

Mapping Civil Society in the Digital Age: Critical Reflections From a Project Based in the Global South

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Abstract

Initiatives to map nonprofit organizations encompass efforts to define the boundaries of the sector and understand its scope and scale. As new technologies make it possible to digitize and analyze information in new ways, further questions about mapping civil society emerge. We integrate nonprofit scholarship, critical work on computational methods, and reflection on our experiences using machine learning to map nongovernmental organizations in Ghana, to develop a critical framework for mapping civil society in the digital age. The issues we raise about computational methods are embedded within greater concerns about the taken-for-granted assumptions in mapping civil society, and mapping as a tool to control, manage, and manipulate civil society. We are particularly attentive to the power within mapping as a mode of knowledge production.

Keywords

mapping civil society, critical theory, statecraft, machine learning, bias, Global South

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Initiatives to map civil society¹ include efforts to define sector boundaries, identify and classify the actors and activities encompassed within it, and understand the scope and scale at which they occur. Various groups, including governments, research institutes, and domestic and international nonprofits have worked to conceptualize and quantitatively map civil society within and across diverse national contexts (Chambers & Kymlicka, 2002; Heinrich, 2005; Salamon & Anheier, 1998; Salamon & Sokolowski, 2016; Taylor, 2002). Foundational to civil society, mapping is a belief in “. . . the old aphorism that ‘what isn’t counted doesn’t count’” (Salamon & Sokolowski, 2016, p. 1522). This aphorism illuminates the knowledge production function and power inherent in maps and mapping processes. That is, civil society can only be legitimate and understood if the organizations and groups within it can be measured, aggregated, studied, and compared across various contexts. Moreover, we assert that this aphorism highlights a need to take a critical perspective to examine the processes for mapping civil society.

Critical work about civil society mapping draws on Scott’s (1998) “maps of legibility” to examine mapping as a process of domination and resistance. Scott recognizes mapping as a process to measure, codify, and simplify natural and social environments—in our case civil society—to control, manage, and manipulate them for the fulfillment of fiscal or administrative goals. While mapping makes civil society more *legible* and, as a result, more *instrumental* to governments and other actors, it can only ever capture a “selective reality,” as seen through the lens of the “official observer” or mapmaker (Scott, 1998). Following Scott’s arguments, research has placed claim on the need to underline the assumptions taken when mapping civil society. For example, Appe (2011, 2012, 2013) calls attention to the positionality of the mapmaker—or the *who* in mapping, whereas Nickel and Eikenberry (2016) question the purpose of mapping—or *why* we engage in mapping. In light of new computational methods that can facilitate quantitative civil society mapping, these critical perspectives must be newly examined and extended.

In the modern age, digital information is voluminous and ubiquitous; we generate big data daily through the use of social media, smartphones, and so on, and information contained in hard-copy archives can be digitized. Computational methods for information extraction, including machine learning (ML), can be used to build quantitative data sets from digital repositories of unstructured data (Anastasopoulos & Whitford, 2018). Computational approaches to information extraction are often championed as objective (Lepri et al., 2018); however, critical work cautions that computational methods are not bias-free (Friedman & Nissenbaum, 1996) and can reinforce oppressive systems (Corbett-Davies & Goel, 2018; O’Neil, 2016). These perspectives underscore the need to examine the ways that technical choices regarding data and methods shape maps and mapping processes beyond actors and goals.

Our article addresses this need for critical research at the intersection of computational methods and civil society mapping. To do so, we integrate three bases of knowledge: research on civil society mapping, critical work on computational methods, especially ML, and reflexive analysis of the authors’ ongoing research project using computational methods to map nongovernmental organizations (NGOs) in Ghana.

Reflexive analysis is essential for uncovering the “hidden assumptions” and “ideological inscriptions” of computational methods used for quantitative research (Kincheloe & McLaren, 1994, p. 144), including large-*N* civil society mapping projects. Integrating these three bases of knowledge allows us to critically examine the ways in which the who (actor positionality), the why (goals), the what (data), and the how (computational methods) of mapping shape civil society mapping processes and outcomes in the digital age. Although we focus on computational methods, we ground our research in the tenets of critical scholarship by “challenging structures of domination, questioning taken-for-granted assumptions, going beyond instrumentalism, and paying attention to power” (Coule et al., 2020, p. 3). Our framework illuminates the ways that taken-for-granted assumptions about mapping and computational methods interact to create both new issues and new opportunities.

Our work makes several contributions. First, it answers calls for reflexivity in nonprofit scholarship (Coule et al., 2020; Harris, 2001) and in computational and quantitative methods (Burrell, 2016; Elish & Boyd, 2018; Kitchen, 2017; Stage, 2007). Second, it extends critical nonprofit work on civil society mapping that questions the objectivity of mapmakers and their goals by considering how technical decisions and methodological assumptions shape mapping processes and outcomes. Third, it illuminates the knowledge production function and power inherent in mapping and computational methods, as well as their intersection. Finally, it offers a framework that can inform mapping practice and critical research on civil society mapping moving forward.

Our article is structured as follows. “Part I” contextualizes the three bases of knowledge we use to build our framework. “Part II” presents and discusses our framework that uncovers hidden assumptions and raises critical issues about the who, the why, the what and the how of mapping civil society in the digital age. Discussion of implications is largely integrated in the presentation of our framework and our conclusion highlights the contribution of our work to critical theory and mapping research and practice.

Part I. Contextualizing Bases of Knowledge

In this section, we examine mainstream and critical nonprofit research on civil society mapping. We then attend to critical work on computational methods, especially ML, to discuss their promise and peril for civil society mapping. Finally, we discuss the importance of reflexive analysis about our mapping project on NGOs underway in Ghana.

Mapping Civil Society: Comparing Mainstream and Critical Approaches

Mainstream approaches to civil society mapping involve collating standardized information on nonprofits, NGOs, and voluntary organizations and groups, and, often, making these data publicly available (Appel, 2013). The benefits ascribed to civil society mapping include enhancing our understanding of the size and scope of the sector (Grønbjerg, 1994; Lampkin et al., 2001), facilitating comparison of the sector across

various contexts (Heinrich, 2005; Salamon & Anheier, 1998; Salamon & Sokolowski, 2016), improving economic and democratic efficiency through regulation and collaboration (Fioramonti & Kononykhina, 2015; Never, 2011; Salamon & Sokolowski, 2016), and legitimizing the role of civil society in burgeoning democracies (Appe, 2011, 2012, 2013).

Mainstream civil society mapping projects draw upon standardized definitions to “isolate the phenomenon and manage complexity” (Ospina et al., 2018, p. 594). Most often, legal and/or conceptual definitions are used to define the boundaries of the sector and units of analysis. Legal definitions reflect the status granted to organizations by a government through legislative or executive action and may not apply outside of a particular national context. A challenge to using legal operationalizations of the sector is reliance on data collected for government (e.g., tax collection and regulation) rather than research purposes (e.g., Roudebush & Brudney, 2012). In contrast to legal definitions, conceptual definitions come from a variety of actors, can be context based, and have resulted in a debate around definitions in use and motives.

A variety of civil society mapping projects have sought to develop definitions of civil society by combining legal and conceptual definitions. To illustrate, we briefly highlight two global mapping projects seeking to create comparative country-level indexes of civil society—the CIVICUS Civil Society Index and Johns Hopkins Comparative Nonprofit Sector Project (CNP). CIVICUS seeks to assess the openness of civil society by defining civil society organizations through the civil society spaces in which they operate (Heinrich, 2005). In contrast, the CNP focuses on the scope and role of civil society organizations using definitions based on organizational attributes (Salamon & Anheier, 1998; Salamon & Sokolowski, 2016). Although each of these mainstream mapping efforts assumes a detached stance—that they are observing an external reality—the actors (“who”) and goals (“why”) of each project shape their mapping processes (e.g., conceptual definitions, sampling), resulting in different civil society maps.

In contrast to mainstream efforts, critical research on civil society mapping homes in on hidden assumptions of actors and goals and their implications. Van Til (1988) and Smith (1997) were the first to launch critical discussions of civil society mapping. Van Til (1988) presented “social maps” as “images that reflect the institutional terrain of society” (p. 71). He noted the potential to take for granted choices in producing maps—that different initial assumptions and process objectives could result in divergent maps. Later, Smith voiced concerns about mainstream conceptualizations of the nonprofit sector and their implications for civil society mapping. He noted that the collection of data on nonprofits and the research generated from these data are “incomplete, distorted, and misleading in systematic ways” (Smith, 1997, p. 114). By only observing formal, registered nonprofits with paid staff and ignoring informal grass-roots organizations, Smith (1997) asserts that mapping efforts may be omitting up to 90% of the sector, leading to misguided or underdeveloped theory.

Recent critical approaches to civil society mapping examine the knowledge production function and the relative power of the actors engaged in the mapping process. Maps are tools used to produce meaning, by rationalizing (Appe, 2013) and

instrumentalizing civil society as a form of modern statecraft for surveillance and regulatory enforcement (Nickel & Eikenberry, 2016). Maps, moreover, have a “discourse function” (D. Wood, 2010) and are a means for mapmakers—particularly governments and funders—to exert power (Crampton, 2001). These critical understandings allow us to identify ways in which mapping becomes an instrumental, one-size-fits-all approach to define and control civil society. As such, quantitative mapping and standardized definitions may fail to reflect the local knowledge and practices of nonprofit and voluntary organizations within specific contexts.

Still, critical work on civil society mapping has overly focused on definitions, actors, and goals in mapping. It does not consider how computational methods employed to map the sector (e.g., Fyall et al., 2018; Litofcenko et al., 2020; Ma, 2021) shape mapping processes and outcomes (see Kincheloe & McLaren, 1994). To address this gap, we integrate research on civil society mapping with critical work on computational methods presented in the next section.

The Promise and Peril of Computational Methods for Civil Society Mapping

Computational methods make it possible to render information from large paper archives and big data repositories relatively quickly. Image scans of hard copy documents can be converted into machine-readable files and information from organizational websites can be scraped and stored. These raw data become inputs for information extraction processes, with the goal of producing structured data sets.

The promise of computational methods is the flexibility they offer to extract information that reflects different human understandings of the world. Computational approaches allow mapmakers to privilege nuanced, local understandings of the sector without having to rely on standardized classification rules. For example, Fyall et al. (2018) use an automated dictionary approach to classify nonprofits based on self-reported mission statements. The authors identified twice as many housing and shelter nonprofits than were coded as such in the U.S. National Taxonomy of Exempt Entities (NTEE), the dominant classification system in the United States. The difference between the Fyall et al. and NTEE maps is remarkable, and powerfully illustrates the potential for using computational methods to map civil society in ways that are not dependent on one-size-fits-all conceptualizations of the sector. The NTEE codes reflect a broad operationalization of civil society in the United States. In contrast, Fyall and coauthors use computational methods to create a fine-grained snapshot of organizations in the housing and shelter space in the state of Washington, which leverages local understandings of organizational purpose reflected in mission statements. This example illustrates the potential of computational approaches to shed greater light on local knowledge and the “below-the-radar” activity of the sector (Soteri-Proctor & Alcock, 2012). Importantly, this example also shows that, while both localized and standardized maps are meaningful, each is shaped by the actors, goals, and technical choices about data and computational methods used during the mapping processes.

The peril of computational methods to information extraction is rooted in the tendency to perceive them as objective, whereas they are inherently shaped by human understandings of the world (see Gillborn et al., 2018). Information extraction includes traditional approaches (e.g., automated content analysis and categorization using keyword dictionaries) and inductive ML approaches. Both traditional and ML approaches involve computer algorithms, defined as structured procedures executed by a machine (Kitchen, 2017). Traditional approaches start by leveraging human intelligence to identify rules that are then translated into computer code. With ML, computers “learn” or are “trained on” data rather than a set of preestablished rules, meaning that computers identify and use patterns in the data for information extraction (Rebala et al., 2019). In both traditional and ML approaches, humans select data, keywords, and categories, label data for training purposes, choose the algorithms to be used and interpret their results. Whether explicitly acknowledged or not, these choices are grounded in distinct values and understandings of causation and data generation that shape mapping processes and outcomes.

A seminal article by Friedman and Nissenbaum (1996) on bias in computer systems² enhances our understanding of the way human values and understandings are embedded in such technical choices and provides a cornerstone for our framework. The authors define bias broadly as “slant” but focus specifically on bias in computer systems that “*systematically and unfairly discriminate[s]* against certain individuals or groups of individuals in favor of others” (Friedman & Nissenbaum, 1996, p. 332, with original italics). Our framework considers Friedman and Nissenbaum’s broad and specific definitions of bias to examine how computational methods shape mapping processes and outcomes, using their three categories of bias: preexisting, technical, and emergent. Preexisting bias has origins in social institutions, attitudes, and practices that become embedded in computer systems when the perspectives and objectives of designers are unexamined and unchecked. Technical bias emerges from constraints or considerations, including hardware and software limitations and trade-offs that result from the need to quantitatively represent complex human constructs, such as judgments and discourse. Finally, emergent bias results from the context of use. For example, over time, computer systems may not reflect new societal knowledge or may be uncritically applied across diverse contexts where they are misaligned with local knowledge, values, and/or expertise of human users.

Friedman and Nissenbaum (1996) problematize computational methods by considering the ways that social structures and institutions, as well as technological constraints, shape technical choices, whereas changes in context of use influence algorithm application and outcomes. As such, their work is central to our framework for mapping civil society in the digital age. To fully integrate nonprofit research on civil society mapping and critical scholarship on computational methods, we apply reflexive analysis to our experiences, using such methods to map NGOs in Ghana.

Reflexivity and Our Project Mapping NGOs in Ghana

Reflexivity, or reflexive analysis, is a process that allows for the questioning of both our social world and processes of knowledge production (Giddens, 1984). It draws

attention to the means and contexts in which knowledge is produced and underscores that knowledge and its production are not neutral (Coule et al., 2020). This approach prompts researchers to acknowledge their “subjectivities” and “positionalities” through “the process of reflecting critically on the self as a researcher, the ‘human as instrument’” (Lincoln & Guba, 2000, p. 183). Such transparency brings to light assumptions and contextualizes experiences and understandings that influence knowledge production processes and outcomes.

Although reflexivity has become more common in other fields of scholarship and practice, Harris (2001) called attention to the limited reflexivity in nonprofit studies. Whereas reflexivity is often incorporated into qualitative research designs to enhance rigor and respond to liabilities related to validity or credibility (Merriam & Grenier, 2019), quantitative scholars are also turning to reflexive analysis to recognize tensions grounded in their own methodologies and technical choices (e.g., Stage, 2007).

As researchers leveraging computational methods, specifically ML, to map the NGO sector in Ghana, we use reflexivity to integrate and extend previous work on civil society mapping and computational methods. A more detailed description of our NGO mapping project³ and the computational methods we employ is available in the Supplemental Appendix. However, we provide a brief overview of our project here.

As of 2016, there was no database—electronic or otherwise—of all the NGOs doing work in Ghana. For decades, however, the government has been retaining paper records on registered NGOs operating in the country. Through professional connections, the research team—comprising American and Ghanaian scholars—approached the Ministry of Gender, Children, and Social Protection (the Ministry) about digitizing paper NGO records. The project goal is to extract digital data from the records available to the Ministry for administrative and research purposes. To map NGOs operating in Ghana, we scan and convert each paper record into a machine-readable file. We label, or classify, a subset of the digitized records by hand, based on the activities and beneficiaries (e.g., “Health,” “Children”) described in the record. This hand-labeled subset is used to train a series of supervised ML algorithms (naïve Bayes, support vector machine, and random forest) to classify the records by activity areas and beneficiary groups. We ultimately apply the most effective classification models to unlabeled records to create a quantitative longitudinal data set, or map, of NGOs registered to operate in Ghana.

Part II. Critical Framework and Discussion on Mapping Civil Society in the Digital Age

Critical nonprofit research uncovers the ways in which actors and goals shape civil society mapping processes and outcomes. Critical work on computational methods, particularly Friedman and Nissenbaum’s (1996) typology, underscores that computational methods are not bias-free because they are shaped by social structures and institutions, technical constraints, and changes to their context of use (preexisting, technical, and emergent biases). We integrate these bodies of research using reflexive analysis of our own mapping experiences to develop a framework that uncovers

critical issues around the who, the why, the what, and the how of mapping in the digital age (see Table 1). In this section, we discuss the potential benefits of computational methods and the need to identify taken-for-granted assumptions when using them to map civil society.

The Who of Mapping

Nonprofit scholarship illuminates how the social position and power of mapmakers shape civil society mapping processes and goals (Appe, 2012, 2013). Positionality of mapmakers, and other stakeholders, shape how a map is used and therefore its meaning (Appe, 2011, 2012). Positionality includes actors' social identities and mapping roles, their access to technical expertise and skills, and their level of control over mapping and interpretive processes (from Table 1). Based on their positionality, mapmakers uncover—or make legible (Scott, 1998) different civil societies.

We integrate this existing mapping scholarship with our other bases of knowledge, first considering the influence of social structures and institutions on design choices. We note that the positionality of our partner, the Ministry—and stakeholders not currently engaged in the mapping project, such as NGOs—have shaped the design choice to map NGOS based on activity areas and beneficiaries. As a team that includes both Ghanaians and Americans, we notice the ways in which our cultural backgrounds shape our understandings of phrases used to describe activity areas and beneficiaries in NGO records, which in turn inform the way we label records to train ML algorithms (further discussed in “The What of Mapping” section). As a team with members who identify as both critical and quantitative scholars, we also recognize that our identification with particular methodologies shapes our use of both computational methods and reflexive analysis.

We next link to Friedman and Nissenbaum's (1996) discussion of how technical constraints shape computational methods. When maps are developed using computational methods, lack of technical expertise and differential access to tools may limit a mapmaker's ability to account for preexisting bias in data. As such, we are cognizant of the power differentials on our team rooted in disparate access to the technical training and equipment needed to implement computational methods.

Finally, we consider context of use. As we and other researchers (see Fyall et al., 2018; LePere-Schloop, forthcoming; Litofcenko et al., 2020; Ma, 2021) more readily apply computational methods to mapping, unreflexive mapmakers may reify our methods and/or algorithms as “objective,” potentially leading to their inappropriate application to data from different social and historical contexts (Lepri et al., 2018; O'Neil, 2016). We further note that the positionality of our partner, the Ministry, will shape the interpretation of our project's map. We summarize these insights on *the who* of mapping in the top row of Table 1, concluding that reflection on the who of mapping should be iterative throughout the mapping process.

Table I. Critical Framework for Mapping Civil Society in the Digital Age.

Critical issues rooted in	Influence of social structures and institutions on design choices "Preexisting bias"	Technical constraints, limitations, and trade-offs "Technical bias"	Changing social and historical context of use "Emergent bias"
<i>The who</i> Actors and their positionality	<ul style="list-style-type: none"> - Control of mapping processes and goals - Control of preliminary interpretive processes and the meaning of the data - Designer preferences for certain methodologies 	<ul style="list-style-type: none"> - Disparate access to technical expertise and equipment needed to use computational approaches for mapping - Disparate access to technical skills needed to detect and/or control for preexisting bias in training data 	<ul style="list-style-type: none"> - Control of interpretive processes and the meaning of the map - Reification of computational methods and outputs as "objective" shapes interpretive and diffusion processes
<i>The why</i> Goals	<ul style="list-style-type: none"> - Reproduction or resistance to instrumentalization of civil society to statecraft - Reproduction or resistance to power structures through mapping processes - Computational methods training and publication norms prioritize maps of legibility over resistance 	<ul style="list-style-type: none"> - Actors with computational methods training likely to prioritize legibility over resistance 	<ul style="list-style-type: none"> - Reproduction or resistance to power structures through interpretive processes - Reproduction or resistance to power structures through transparency of maps produced - International scale of statecraft may facilitate diffusion of maps and algorithms aligned with statecraft
<i>The what</i> Data and categories	<ul style="list-style-type: none"> - Flexibility to privilege different knowledge (e.g., <i>mētis</i>, academic, and statecraft) based on data selection and category definitions - Potential to reproduce power disparities and oppressive systems by training algorithms on biased data 	<ul style="list-style-type: none"> - Data availability limitations make it easier to produce maps of legibility over resistance - Controlling for biased data may not be technically feasible - Lack of consensus around approach to implement and verify algorithmic equity 	<ul style="list-style-type: none"> - Data selection and category definition decisions may not be updated to reflect new understandings - Reification of computational methods and outputs as "objective" may lead to diffusion of maps and algorithms shaped by biased training data
<i>The how</i> Algorithms	<ul style="list-style-type: none"> - Intentionally opaque algorithms reproduce power structures through control over mapping processes and outcomes - Regulation and professional norms shape actors' ability to create and deploy intentionally opaque algorithms 	<ul style="list-style-type: none"> - Disparate access to technical training and equipment needed to use computational approaches for mapping exacerbates algorithmic opacity and reproduces inequality - Algorithm and training data complexity make it more difficult to trace impact of biased data on mapping processes and outcomes 	<ul style="list-style-type: none"> - Algorithm and training data complexity make it more difficult for stakeholders to contest the "objectivity" of computational methods and mapping outcomes

The Why of Mapping

Nickel and Eikenberry (2016) and Scott (1998) assert that actors exert power through mapping processes by setting priorities, promulgating certain worldviews, and producing knowledge. Mainstream mapping approaches conform to this agenda on practical, theoretical, and empirical grounds (Vakil, 2018). For example, the U.S. Federal Government has classified nonprofits into “tax categories—in order to make them ‘fiscally legible’” (Scott, 1998, p. 68, as cited in Nickel and Eikenberry, 2016, p. 399). Academic projects focused on the Global North (Never, 2011; Roudebush & Brudney, 2012), Global South (Brass, 2012; Fruttero & Gauri, 2005), and comparative mapping across both (Salamon & Sokolowski, 2016) assert that nonprofits are not legitimate policy actors if they are not formally defined, making mapping essential to legitimization of the sector. Mainstream efforts to map civil society thus reproduce “a mode of knowledge inquiry that facilitates statecraft” (Nickel & Eikenberry, 2016, p. 398) and maps comprising “uniform governable units” (p. 394).

The project of statecraft is particularly important in postcolonial contexts throughout the Global South, such as Ghana. Statecraft is shaped by international interests with a stake in democracy building and incentivized through fiscal policy tools of Global North countries and multilateral institutions such as the World Bank and International Monetary Fund. Since the 1980s and 1990s, these democracy-building projects often hail NGOs at their center through structural adjustment policies; shifting powers of government from direct service delivery to rule of law provision and macroeconomic oversight (J. Wood, 2016). Throughout the Global South, governments have rolled back direct provision of public goods (Gary, 1996) as international funding has been reallocated to NGOs (Konadu-Agyemang, 2001; Sachikonye, 1993). Reallocation of international assistance has instigated or increased tensions between states and civil society (Banks et al., 2015; Gary, 1996; Ndegwa, 1994; J. Wood, 2016). As a result, governments have used the power of regulation to coerce, limit, and coopt civil society (Banks et al., 2015). This institutional context powerfully shapes the goals of civil society mapping projects.

The goals of our mapping project are shaped by the institutional contexts of statecraft and the academy. International and national policies create pressure on the Ministry to convert their services to electronic processes and create digital records.⁴ New legislation in Ghana mandating e-services and digital records facilitates our mapping partnership. Moreover, our goals as a research team are shaped by an awareness that post-positivist, quantitative research is more likely to be published in academic journals (Burrell, 2016; Coule et al., 2020; Harris, 2001; Stage, 2007). We find that civil society mapping is shaped by institutional pressures that align with statecraft and the values and norms of post-positivist quantitative research.

Reflexivity on our mapping effort reveals that the goals of civil society mapping can reproduce and/or resist existing power structures and the instrumentalization of civil society. Computational methods can make it easier to create maps of legibility, privileging certain actors to reproduce dominant power structures. Concurrently, maps that are transparent provide flexibility for map users, and/or privilege local knowledge, which

in turn, can resist dominant power structures by facilitating power dispersion and divergent civil society understandings, roles, and values. For example, while the Ministry has an interest in statecraft through regulation of NGOs, it also has goals to leverage information, communication, and technology (ICT) to improve the quality and transparency of public services in Ghana (see Adjei-Bamfo et al., 2019). This includes improving access to and between NGOs in Ghana. Although the primary stated goal is to engage in statecraft and oversight, the Ministry engages in other goals that may disperse power, increase transparency, and privilege map users.

Whether the mapping process conforms to the statecraft agenda or not, interpretive processes that emerge in the context of use can reproduce and/or resist dominant power structures. Given the international scale of statecraft projects, it is important to consider how maps and algorithms for mapping that align with the statecraft agenda diffuse cross-nationally. We summarize these points about *the why* of mapping in the second row of Table 1 to encourage reflexivity about the goals and motivations of mapping processes and outcomes.

The What of Mapping

Maps encode a particular shared understanding or knowledge of reality. To distinguish some of the different kinds of knowledge that may shape civil society mapping, we return to Scott's (1998) maps of legibility that posits certain forms of knowledge and control, including that of statecraft, require a narrowing of vision: "The great advantage of such tunnel vision is that it brings into sharp focus certain limited aspects of an otherwise far more complex and unwieldy reality" (p. 11). Mapping civil society for legibility privileges a standardized, instrumental knowledge (Nickel & Eikenberry, 2016) and obscures what Scott (1998) calls *mētis*, or "practical knowledge, informal process and improvisation in the face of unpredictability" (p. 6). In the case of civil society mapping, *mētis* might include local understandings of organizational forms, services, or beneficiaries based on practice and lived experience.

Efforts to map civil society usually rely on one of two types of data and categorization schemes that reflect distinct types of knowledge. Large data sets and typologies reflect standardized knowledge (e.g., Global Civil Society Index or NTEE), whereas smaller data sets and categorization approaches reflect local knowledge (e.g., Brass, 2012; Fruttero & Gauri, 2005). Computational methods for information extraction provide mapmakers with the flexibility to prioritize either local or standardized knowledge when building large data sets. We reflect on our own experiences to consider the knowledge we privilege in our data selection and category definition choices. To do so, it is important to understand the characteristics and context of the NGO records we use for mapping.

Since the end of colonialism in Ghana, in part due to international and national statecraft, the NGO sector has grown significantly in size and scope (Bawole, 2018; Musah-Surugu et al., 2019). Standardized registration forms in Ghana reflect ongoing efforts at statecraft. The forms prompt NGOs to self-select into predetermined and internationally recognized activity areas that include environmental protection, human

rights, and economic development. Some indigenous NGOs, however, continue to provide traditional medicine, apprenticeship, midwifery, and communal farming (Bawole, 2013). These activities may not be captured in the standardized form but may be articulated in more nuanced ways in unstandardized annual reports that are often included in NGO registration files.

For example, “Religious Development” is one of the NGO registration document categories. When conducting an automated process to identify NGO files that include the words “church” and “mosque,” we found that 3 times as many NGOs mentioned sites of worship in their annual reports than the indicated “Religious Development” on their form. This points to a distinction between our understanding of the standardized category “Religious Development” and use of the category by NGOs. We might conclude that the discrepancy results from NGOs misunderstanding the category and decide not to use “Religious Development” for algorithm training, or we could choose to engage local stakeholders to improve our understanding of the category selection process. These choices reflect the type of knowledge we choose to privilege in our mapping process—choices facilitated by the flexibility of computational methods and the critical questions we ask as we map civil society.

Our reflexive analysis illustrates the promise of computational methods particularly related to their flexibility to privilege different knowledge. The NGO records we use for our project have the potential to reflect both standardized and local knowledge. By choosing to extract information from standardized forms using internationally legible categories, we can privilege the knowledge of statecraft. However, we can also use computational methods to privilege *métis* by using data from unstandardized annual reports and a grounded coding scheme.

The peril of such computational methods for information extraction rests on the perception that their application and outputs are value-neutral and objective. O’Neil (2016) describes the danger of this misperception and illustrates the ways that preexisting, technical, and emergent bias shape the training and (mis)application of ML algorithms. Predictive policing algorithms, for example, allocate police resources based on the level of criminal activity previously reported in a neighborhood. O’Neil (2016) explains how discrimination is embedded in the neighborhood crime data used to train predictive policing algorithms because such neighborhoods have traditionally been over-policed. When a predictive policing algorithm trained on these biased data then allocates more officers to these neighborhoods, it leads to more police-reported instances of criminal activity, resulting in higher levels of officer deployment in these neighborhoods. In sum, it creates a vicious cycle of over-policing based on algorithm-assisted decision-making.

In addition, predictive policing algorithms are often trained using data on violent crimes *and* “nuisance” crimes, such as vagrancy and drug consumption. In such cases, data selection is grounded in the theory of “broken-windows policing” that identified a correlation between violent and nuisance crimes (Wilson & Kelling, 1982). Despite evidence contradicting this theory, predictive policing algorithms have not been updated to reflect these new understandings, thus biasing their results (O’Neil, 2016). What is more, as an “objective” tool to support officer allocation decisions, law

enforcement agencies across the United States have adopted predictive policing without necessarily considering bias trained into algorithms. In theory, this bias could be controlled for in the algorithm training process, but the long history of institutional racism in the United States makes this a difficult challenge (O'Neil, 2016). While emerging scholarship on fair ML seeks to ensure that algorithm-assisted decisions are equitable, practitioners and scholars have not converged on an approach to implement and verify algorithmic equity in practice (Corbett-Davies & Goel, 2018). Indeed, data selection decisions are connected to important technical limitations and trade-offs.

Decisions about *the what* of mapping have important consequences for decision-making broadly and mapping specifically. These are summarized in Row 3 of Table 1. This discussion underscores the opportunity and importance of identifying the types of knowledge (e.g., mētis, academic, and statecraft) privileged in mapping processes and understanding the ways that data selection and category definition are influenced by and can reproduce existing social and technical inequality and oppressive systems.

The How of Mapping

The promise of computational methods rests in part on the variety and flexibility of the algorithms that exist. These algorithms become *how* we map. However, there are liabilities associated with their variety and flexibility: Different algorithms facilitate different levels of transparency, or the degree to which an algorithm is understandable to those who use or are affected by it. Opacity can reproduce power structures, making it more difficult to trace the impact of biased data on mapping processes and contest the "objectivity" of computational methods and mapping outcomes. Burrell (2016) identifies three different types of opacity related to computer algorithms: (a) intentional opacity stemming from state or corporate secrecy, (b) technical literacy as opacity, and (c) opacity resulting from algorithm characteristics and data volume.

In consideration of civil society mapping, the first challenge to transparency arises when mapmakers have some vested interest in secrecy. For example, a government may keep a mapping algorithm a secret to hinder bad actors from gaming regulatory mechanisms or (more ominously) to control and manipulate civil society. Intentional opacity is shaped by social structures and institutions, including regulations and professional norms.

The second challenge to transparency identified by Burrell (2016) stems from the technical competence needed to understand computer code. As of 2020, we only identified four articles using computational methods for civil society mapping (Fyall et al., 2018; LePere-Schloop, forthcoming; Litofcenko et al., 2020; Ma, 2021), which underscores the challenge of acquiring the technical skills necessary to apply computational methods to map civil society. Reflection on our experiences further suggests that algorithmic opacity based on technical competence is particularly problematic, given disparate access to technical training and computational resources, for example, between the Global North and South. In this way, algorithmic opacity based on technical competence and access to computer equipment reproduces inequality.

The third challenge to transparency that Burrell (2016) identifies relates both to algorithm characteristics and the volume of training data. To illustrate this challenge, we consider two different ML algorithms—a naive Bayes model and a neural network. Naive Bayes models allow humans to examine the weights given to factors/variables, which facilitates transparency. However, neural networks—which are among the most effective algorithms for working with high-dimensional data—are complex systems that transform input across multiple layers of algorithms. While a human may understand the inputs, architecture, and outputs of a neural network, our brains do not have the capacity necessary to follow their inner workings. In addition, even with relatively simple algorithms, like naive Bayes models, the volume and dimensionality of data used in training may be so large that it is beyond the capacity of the human mind to understand how the data shape the algorithm and its outputs. Faced with such complexity, it becomes easier for end users to reify the algorithm as objective, which in turn makes it difficult to scrutinize or contest mapping processes and outcomes.

It is beyond the scope of this article to describe the full family of ML algorithms (see J. Friedman et al., 2001; James et al., 2013). What is important here, however, is that the kind of algorithm used for mapping—the how—can either facilitate or limit transparency. In Table 1, Row 4 of our framework synthesizes the key points on opacity and *the how* of mapping civil society. This is particularly important, given our earlier discussion about understanding and controlling for biased training data and its effects on mapping algorithms and outcomes.

Concluding Thoughts

Our framework highlights the importance of critically examining civil society mapping processes and outcomes and how researchers engaged in mapping might use reflexivity to influence the application of computation methods. We draw on three bases of knowledge to inform our contribution: nonprofit research on civil society mapping, critical work on computational methods—especially ML—and our experience mapping Ghana's NGO sector. Integrating these bases of knowledge illuminates links between the who (positionality), the why (goals), the what (data), and the how (algorithms) of mapping shape civil society in the digital age. They highlight the need to examine the

- positionality of actors involved, including their technical competence, preexisting biases, and power to assign meaning (the who);
- goals, motivations, and priorities of actors, how they shape mapping processes, and how goals are shaped by the broader mapping context (the why);
- ways data and category selection privilege different knowledge; the ways this reinforces or redistributes power (the what); and
- selection of algorithms and how opacity reinforces or redistributes power among different stakeholders throughout the mapping process and output interpretation (the how).

Our work makes several contributions. First, it responds to calls for reflexivity from nonprofit and computational methods research. Our approach is distinct in nonprofit studies; while we criticize and underline the liabilities of computational methods for mapping, we are fully engaged in a quantitative project mapping Ghana's NGO sector. This runs parallel to emerging work by critical quantitative scholars who continue to question and illuminate tensions in the use of quantitative methodologies while employing them for research (Stage, 2007).

Second, it extends work challenging the objectivity and assumptions of civil society mapping. Critiques of civil society mapping have challenged the dominant structures and choices in the mapping process but until now have not addressed computation methods used for mapping. Nonprofit scholars have questioned the taken-for-granted assumptions in mapping practice and its normalized acceptance by examining how maps are shaped by mapmakers and their motivations (Appel, 2011, 2012, 2013; Nickel & Eikenberry, 2016). However, in light of computational methods applied to mapping, our article provides additional critical insights by illuminating the ways that human values and understandings inform technical choices regarding data and methods and, in turn, shape mapping processes and outcomes.

Third, our framework illuminates the knowledge production function and power inherent in mapping, computational methods, and their intersection. By revisiting seminal work by Scott (1998) and integrating critical work on computational methods, we contribute to critical nonprofit studies' commitment to theorize about civil society and the role that mapping practices play in privileging different kinds of knowledge. In addition, we assert that critical work on computational methods will be important to our field in evaluating knowledge production such as civil society mapping. Emergent "QuantCrit" scholars propose using principles, similar to our framework, that serve as "a kind of toolkit" (Gillborn et al., 2018, p. 169) to help guide reflexive quantitative research processes.

Finally, our article offers a framework that both raises critical questions for future research and provides a path forward for reflexive mapping practice. This aligns with one of the primary tenets of critical social science research—the integration of theory and practice (Schwandt, 1997). As the field of nonprofit studies continues to explore new technologies for mapping, we urge researchers *and* practitioners to utilize and extend this framework to engage and scrutinize new technologies to better understand civil society.

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Supplemental Material

Supplemental material for this article is available online.

Notes

1. We draw upon literature that defines and describes the civil society/third sector/nonprofit sector in various ways. In addition, our framework is relevant to maps of both formalized organizations and less formalized groups and associations. Given these practical considerations, we generally use the inclusive term “civil society” and the particular term “non-profit organization” to describe the mapping subjects of interest throughout this article.
2. Although the “computer systems” described in the article include computer hardware and networks, most of the authors’ examples involve computational algorithms used for recommendation and classification.
3. Several authors (Adjei-Bamfo, Bawole, LePere-Schloop, and Zook) have been directly involved in the NGO project on the ground in Ghana; the remaining author (Appe) has been involved from a distance by drawing on critical scholarship to inform and evaluate the project.
4. In 2003, the Ghanaian government launched the information, communication, and technology (ICT) for Accelerated Development policy (GOG, 2003), followed by the Electronic Transactions Act 772 in 2008 (GOG, 2008).

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