Use of Mobile Phone Data. *Issues in Technology Innovation*.

Morozov, E. (2013). *To save everything, click here: The folly of technological solutionism*. PublicAffairs.

Mullins, B., & Nicas, J. (2017, July 14). Paying professors: Inside Google's academic influence campaign. *The Wall Street Journal*.

Neff, G., Tanweer, A., Fiore-Gartland, B., & Osburn, L. (2017). Critique and contribute: A practice-based framework for improving critical data studies and Data Science. *Big Data*, *5*(2), 85–97. http://doi.org/10.1089/big.2016.0050

Reason, P., & Bradbury, H. (Eds.). (2001). *Handbook of action research: Participative inquiry and practice*. Sage.

Research, N. C. for the P. of H. S. of B. and B. (1979). *The Belmont Report*. Was. Retrieved from http://www.hhs.gov/ohrp/policy/belmont.html

Robertson, T., & Simonsen, J. (Eds.). (2013). *Routledge international handbook of participatory design*. New York: Routledge.

Selsky, J. W., & Parker, B. (2005). Cross-sector partnerships to address social issues: Challenges to theory and practice. *Journal of Management*, *31*(6), 849–873.

Selsky, J. W., & Parker, B. (2010). Platforms for cross-sector social partnerships: Prospective sensemaking. *Journal of Business Ethics*, *94*, 21–37. http://doi.org/10.1007/sl0551-011-0776-2

Sullivan, G. (2014, July 1). Cornell ethics board did not pre-approve Facebook mood manipulation study. *Washington Post*.