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The ethnographer and the algorithm: beyond the black box

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Abstract
A common theme in social science studies of algorithms is that they are profoundly opaque and function as "black boxes." Scholars have developed several methodological approaches in order to address algorithmic opacity. Here I argue that we can explicitly enroll algorithms in ethnographic research, which can shed light on unexpected aspects of algorithmic systems—including their opacity. I delineate three meso-level strategies for algorithmic ethnography. The first, *algorithmic refraction*, examines the reconfigurations that take place when computational software, people, and institutions interact. The second strategy, *algorithmic comparison*, relies on a similarity-and-difference approach to identify the instruments' unique features. The third strategy, *algorithmic triangulation*, enrolls algorithms to help gather rich qualitative data. I conclude by discussing the implications of this toolkit for the study of algorithms and future of ethnographic fieldwork.

Keywords Algorithms · Enrollment · Ethnography · Opacity

Over the past decade, many studies have examined the construction, implications, and effects of algorithmic systems. A common theme emerging from this literature is that algorithms are profoundly opaque and function as inscrutable "black boxes" that can only be analyzed in terms of their inputs and outputs (Pasquale 2015; Introna 2016; Burrell 2016). Most scholars judge this opacity to be inherently problematic, both in terms of academic inquiry and for the purposes of accountability and regulation (Pasquale 2015; O'Neil 2016; Eubanks 2017; Zuboff 2019). Consequently, efforts have emerged to enhance "algorithmic transparency" and bypass technological opacity through a variety of means (Diakopoulos 2013; Sandvig et al. 2014; Angwin et al. 2016). Yet researchers also emphasize the limitations of the concept of transparency in

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this context, arguing that we need to stop thinking about algorithms as neatly bounded technical objects that need to be "opened up" (Ananny and Crawford 2016). Alternative approaches understand algorithms as complex sociotechnical assemblages involving long chains of actors, technologies, and meanings (Gillespie 2016; Seaver 2017; Lange; Lenglet; and Seyfert 2018).

Given the opacity of algorithms and the limitations of the concept of transparency, how should we study algorithmic systems? This article seeks to strengthen the methodological framework of algorithmic studies by focusing on the role of ethnographic methods. I suggest that enrolling algorithms in ethnographic research is a productive way to analyze complex and opaque computational procedures. After discussing the different dimensions of algorithmic opacity and the primary methodological perspectives that have emerged to bypass such opacity—namely algorithmic audits, cultural and historical critiques, and ethnographic approaches—I draw on the sociology of translation (Callon 1986) to examine algorithmic enrollments. I offer three practical strategies for ethnographic studies of algorithms in society. The first strategy, *algorithmic refraction*, examines the reconfigurations that occur when algorithms, people, and institutions interact. The second strategy, *algorithmic comparison*, relies on a similarity-and-difference approach to identify the specific features of algorithmic systems. The third strategy, *algorithmic triangulation*, enrolls algorithms to help gather qualitative data. I conclude by discussing the implications of this toolkit for the study of algorithms and future of ethnographic research, online and offline.

I. Studying black box algorithms

Why are algorithms opaque? Why does this matter? And how does it affect the methods we can use to study them? This section introduces the different ways in which algorithms can be opaque and the situations in which this opacity becomes particularly problematic. Here I define "algorithms" as sequences of logical operations providing step-by-step instructions for computers to act on data (Barocas et al. 2014). In practice, algorithms are typically software programs that perform computational tasks based on some kind of digital data.

Drawing on Burrell's (2016) analysis, there are four ways in which algorithms can be opaque. First, algorithms are typically characterized by *intentional secrecy*: data and codes are kept secret by companies or administrations guarding them as valuable intellectual property. Consequently, observers do not have access to the algorithms because companies do not make them public. Second, even when companies decide to share their algorithms with users and researchers, another dimension of opacity emerges: *technical illiteracy*. Algorithms are made of code written in programming languages; most users do not have the training to interpret these programming languages, limiting their understanding of the inner workings of the algorithms. Third, machine learning algorithms have an added layer of opacity because they evolve over time in ways that are typically *unintelligible* by humans, regardless of the humans' training in programming languages. In Burrell's words, "When a computer learns and consequently builds its own representation of a classification decision, it does so without regard for human comprehension" (Burrell 2016, p. 10). Thus, even if we could read and decipher lines of codes, we may not be able to understand how algorithms make decisions. To these three layers of opacity, one must add a fourth: the sheer *size* of most algorithmic systems. For instance, Google's internet services rely on more than 2 billion lines of code (Metz 2015). Such an order of magnitude often makes it impossible for anyone (including the programmers who designed the algorithm) to identify which part of the system is responsible for a specific decision.

Drawing on these four dimensions, scholars refer to algorithms as "black boxes," or devices that can be only be understood in terms of their inputs and outputs, without any knowledge of their internal workings (Mols 2017). Building on this concept, legal scholar Franck Pasquale wrote about the development of a "black box society" (Pasquale 2015). Pasquale examined the asymmetric distribution of data and information in a world where unaccountable algorithms are increasingly making decisions hidden behind corporate walls and layers of code. This opacity in turn is particularly problematic since algorithms are often biased (Barocas and Selbs 2016): since they draw on historical data, which itself is shaped by long histories of inequality and discrimination, algorithms can function as "weapons of math destruction" (O'Neil 2016) that end up "automating inequality" (Eubanks 2017). Not being able to analyze how such biased decisions are made poses a serious threat to the notion of due process in democratic societies (Crawford and Schultz 2014; O'Neil 2016; Eubanks 2017; Chesterman 2020).

The growing realization that most algorithms are opaque, discriminatory, and unaccountable has led to the development of a range of methodological strategies in order to bypass these layers of impenetrability and document the inner workings of computational systems. Here I distinguish among three kinds of methods: algorithmic audits, cultural and historical critiques, and ethnographic studies. I discuss the benefits and limitations of each method before focusing more specifically on ethnography.

Algorithmic audits

The first approach, algorithmic audits, relies on statistical and computational methods in order to examine the outputs of algorithmic systems, specifically (but not exclusively) their discriminatory impact.

Many algorithmic audits rely on online field experiments. According to Sandvig et al. (2014, p. 5), "audit studies are typically field experiments in which researchers or their confederates participate in a social process that they suspect to be corrupt in order to diagnose harmful discrimination. In one common audit study design, researchers create a fictitious correspondence purporting to be from a job applicant seeking employment, and target it at real employers." Adapting the audit methodology to online platforms, Sandvig et al. distinguish among different kinds of research designs, including code audits, noninvasive user audits, scraping audits, sock puppet audits, and crowdsourced audits. Existing instances of research using these methods have found important discriminatory features in algorithmically mediated platforms, including racial discrimination in online advertising delivery (Sweeney 2013) and price discrimination on e-commerce websites (Hannak et al. 2014; Diakopoulos 2013).

In addition to online field experiments, other computational methods have been used to investigate the inner workings and discriminatory impact of algorithmic systems. For instance, Angwin and her colleagues at the non-profit news organization ProPublica analyzed more than 10,000 criminal defendant files in Broward County, Florida, accessed through Freedom of Information Act requests (Angwin et al. 2016). Following a statistical analysis of the cases and of the scores provided by a risk-assessment tool called COMPAS, they issued a critique of Equivant (the company that owned COMPAS) for building an algorithm that discriminated against African Americans. ProPublica made the data publicly available; academics used it to offer different measurements of algorithmic fairness (Corbett-Davis et al. 2016). In their study of discrimination in facial recognition tools, Buolamwini and Gebru (2018) relied on similarly creative quantitative methods. They built a new and diverse facial analysis dataset, which they used to evaluate three commercial tools: they found that mainstream facial recognition programs miscategorized darker-skinned women at a significantly higher rate than any other groups. Such studies belong to the family of algorithmic audits, in the sense that they shed light on opaque (and potentially discriminatory) algorithmic systems through sophisticated online research designs and statistical analysis.

Following the publication of these findings, scholars suggested adopting new forms of documentation in order to minimize the opacity and discriminatory potential of algorithmic systems. For instance, computer scientists argued in favor of providing "model cards," short documents for trained machine-learning models that would include core metrics about bias, fairness, and inclusion (Mitchell et al. 2019). Others have suggested adding constraints to algorithmic models in order to curb their discriminatory potential (Diakopoulos and Friedler 2016). Many of these initiatives have emerged within the FAccT (Association of Computing Machinery Fairness, Accountability, and Transparency, formerly FAT*) intellectual community. Such approaches in turn have been criticized for their emphasis on "technical fixes" instead of larger social and political questions (Powles and Nissenbaum 2018; see also Abebe et al. 2020), their focus on transparency as a catch-all term (Ananny and Crawford 2016), and their epistemological choices, which could end up entrenching algorithmic opacity instead of lessening it. As Seaver noted, "by treating the 'inside' of the algorithm as unknowable, these approaches (e.g., algorithmic audits) participate in enacting an understanding of the algorithm as a black box, as knowable only through the relation between inputs and outputs" (Seaver 2017, p. 5). Such limitations in turn are precisely what the next set of methods aims to address.

Cultural and historical critique

The second methodological perspective developed to bypass the opacity of algorithmic systems comes from what I call cultural and historical critique or scholarship that builds on critical social theory to analyze the role of computational software by situating it within broader political, racial, cultural, and economic formations. Scholars typically rely on design critique as well as close readings of industry publications, promotional material, and journalistic articles about algorithms, which they mobilize to connect recent incidents within longer historical trajectories. Critical approaches have analyzed how algorithms reproduce and reinforce existing structures of racial inequality, surveillance, and marketization.

First, drawing on Critical Race Theory, scholars demonstrate the racial underpinnings of most algorithmic systems. For instance, in *Race After Technology* (2019), Benjamin develops the concept of the "New Jim Code" to emphasize how algorithms can encode patterns of oppression against people of color. Tying the rise of algorithms to the structures that have sustained racial domination over time in the United States, including the Jim Crow legal system, Benjamin illuminates one key effect of algorithms in current societies, namely, to maintain and reinforce racial inequalities (see also Eubanks 2017). Drawing on this framework, she analyzes the racist and eugenicist values shaping algorithmic systems through multiple empirical cases, including the one of "Beauty AI," "the first international beauty contest judged by artificial intelligence," where out of 6000 submissions from 100 countries, only one finalist (out of 44) had visibly dark skin (Benjamin 2019, p. 50). Noble offers a complementary analysis in *Algorithms of Oppression* (Noble 2018), where she examines the cultural role of online search engines in reproducing existing discriminatory beliefs about people of color. She takes the example of searching for the term "black girls" on Google and finding sexually explicit content prominently displayed on the first page—a result not replicated when she searched for "white girls." Such analyses show how, under the patina of innovation, objectivity, and convenience, algorithmic systems often reproduce and reinforce racial hierarchies.

Second, scholars have examined the role of algorithms in a longer history of surveillance and information asymmetry (Zuboff 2019; Pasquale 2015). In this view, the input data needed by algorithms to function is constantly (and often secretly) extracted from us through online tracking. This personal data is relentlessly sold and mined to expand the knowledge infrastructure of governments and for-profit corporations. Such surveillance regimes in turn shape our identities and representations, turning us into specific kinds of subjects through distant assemblages of control and governmentality (Lyon 2018; Haggerty and Ericson 2003). Existing work on data extraction examines the cultural and political institutionalization of the current economic model, in which online users share their data and labor for free with platforms that make enormous profits based on this behavioral surplus (Terranova 2000; Scholz 2013). For instance, Andrejevic (2003) finds that reality television provided a cultural template for the emergence of a surveillance-based interactive economy in which being watched is increasingly seen as a "productive" development—one that can lead to celebrity, wealth, and even personal growth. Other studies relate digital tracking to the broader power dynamics of older surveillance apparatuses. From the plantation system to factory floors, surveillance primarily targeted black, brown, poor, and so-called "deviant" populations; digital surveillance is no exception (Browne 2015; Foucault 1975).

Last but not least, critical studies have analyzed the role of algorithms in broader economic logics of rationalization, connecting the multiplication of algorithms, data, and metrics to larger processes of commensuration (Espeland and Stevens 1998), homogenization (Lamont et al. 2014), and neoliberal marketization (Beer 2018). For instance, in *The Metric Society*, Mau (2018) argues that the algorithmic systems and the metrics they provide reinforce the existing processes of status-related comparison and market competition, which in turn have an impact on how people and organizations relate to quantified forms of inequality. Mau takes the example of health, mood, and exercise self-tracking apps, which he argues turn bodies into sites of data-driven status competition (Mau 2018, p. 103). By locating algorithms within broader dynamics of commensuration and competition, these economic critiques contribute to a better understanding of the role of computational systems in promoting a specific kind of moral worldview—one that sees explicit value in rationalization and standardization across domains (Fourcade and Healy 2017).

These studies rooted in cultural, historical, and economic critique examine the connections between algorithms and the broader structures of social life. They make essential contributions to the study of algorithmic black boxes, showing how the dominant discourse of technological wizardry and algorithmic unintelligibility can serve as a smokescreen that masks the role of algorithms in the reproduction of important social processes such as discrimination, surveillance, and standardization. One potential limitation of these approaches stems from their high level of generality: they do not often pay close attention to the local practices and contextual features shaping the construction, diffusion, and reception of algorithms. This is precisely the question that ethnographic methods seek to address.

Ethnographic studies

A key tenet of ethnographic methods is to understand the representations, practices, and cultures of the people being analyzed, typically through in-person interviews and observations.[1] How can ethnographers study algorithms, especially given the multiple layers of opacity that surround them? While few studies explicitly focus on the inner workings of algorithmic systems, ethnographers coming from multiple disciplinary backgrounds (including anthropology, sociology, communication, management, and media/cultural studies) have made important contributions to our understanding of computational technologies, approaching them from two sides. On the construction side, ethnographers have examined the cultural and structural forces shaping how algorithms are built. On the reception side, scholars have analyzed the daily practices and representations affecting how algorithmic outputs are put to use.

First, regarding the production of algorithmic systems, there is a rich body of ethnographic work focusing on the technology sector, where ethnographers analyze the role of cultural and organizational processes in shaping the kind of technologies that are built. For instance, Silicon Valley companies—and their imitators—have developed specific professional norms and organizational forms in their production process. These include flat hierarchies, project-based thinking, constant self-actualization, collective effervescence, and intense competition among engineers (Kunda 2006; Kunda 2006; Turner 2009; Zukin and Papadantonakis 2017; Marwick 2013). Such structural conditions in turn shape how technology and media workers relate to their work and career, through constructs that scholars have called "aspirational work" and "venture labor," wherein workers try to capitalize on future career developments in addition to current compensation (Neff 2012; Duffy 2017; Duffy and Hund 2015).

[1] While there are many variations on what people mean by ethnography, ethnographers across disciplines typically agree on several points. Epistemologically, many ethnographers rely on some version of "grounded theory" (Glaser and Strauss 1967, but see also Burawoy 1998, Timmermans and Tavory 2012 for different approaches), starting with a preliminary research question that evolves based on the data collected during fieldwork. Theoretically, ethnographic methods share multiple affinities with symbolic interactionism, which understands individual interactions as a key building block of social life (Mead 1967; Blumer 1969; Goffman 1959). In terms of methods, ethnography often involves participant observation, in which observers actively engage in the activities of the people they study.

In particular, because of the pressure to "scale," itself tied to the role of venture capital, ethnographers find that technology engineers tend to rely on a "permanently beta" view of the world, which Neff and Stark define as "a fluid organizational form resulting from the process of negotiation among users, employees, and organizations over the design of goods and services" (Neff and Stark 2003, p. 175). Such a mindset often leads engineers, computer scientists, and project managers to oversell the capabilities of their algorithmic software—especially the software's ability to scale without failure—and conceal the extent of the involvement of human workers who perform some of the labor that algorithms are supposed to be doing (Shestakofsky 2017; Sachs 2019). As Irani (2015) points out, "software-as-a-service" often conceals a reliance on "humans-as-a-service," a less salable but more realistic motto. The human workers performing algorithmic piecework for technology companies—data annotators, content moderators, and other "ghost workers"—in turn experience precarious employment statuses and grueling work conditions (Robert 2019; Gray and Suri 2019). The employment structures of technology firms in turn affect their algorithmic outputs. For instance, Seaver (2018) shows how the repertoire of "trapping" users is evoked by engineers when they describe recommendation algorithms in streaming platforms. Such a view of users as fleeting wildlife whose attention must be retained at all costs should be understood within the "permanently beta" framework, in which labor, attention, and capital are also conceptualized as scarce resources that must be captured.

Second, ethnographers have examined the reception side of algorithmic systems, analyzing the practices and representations of users. Drawing on Science and Technology Studies, specifically on what Suchman et al. (1999) call the "technologies-in-use" paradigm (see also Orlikowski 2000), studies show that most people have become well aware of the role of algorithms and have adjusted their online practices accordingly. Many users find algorithms profoundly opaque and resent this inscrutability. This emerges particularly clearly from studies analyzing how "gig workers" make sense of digital platforms (Uber, Lyft, Care.com, UpWork, and so on): many of them complain about the impenetrability of the algorithms assigning tasks and making their profiles visible on the platforms (Rosenblat 2018; Ticona and Mateescu 2018; Rosenblat and Stark 2016)—a process Gray and Suri (2019) analyze as a form of "algorithmic cruelty." Users also develop their own representations and models for how these complex systems operate, thus relying on "algorithmic imaginaries" that shape how they interact with algorithms (Bucher 2016; Baym 2018). In addition, they often rely on "algorithmic gossip" (Bishop 2019) to share information among peers about how to make their content "algorithm-ready" (Gillespie 2016).

Overall, ethnographic approaches shed light on the complex intermingling of social, cultural, and technological aspects of computational systems in our daily lives. They provide rich and fine-grained data on how algorithms are built and used. On the production side, ethnographic studies highlight important affinities between workplace cultures and algorithmic design. On the reception side, they show how social practices mediate the uses and actual impact of algorithms. In doing so, ethnographic approaches shed light on algorithmic opacity by revealing the necessary inscription of technology in the social world (Orr 1996; Leigh Star 1999). That said, most ethnographers do not explicitly focus on algorithms per se. There is a good reason for this: ethnographers can only study places and practices to which they have access. The different dimensions of algorithmic opacity mentioned above (e.g., corporate secrecy, technical illiteracy, unintelligibility, and size) make it inherently difficult for ethnographers to center their analysis on algorithms.

One of the few ethnographers to study algorithms explicitly, Seaver delineates several "tactics" for "making algorithms ethnographically tractable" (Seaver 2017, p. 7; see also Lange et al. 2018). Seaver suggests relying on "scavenging" methods to collect relevant material across loosely connected locations (off-the-record chats, press releases, social media updates, industry conference hallways, and so on). He also argues that ethnographers need to take corporate material seriously, paying close attention to the "heteroglossia" and conflicting values that often shape press releases and publications. The next section builds on Seaver's approach to strengthen the methodological framework for the ethnographic study of algorithmic systems. In order to bypass some of the problems linked to algorithmic opacity, I suggest adopting an epistemological perspective distinct from the "black box" framing, drawing instead on the concept of "enrollment" from the sociology of translation.

II. Beyond the black box: Enrolling algorithms in ethnographic research

So far, I have discussed the opacity of algorithms as an empirical difficulty, not so much an epistemological one. Yet describing algorithms as black boxes is not a neutral choice. In fact, "black boxing" is usually far from an accidental process; nor is this metaphor only used to describe algorithmic systems. Across sectors, black boxing can be analyzed as an artefact of scientific and technological legitimacy.

Latour makes precisely this argument when he writes that "scientific and technical work is made invisible by its own success. When a machine runs efficiently, when a matter of fact is settled, one need to focus only on its inputs and outputs and not on its internal complexity. Thus, paradoxically, the more science and technology succeed, the more opaque and obscure they become" (Latour 1999a, p. 304). To deconstruct the strict divide between technology and society established through black-box framings, Latour suggests focusing on substitutions and associations within assemblages of humans and non-humans. Such a fluid approach refuses to take technological black boxes for granted and shifts existing sites of study, going "from final products to production, from 'cold' stable objects to 'warmer' and unstable ones […] before the box closes and becomes black" (Latour 1987, p. 21). It explicitly inscribes scientific and technical objects within the longer chains of humans and non-human actants who participate in the creation, diffusion, and institutionalization of scientific and technical knowledge.

Key in this framework is the concept of "enrollment," most explicitly theorized by Callon (1986). According to Callon, it is essential to analyze the dynamics of association, translation, and entanglement that take place whenever humans and non-humans interact. Following these flows of association involves paying close attention to the process of "enrollment" through which humans and non-humans start working together. In Callon's words, "to describe enrollment is thus to describe the group of multilateral negotiations, trials of strength and tricks that accompany the interessements [*sic*] and enable them to succeed" (Callon 1986, p. 211). Callon (1986) further exemplifies what he means by "interessement"—which can be translated as a form of incentivization—and "enrollment" by examining the relationships among fishermen, researchers, and scallops in the St. Brieuc Bay, in France, over the course of the 1970s. Following a period of overharvesting that depleted the number of scallops in St. Brieuc Bay, a team of French marine biologists sought to implement a cultivation method they had seen in Japan: larvae were anchored to collectors immersed in the sea, where they could grow sheltered from predators, then released in the ocean before being harvested. They convinced the local fishermen, who were initially reluctant, to let them try this method in the St. Brieuc Bay. This meant that fishermen could not harvest scallops during the time of the experiment, thereby incurring financial loss. While the first year of the experiment was successful (the larvae anchored themselves on the collectors), the next iterations failed, for a range of reasons: larvae did not grow on the collectors, fishermen resumed fishing the scallops, new predators appeared, and so on. The fragile pact that had temporarily brought together the marine biologists, local fishermen, and scallops collapsed. As Callon concludes, "Certainly the actors studied were confronted with different types of uncertainties. […] They worked incessantly on society and nature, defining and associating entities, in order to force alliances that were confirmed to be stable only for a certain location at a particular time" (Callon 1986, p. 222). Note that the concept of enrollment refers to more performative processes than simple social interactions: for Callon, successful enrollments can create collective dynamics by aligning the interests of heterogeneous constellations of actors—here they were researchers, fishermen, and scallops.

Such fine-grained descriptions of the negotiations and enrollments between humans and non-humans actants are at the core of Latour and Callon's framework, which is often called "Actor-Network Theory" (ANT), though Latour (1999) disagrees with the term. The ANT approach has been applied fruitfully in existing studies of digital and algorithmic technologies (Turner 2005; Lewis and Westlund 2015). For instance, scholars have relied on ANT to follow the chains of associations and enrollments that take place in cases as varied as electoral maps, content management systems, and abandoned luggage algorithms (Anderson and Kreiss 2013; Neyland 2019; Bellanova 2017). This means studying what Ananny and Crawford (2016) call algorithmic assemblages: "an algorithmic system is not just code and data but an *assemblage* of human and non-human actors. (…) We might reframe the question as: what kind of claims can be made to *understand* an actor-network, and how is this understanding related to but distinct from simply *seeing* an actor-network?" (Ananny and Crawford 2016, p. 11, emphasis in the original).

My answer to Ananny and Crawford's methodological question is to use ethnographic methods and algorithmic enrollments together. Ethnographic methods and thick ethnographic descriptions are often the preferred approach for the study of enrollments and associations, especially when they relate to science and technology. As Latour writes, "If we display a socio-technical network—defining trajectories by actants' association and substitution, defining actants by all the trajectories in which they enter, by following translations and, finally, by varying the observer's point of view—we have no need to look for any additional causes. The explanation emerges once the description is saturated" (Latour 1999b, p. 129). Latour relied on this kind of saturated ethnographic description to convey the collective efforts of scientists, mice, and peer-reviewed articles in laboratory settings (Latour and Woolgar 1986); clerks, clients, and weighted keys in hotels (Latour 1991, 1999a); or judges, hallways, paper files, and dust at the Conseil d'Etat (Latour 2010). Science and technology scholars further argued that ethnographic methods are particularly suited to analyze the emerging practices and translations that go into "science in the making" (Latour and Woolgar 1986; Knorr Cetina 1999; see also Suchman et al. 1999; Leigh Star 1999).

Hence, using ethnographic methods and the sociology of enrollments together can help escape some of the intractable issues related to algorithmic opacity by decentering the analysis. Instead of focusing on algorithmic "black boxes," ethnographers can study how collectives of human and non-human actors emerge, solidify, and evolve over time. To map out what such an approach could look like, the rest of this section follows Seaver (2017)'s suggestion to share concrete "tactics." I offer a toolkit of practical strategies—algorithmic refraction, algorithmic comparison, and algorithmic saturation—that I found helpful in my own work as an ethnographer studying algorithmic systems.

Algorithmic refraction

The concept of refraction is derived from physics, where it refers to the changes in direction and strength that occur whenever a wave of light or sound passes from one medium to the next. Applied to algorithms, studying refraction entails paying close attention to the changes that take place whenever algorithmic systems unfold in existing social contexts—when they are built, when they diffuse, and when they are used.

Algorithms never exist in a social vacuum. As we saw above, the construction, circulation, and reception of algorithmic systems always take place within dense social networks and institutional structures. These include individual interactions, group representations and norms, organizational dynamics and cultures, and field-level structures. Whenever algorithmic systems enter these tight-knit layers, existing arrangements are reconfigured as people position themselves with respect to algorithms and seek to enroll them in their institutionalized ways of doing things. By focusing on the waves and ripples that take place between algorithms and social actors, we can examine the refractions that such objects create, and in the process analyze the chains of representations and practices that travel across algorithmic systems, shaping their impact in the process. To use a related metaphor, this perspective implies that algorithms typically function as *prisms* that can reveal existing priorities within groups, organizations, and fields, as well as their changes over time. Such a methodological strategy in turn has precedents: it partly overlaps what Barley labelled "technology as an occasion for structuring" (Barley 1986; Bechky 2003) and what Orlikowski (2007) analyzes as "sociomaterial practices." Yet this lens has not been systematically implemented in the study of algorithms.

To give a sense of what such a perspective entails, one could use a variety of examples on the construction (Shestakofsky 2017; Sachs 2019; Kotliar 2020) and reception sides (Siles et al. 2020; Kolkman 2020; Elish and Watkins 2020). Here I take the case of the reception of web analytics in online news production. Over the course of the 2010s, web editors and journalists started to rely on software programs providing real-time data about reader behavior (including pageviews, social media metrics, time engaged, sources of traffic, among other data). Most newsrooms use this data to manage their editorial process—for instance, the organization of their homepages or the types of headlines they attached to news articles. Several ethnographic studies document the complex dynamics shaping the uses of analytics software programs in web newsrooms (Anderson 2011; Petre 2015; Christin 2018; Christin 2020a).

Based on these studies, several features appear to shape the relationships and enrollments taking place between analytics software programs and editorial teams. First, the internal organization of web newsrooms (in particular the division of labor between editors and journalists) partly determines who is responsible for maximizing traffic. Second, the position of news organizations in the journalistic field and their amount of symbolic capital affect how journalists can protect high editorial ambitions in the newsroom. Third, how journalists see their audience shapes how they make sense of traffic numbers. In this case, as in many others, algorithms function as prisms that mirror and reinforce existing fractures within newsrooms and news organizations. Conversely, newsrooms mirror and reinforce in different ways the symbolic openings created by analytics software programs. For instance, in my own ethnographic research comparing the role of audience analytics in US-based and French newsrooms, I realized that audience analytics could be put to strikingly different uses depending on the organization. In some cases, analytics software programs were compartmentalized, criticized as indicators of market pressure, and condemned as meaningless "vanity metrics." In others, they were welcomed as a form of democratic feedback and a symbol of one's relevance in the algorithmic public sphere (Christin 2020a). These mutual processes of enrollment and interdependence between journalists and analytics also changed over time, reconfiguring the relationships linking technologies and social actors.

Hence, focusing on algorithmic refraction and treating algorithmic tools as prisms that both reflect and reconfigure social dynamics can serve as a useful strategy for ethnographers to bypass algorithmic opacity and tackle the complex chains of human and non-human interventions that together make up algorithmic systems.

Algorithmic comparison

A second strategy for algorithmic ethnography relies on comparison in order to think analytically across cases. By examining algorithms across sectors through a similarities-and-difference approach, ethnographers can help to explain what is specific about each technical instrument, regardless of how opaque its underlying code may be.

Comparative ethnographies have a long history in science and technology studies. Whenever scholars examine settings featuring built-in technical or scientific complexity, case comparison can help shed light on what is specific about each one, especially when the varying features between cases are clearly distinguished. For instance, in her study of epistemic cultures, Knorr Cetina (1999) conducted ethnographic fieldwork in two scientific laboratories, one in molecular biology and one in high-energy physics. She drew on this comparison to identify several lines along which the scientific cultures of laboratories differed, including the epistemological role of empirical data, types of social relations that emerged in laboratories, and regimes of scientific authorship. Similarly, in *The Making of Law* (2010), Latour complemented his ethnographic analysis of the Conseil d'Etat (the highest French administrative court) by comparing it to a neuroscience laboratory, which allowed him to contrast the norms and dynamics of law and science, especially regarding the idea of "stability" (Latour 2010, p. 243).

Such a comparative approach can also shed light on complex and opaque algorithmic systems (Anderson and Kreiss 2013; Christin 2017; Griesbach et al. 2019). To provide a concrete example, I focus here on criminal justice, a domain where algorithms are frequently criticized for their opacity, especially due to their role in perpetuating bias and discrimination, with dramatic consequences for individuals and communities (Angwin et al. 2016; Benjamin 2019; O'Neil 2016). In a comparative ethnography of police departments and criminal courts, we contrasted how the police and legal professionals use predictive algorithms (Brayne and Christin 2020). For the police, these include person-based and place-based predictive software programs; in the courts, judges and prosecutors typically rely on several risk-assessment tools or software providing predictive "risk scores" to assess the recidivism risk of defendants. We first documented similarities: in both organizations, the police and legal professionals feared that algorithms will lead to increased managerial surveillance, deskilling, and potential replacement.

Yet significant differences also emerge in the comparison, first in the intrinsic logic of the algorithms themselves, and second in how they are implemented. In policing, predictive algorithms typically serve as dragnet technologies: they track potential crimes and criminals, store and mine the data they gather over time, while also tracking policemen in a context of limited resources. In courts, instead, risk-assessment tools primarily function as triaging technologies (Christin 2020b): their primary role is not so much to collect data indiscriminately about defendants but rather to classify individual defendants into high- or low-risk categories in order to match them with existing incarceration options and rehabilitation programs. In addition, the algorithms feature different levels of opacity, at least according to the policemen and legal professionals who use them: predictive algorithms in policing are not seen as particularly opaque, whereas legal professionals often find risk-assessment tools deeply mysterious and problematic. These differences between the instruments are amplified by the distinct organizational features of police departments, which are highly hierarchical, whereas criminal courts are more fragmented, especially in places where judges are elected. Consequently, predictive algorithms are implemented more strictly in policing than in criminal courts, leading in turn to different effects on the discretionary power and discriminatory potential of police officers and legal professionals (Brayne and Christin 2020, p. 13).

Hence, algorithmic comparison can shed light not only on the uses of algorithmic systems but also on their inner workings, regardless of how opaque and proprietary they are. The study analyzed above compared algorithms that do not have the same level of opacity. Such a comparison is relevant insofar as it allows ethnographers to analyze the role of what Kiviat (2019) calls "causal theorizing"—lay understandings and justifications of the logic behind algorithmic classifications—in shaping the impact of "black boxed" algorithmic systems.

Algorithmic triangulation

The third and last strategy, which I call algorithmic triangulation, explicitly relies on algorithms in order to gather rich qualitative data. In the social sciences, the concept of triangulation—which is borrowed from geometry and land-surveying techniques—broadly refers to the combination of multiple research methods, angles, and materials in the study of the same phenomenon. Here I use the concept of triangulation more specifically to refer to three challenges of ethnographic research, namely the questions of saturation, positionality, and disengagement. I argue that ethnographers can enroll algorithms to address all three.

First, the concept of saturation in ethnographic methods refers to the question (often asked by students and confirmed ethnographers alike) of when one should stop doing fieldwork. To this question, ethnographers usually answer with the following steps. Ethnographic research is based on a process of iteration (e.g., doing fieldwork, returning to one's notes and transcripts, reading the relevant literature, redefining the research question, going back to the field, and so on). At some point in this cycle, when ethnographers have a clear sense of their research question, they should engage in "theoretical sampling" (Charmaz 2006), which consists in explicitly seeking out people and cases that maximize variation regarding the specific angle they decided to focus on. At some point in this process of theoretical sampling, ethnographers should start to observe the same situations, discourses, and practices over and over again; fieldwork should become repetitive. This means that they have reached empirical saturation; the time might be right to begin disengaging from the field in order to focus on analysis and writing.

Second, and relatedly, ethnographic fieldwork cannot be separated from the question of positionality. A key tenet of ethnographic methods is that knowledge is necessarily situated, in several ways. The ethnographer's access to the field is mediated through their socio-demographic characteristics (gender, race and ethnicity, class, age, and so on) (Bourdieu 1999). Thus, even if they come to the field with the same assignment and research question, two ethnographers with distinct sociodemographic characteristics will never have exactly the same access to the groups and institutions they study, they will not be perceived in the same way, and they will not collect the same data. More profoundly, ethnographers bring their own values, viewpoints, and political beliefs to their research projects; such values necessarily shape what they see and how they interpret it. Instead of obliterating these differences, ethnographers seek to acknowledge this situatedness and make it an explicit component of the research process. A central concept here is the idea of reflexivity (Lichterman 2015). Through reflexivity, ethnographers try to make their own biases and blind spots as explicit as possible, discussing how these may have shaped their research question and data, and more broadly seeking to understand the role that they play as observers and participant observers in the field sites they study. Scholars suggest relying on thought experiments to facilitate this process. For instance, Duneier (2011) offers the idea of an "ethnographic trial," where the ethnographer imagines the reactions of the people who refused to talk to them during fieldwork if they read the final analysis.

Third and last, ethnographic research is necessarily shaped by the dynamics of disengagement—an important yet understudied part of fieldwork. According to Snow (1980), disengagement involves several overlapping questions. When and why do ethnographers leave the field? What are the practical constraints shaping such a disengagement process? And what are the emotions and ethical concerns that affect how ethnographers deal with disengagement? Drawing on classic ethnographic studies involving long travels and in-depth immersion in remote communities, Snow (1980) finds that ethnographers typically experience feelings of alienation when returning "home," as well as a form of guilt towards the informants and interviewees who helped and welcomed them. These emotions shape how ethnographers write and publish their analyses; they also affect the ways in which ethnographers choose to share their findings with the people they studied.

Saturation, reflexivity, and disengagement are three key aspects of triangulation—and more generally of the process of gathering rich ethnographic data. Here I argue that ethnographers can benefit from explicitly enrolling algorithmic systems to address all three issues. First, regarding saturation, algorithms can be mobilized to help expand the boundaries of the field site and engage in theoretical sampling. Once ethnographers have defined their specific research angle, they can enter the key terms and actors into algorithmic systems and scrutinize the outputs, as a means for analyzing variation. Second, with respect to positionality and reflexivity, algorithmic systems can illuminate the ethnographer's position in the field—or, to use Burrell's (2009) term, in the network. Third, algorithmic systems are changing the nature of disengagement, especially through enduring social media connections between ethnographers and their informants. Note that all three dynamics are not completely new: digital and virtual ethnographers mobilized similar strategies in their studies of online groups and virtual worlds (Boellstorff et al. 2012; Coleman 2014; Knox and Nafus 2018; Beaulieu 2010; Hine 2015; Hjort et al. 2017; Markham and Baym 2009). Here I draw on this tradition but add an explicit focus on algorithmic enrollments.

Algorithmic mediations play a particularly central role in ethnographic studies of communities on social media platforms. As an example, one can take the case of content creators and "influencers" producing and sharing online content such as videos, pictures, and blog posts on YouTube, Instagram, Twitter, TikTok, and so on (Marwick 2013; Duffy and Hund 2015; Duffy 2017; Bishop 2019; Stuart 2020; Burgess and Green 2018). The platforms' algorithms determine the visibility and revenues of influencers; they also mediate the relationships taking place among influencers, as well as the contacts between ethnographers and potential interviewees. This is what we experienced in a project about YouTube "drama" or "tea" channels, which produce popular videos covering the conflicts and scandals taking place between top YouTube celebrities (Christin and Lewis 2020). Our ethnographic study explicitly enrolled algorithmic technologies in the research process in several ways. To build a robust sample of drama channels, we read online forums devoted to conversation around YouTube drama, such as the subreddit r/Beauty Guru Chatter. We watched drama creators' YouTube videos and followed them or subscribed to their channels on YouTube, Instagram, and Twitter. Through these social media contacts, we actively mobilized the algorithmic systems underpinning social media platforms as tools to help us identify potential interviewees. Thus, we relied on the platforms' algorithmic recommendations to expand our list of interviewees: we contacted all the relevant creators suggested by YouTube's "Recommended" section, Twitter's "Who to Follow," and Instagram's "Recommended for You."

In addition to enrolling explicitly algorithmic recommendations to expand the boundaries of our field site, social media platforms became indispensable sites for conducting our ethnographic fieldwork. Over time, we realized that drama channels not only covered the drama taking place between top YouTube celebrities, but also frequently covered the drama taking place with each other, posting about and reacting to each other's content. Consequently, in addition to interviewing drama creators and analyzing their online production, we carefully followed these exchanges, taking screenshots and archiving them to keep track of the shifting alliances and feuds shaping the drama community. In doing so, we consciously imitated the practices of our interviewees. Over the course of the interviews, creators explained to us that, in order to gather data about YouTube celebrities, they relied on automatic alerts and so-called "receipts" (e.g., screenshots of compromising social media posts) to track the conflicts erupting on YouTube, Twitter, and Instagram. We ended up adopting the same strategy in our study of drama creators.

Over the course of the interviews, we further realized that our position in the drama community was entirely mediated by social media platforms. Channel creators discussed their interviews with us among themselves, through private messages and group chats on different apps and platforms. Several of them told us they had spoken to others who had already been interviewed to learn what to expect; others had conferred with their contacts before agreeing to the interview at all. In several cases, Twitter messages they exchanged among themselves were accidentally sent to us, giving us a glimpse into their interactions and perceptions of us. Finally, we found ourselves folded into some of the drama taking place between creators. For instance, one of our participants revealed at the end of an interview that they had been recording us and asked if they could post it to their channel; we later realized that this was part of an effort by this drama creator to deflect the attention of the drama community from a racism scandal they were implicated in. This in turn gave us clues about our position in the field. As researchers associated with a prestigious university, whose online presence and social media profiles could easily be analyzed and validated, we represented a potential source of legitimacy for online creators who sometimes described themselves (more or less jokingly) as the "succubus of the internet."

Last but not least, the algorithms of social media platforms continued to shape our understanding of drama channels even once the intensive part of our fieldwork was over. After finishing the first wave of interviews, we continued to follow the interactions between drama creators. We kept following them on social media platforms; drama creators in turn sometimes sent us messages or texts with "receipts," or screenshots they thought could be of interest to us—which itself could be analyzed as an instrumentalization strategy. Many creators followed us on social media platforms (mostly Twitter), sometimes reacting to our posts, which indicated that our profiles were algorithmically visible to them. In this context, "disengagement" took a very different shape from the classical ethnographic studies analyzed by Snow (1980). If anything, this made us realize that *there was no disengagement*: for better or worse, our understanding of the drama community remained informed by the ongoing flow of notifications we received about developments taking place between creators. These ongoing algorithmic connections in turn raise important questions about how to share and publicize ethnographic findings online. In cases where ethnographers studied more problematic or violent online communities, such as the Anonymous group (Coleman 2014) or the so-called "Alt Right" on YouTube (Lewis 2018), the people under study reacted negatively to the publications. Thus, the algorithmic connections between ethnographers and their informants can turn into full-scale online harassment, including doxing (the online publication of private or identifying information) and death threats, thus raising the question of how universities and research institutions can protect researchers from retaliation in these contexts.

In this section, instead of focusing on the intrinsic opacity of black-boxed algorithms, I suggested paying closer attention to the multiple enrollments, refractions, and mediations taking place between social actors and algorithmic systems. In the process, two distinct kinds of enrollments emerged. The first type of enrollments unfolded on the field sites under study—in the organizations, networks, and collectives where algorithms are built, circulate, and are put to use. The second kind of enrollment shaped the research process itself, through the explicit use of algorithmic systems by ethnographers. These two facets of the concept of enrollment should be considered together: social actors, algorithms, and researchers all participate in the same configurations, seeking and often failing to enroll each other into their respective programs. Such an approach reinserts social scientists within the dynamics they study, without granting them unique epistemological qualities.

Discussion and conclusion

In *The Journalist and the Murderer*, Malcolm (1989) discusses the dialectical relationship between journalists and their sources. Whereas many criminal defendants who collaborate with journalists are trying to prove their innocence, journalists are primarily seeking to tell a good story in the hopes of writing a best-seller. Malcolm examines the mutual deception and manipulation that shape their relationship, as well as the power imbalance between them, as each of the two parties seeks to enroll the other for goals of their own. In the opening paragraph, which has become canonical in many journalism programs, she writes: “Every journalist who is not too stupid or full of himself to notice what is going on knows that what he does is morally indefensible. He is a kind of confidence man, preying on people’s vanity, ignorance, or loneliness, gaining their trust and betraying them without remorse” (Malcolm 1989, pp. 3–4).

Malcolm’s analysis has limitations when we apply it to ethnographic fieldwork: it is too individualistic and does not account for the collective and institutional dynamics shaping the relationship between ethnographers and their informants. Yet she raises relevant questions for the social study of algorithms. As we have seen, the relationship between researchers and algorithms is similarly dialectical. Algorithms are powerful and opaque; they want to know more about us, to mine our personal information and provide relevant content to our eyes in order to keep us on the platforms they typically serve. Conversely, to advance their academic careers, researchers try to coax opaque algorithms into providing more information about themselves. In other words, we want to learn more about algorithms, and algorithms want to know more about us. As in the case of the journalist and the murderer analyzed by Malcolm, the complicated dance between researchers and algorithms is primarily based on deception and manipulation.

In this article, I suggested several strategies for clarifying this dance and making it more explicit. Drawing on the sociology of translation, I argued that we should work *with* algorithms in order to bypass their opacity. This methodological framework draws on and seeks to strengthen many excellent ethnographic studies about algorithmic systems, their construction, and their uses. Specifically, I provide three practical strategies for the enrollment of algorithms in ethnographic research: algorithmic refraction, which views algorithms as prisms that both transform and are transformed by the social dynamics around them; algorithmic comparison, which uses a similarities-and-difference approach to identify the distinct features of the technical instruments and their related uses; and algorithmic triangulation, which relies on algorithmic systems in order to gather rich qualitative data, reflect on one’s position in the network, and disengage—or not—from the field.

The suggestions and strategies provided here are not prescriptive. Rather, they draw on my experience as an ethnographer of algorithmic systems and a reader of the literature on the topic. A central value of contemporary ethnographic research is to try to make explicit as much of the research process as possible for the ethnographic community as a whole. Thus, it is important to document and reflect on the choices, values, and shortcuts that shape one's relationship to the field. Researchers studying algorithmic systems may find that algorithmic refraction, comparison, and triangulation are helpful categories to think with; or they may come up with their own strategies and tactics. Overall, the goal is to come up with a more structured and deliberate methodological toolkit in order to approach these complex objects.

To conclude, one can think of limit cases where such an ethnographic approach of algorithmic enrollments may not be feasible. First, the question of access remains crucial and complicated for ethnographers studying algorithms, especially on the construction side. Technology companies and their engineering departments are deeply cautious and secretive, not only about ethnographers and academics but more broadly about all kinds of public discourse and reporting on their inner workings (Silverman 2020). This poses a clear challenge for ethnographers studying algorithms. We can hope that technology companies and research institutions will develop new bridges to enable meaningful access, but in the meantime, following Hannerz (2003, p. 213), we may have to agree that "ethnography is an art of the possible, and it may be better to have some of it than none at all." The strategies delineated here go in this direction by decentering the ethnographic focus from black-boxed algorithms to the study of algorithmic enrollments.

Second, in all the examples of algorithmic systems discussed so far, humans have been central to the picture: they build the technologies, implement them, and use them in their daily lives. In other words, humans are clearly in the algorithmic loop, which makes ethnographic work not only possible but also important. But what about fully automated systems interacting with each other? One can think of autonomous drones, high-frequency trading, or online advertising delivery, among other examples (Knorr-Cetina 2016; McKenzie 2019). Yet even in these cases, ethnographers find people and institutions creeping through the cracks of automated systems, making essential choices in the design, maintenance, and "repair" of the algorithms (Elish 2019; Elish and Watkins 2020). Contrary to dystopian evocations of artificial general intelligence fully decoupled from human intervention, ethnographers need to pay close attention to these evolving forms of social responsibility within automated systems.

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