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Toward an Ethics of Algorithms: Convening, Observation, Probability, and Timeliness

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Abstract

Part of understanding the meaning and power of algorithms means asking what new demands they might make of ethical frameworks, and how they might be held accountable to ethical standards. I develop a definition of networked information algorithms (NIAs) as assemblages of institutionally situated code, practices, and norms with the power to create, sustain, and signify relationships among people and data through minimally observable, semiautonomous action. Starting from Merrill's prompt to see ethics as the study of "what we ought to do," I examine ethical dimensions of contemporary NIAs. Specifically, in an effort to sketch an empirically grounded, pragmatic ethics of algorithms, I trace an algorithmic assemblage's power to convene constituents, suggest actions based on perceived similarity and probability, and govern the timing and timeframes of ethical action.

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What new approach to media ethics might algorithms require? In comparison to concerns over how to produce or circulate media ethically, train ethical media professionals, or ethically regulating media industries, what might it mean to take an algorithmic assemblage—a mix of computational code, design assumptions, institutional contexts, folk theories, user models—with semiautonomous agency as a unit of ethical analysis?

This essay is an attempt to define a networked information algorithm (NIA) and suggest three dimensions for scrutinizing its ethics: the ability to *convene* people by inferring associations from computational data, the power to judge *similarity* and suggest *probable* actions, and the capacity to organize *time* and influence when action happens. I argue that such a framework might give starting points for holding algorithmic assemblages accountable and develop this argument through critical readings of NIAs in contemporary journalism, online commerce, security and policing, and social media.

Three Approaches to the Intersection of Information Technology and Ethics

Most basically, ethics is "the study of what we ought to do" (Merrill 2011, 3) and is usually divided into three subareas. The first, associated with Kant's ([1785]2002) call for categorically guided action through reason, is a *deontological* approach: a fixed set of duties, rules, and policies define actions as ethical. Break these rules and you have behaved unethically. The second, associated with the utilitarian philosophies of Jeremy Bentham and John Stuart Mill and related to the American school of pragmatism, is a *teleological* approach focused on the consequences. Ethics should help people choose "the action that will bring the most good to the party the actor deems most important" (Merrill 2011, 11). Finally, the *virtue* model of ethics (Hursthouse 1999) is unconcerned with duties or consequence, focusing instead on the subjective, idiosyncratic and seemingly nonrational impulses that influence people in the absence of clear rules and consequences. It is "more spontaneous" and "motivated by instinct or a spiritually motivated will" (Merrill 2011, 12).

These frameworks have rough parallels to dominant ways of understanding the ethical dimensions of technologies. The first, rooted in policies and regulations, attempts to codify the ethical development and use of technologies, creating standards for punishing errors, teaching best practices, and preventing future failures. For example, the rapid proliferation of intercontinental ballistics spurred the Computer Professionals for Social Responsibility group to create a "Ten Commandments of Computer Ethics" (Computer Ethics Institute 2011) for engineers to ethically develop and use computational weapons systems. Such codes have become the key techniques for teaching engineering students how to ethically build and use semiautonomous cybernetic systems, decision support technologies (Cummings 2006), and robotic "artificial moral agents" (Wallach and Allen 2008).

Instead of applying ethical rules to technologies, a second approach tries to anticipate ethical concerns raised by technological innovation. For example, bioethics emerged as a field largely because new technologies were introduced "with great hopes but little forethought" into a world in which "physicians had almost total control of information and decision-making power" (Levine 2007, 7). It was impossible to apply the existing ethical frameworks because new technologies were fundamentally reconfiguring relationships among doctors, nurses, technicians, patients, and families; new questions about risk, health, life, and death stretched beyond the scope of the existing ethical framework. Similarly, the definition of ethical journalism as the disinterested pursuit of neutral facts for broad consumption emerged, in part, from sociotechnical innovations. The telegraph made it possible to think of stories as the transmission of "pure" information for rational consumption (Carey 1989), and mass-scale advertising and distribution regimes rewarded risk-averse newspapers that appealed to the widest possible array of audience preferences (Schudson 1978). Technologies and economics thus created a journalistic objectivity that outstripped the profession's existing professional frameworks (Schiller 1979), showing of any era's definition of ethical journalism always reflects rapidly coevolving press tools and practices.

The third approach focuses on the values and beliefs of technologists themselves. Grounded in the claim that artifacts with "political qualities" (Winner 1986, 20) give certain people, ideas, and events more visibility and power than others, it asks how "designers and producers include values, purposively, in the set of criteria by which the excellence" of their artifacts are judged (Flanagan, Howe, and Nissenbaum 2008, 322). Such approaches trace the clues that designers leave about their *own* ethical standards in everything from web browser cookie management systems, workplace plasma displays, and urban simulation software (Friedman, Kahn, and Borning 2006).

Such standards are not explicit in official codes of conduct but exist at the level of individual, seemingly idiosyncratic practice. They emerge informally as designers create systems with “value levers” (Shilton 2012) that users can use to enact what *designers* see as acceptable and desirable applications. Akin to the “virtue approach,” this approach takes the designer and his or her context as the primary units of analysis, tracing how ethics emerges not from formal standards or broad institutional patterns, but from a technologist’s own values and choices.

In reality, technology ethics emerges from a mix of institutionalized codes, professional cultures, technological capabilities, social practices, and individual decision making. Indeed, ethical inquiry in any domain is not a test to be passed or a culture to be interrogated but a complex social and cultural *achievement* (Christians et al. 2009). It entails anticipating how the intersecting dynamics of a sociotechnical system—design, interpretation, use, deployment, value—“matter” for the future (Marres 2007)—and figuring out how to hold these intersections accountable in light of an ethical framework.

Media ethics usually frames accountability in terms of two questions: “accountable *for what*?” and “accountable *to whom*?” (Glasser 1989, 179), but these questions are usually asked of mature media systems (McQuail 2003)—technologies, institutions, and professions that are relatively stable and understood well enough to describe how they behave and how they should be regulated. There may be little consensus on how *exactly* to hold newspaper, television, radio, or cable television industries accountable, but their form, power, meaning, and genres are understood clearly enough to debate with some clarity which standards and people should hold them accountable.

But when technologies and media systems like algorithms are new—before the “wider social-cultural milieu” has prevented them from having “more than one interpretation” (Pinch and Bijker 1984, 409)—they need ethical critiques that keep flexible and contestable their fundamental forms, power, and meanings. Before “social interactions between and within relevant social groups” have made systems “less and less ambiguous” (Bijker 1995, 270-71) and harder to reinterpret, there is an opportunity to intervene and influence their ethics. If what they are or might be can be placed clearly and creatively in terms of an ethical framework, we may discover new ways of holding them accountable before forces of "closure and stabilization" (p. 279) limit debate about how they work and what they mean.

Defining NIAs

Computer science defines an algorithm as a "description of the method by which a task is to be accomplished" (Goffey 2008, 15). Rendered in any programming language and judged according to how quickly and reliably they transform known inputs into desired outcomes, algorithms are generic solutions for well-defined problems. They are the clearest evidence of computation's power to be "a positivistic dominant of reductive, systemic efficiency and expediency" (Galloway 2011, 100).

But this computational definition belies algorithms' sociological and normative features, for example, their power to:

- sort and rank the social web, signaling search quality (Mager 2012) and organizing online communities (Bucher 2012);
- spur commercial activity and direct flows of online capital (Webster 2010);
- organize people into audiences (C. W. Anderson 2011) while automatically creating (Carlson 2015), recommending (Beam 2014), and reading news (Kleinnijenhuis et al. 2013) with little human oversight (Diakopoulos 2015);
- optimize international online labor markets (Kushner 2013);
- create "cyborg finance" (Lin 2013) systems that operate faster than human comprehension (Arnuk and Saluzzi 2012);
- direct military drones to target locations before requesting firing authority from human operators (Calo 2015).

I use the term "networked information algorithm" for two reasons: to distinguish the object of study in this article from computer science's purely mathematical, mechanistic focus and to make it possible to consider the ethics of the sociotechnical *relationships* producing, interpreting, and relying upon the formation processed by computational algorithms. The aim is to describe a unit of ethical analysis—a target for media accountability—that is not a code or a human action on code but, rather, an intersection of technologies and people that makes some associations, similarities, and actions more likely than others.

Algorithms "govern" because they have the power to structure possibilities. They define which information is to be included in an analysis; they envision, plan for, and execute data transformations; they deliver results with a kind of detachment, objectivity, and certainty; they act as filters and mirrors, selecting and reflecting information that make sense within an algorithm's computational logic and the human cultures that created that logic Gillespie (2014). Algorithms do not simply *accelerate* commerce, journalism, finance, or other domains—they are a discourse and culture of knowledge that is simultaneously social and technological, structuring how information is produced, surfaced, made sense of, seen as legitimate, and ascribed public significance (Beer 2009; Bucher 2012; Striphas 2015).

Various types of resistance and dissent are emerging in response to such power. Some criticize the intellectual property and professional norms that keep algorithms private and call for transparent code (Diakopoulos 2015; Pasquale 2011). Others challenge algorithms as unconstitutional when they make "editorial decisions that are neither obvious nor communicated to the reader" (chilling speech) or "single out speakers" without their consent (invading privacy; Benjamin 2013, 1446). Others suggest hiding from algorithms by de-indexing files from search engine crawlers or using anonymous currencies like bitcoin (Maurer, Nelms, and Swartz 2013). Others audit them to derive their inner workings (Sandvig et al. 2014) or purposefully give "misleading, false, or ambiguous data with the intention of confusing" algorithms (Brunton and Nissenbaum 2011, np).

Part of the challenge of critiquing and resisting algorithms is locating them in the first place. Like infrastructure (Star and Ruhleder 1996), algorithms are embedded within the sociotechnical structures; they are shaped by communities of practice, embodied in standards, and most visible when they fail. But, distinct from infrastructure, the relevance, quality, and stability of algorithms depend upon end users. Machine learning algorithms need a great deal of data before they are useful or reliable, social network algorithms require a significant number of nodes before they are able to describe or influence an online community, and recommendation and prediction algorithms observe data flows for long periods of time before they create useful forecasts. It matters little if the "black boxes" of algorithm code (Pinch and Bijker 1984) are opened or comprehensible since they only become *ethically* significant in relation to others.

Understanding how algorithmic ethics is relationally achieved can be helped by applying frameworks designed to trace networks of sociotechnical power. Latour (2005) traces how humans and nonhumans together create and stabilize controversies, produce knowledge and associations, and surface ethical tensions. Similarly, "neo-institutional" studies of organizational technologies (Orlikowski 2010) show how "loosely coupled arrays of standardized elements" (DiMaggio and Powell 1991, 14)—individuals, laws, norms, professional ideals, economic priorities—combine to make technologies that a network *sees* as workable or socially acceptable (or not). Napoli (2014) goes so far as to define algorithms *as* institutions because of their power to structure behavior, influence preferences, guide consumption, produce content, signal quality, and sway commodification.

With these relationships in mind, I define an NIA as an assemblage (DeLanda 2006; Latour 2005) of institutionally situated computational code, human practices, and normative logics that creates, sustains, and signifies relationships among people and data through minimally observable, semiautonomous action. Although code, practices, and norms may be observed *individually* in other contexts, their full "meaning and force ... can only be understood in terms of relations with other modular units" (Chadwick 2013, 63). For example, Google News' results differ as the page rank algorithm changes, as it is personalized for different individual user profiles, and as Google judges some different news as more worthy of indexing than others. It makes more sense to talk about the ethics of a particular Google News assemblage than the ethics of its algorithm.

Studying the ethics of such assemblages entails not just reading black boxes of code for values (Steen 2014) but also criticizing assemblages "in ways that might serve the ends of freedom and justice" (Winner 1993, 374-76). Such an ethics ignores the unanswerable question of whether code is biased or not (Edelman 2011) and instead asks whether different assemblages "help us get into satisfactory relation with other parts of our experience" (James 1997, 100). The crux of this ethics, of course, rests upon a rich and diverse debate about what "satisfactory relation" means and assemblages create the conditions under which an algorithm might be seen as "wrong" (Gillespie 2012). This pragmatic focus answers Latour's (2004) call for studies of science and technology to move beyond "matters of fact"—deconstructing and explaining sociotechnical systems—to "matters of concern."

Critiquing NIAs

In identifying the matters of algorithm concern, my approach breaks down Merrill's claim—that ethics is the study of "what we ought to do"—into constituent concepts that can be traced across algorithmic assemblages. This critique is not intended as a comprehensive account of algorithmic ethics—other ethical claims could be operationalized and other assemblage dimensions could be analyzed—but it attempts to move *toward* a model of algorithm ethics by asking *when*, *how*, and for *whom* NIAs work. Specifically, how do NIAs convene a "we" (a collective of ethical concern)? How do algorithms encode chance and certainty, suggesting what should probably happen (the likely set of influences and outcomes needing ethical critique)? And how does an assemblage's construction of timing and timeliness influence when action is taken (creating timeframes over which ethical concerns can play out)?

Convening Constituents by Algorithmically Inferring Associations

Publics emerge when technologies create associations by aggregating people. "Who is inside and outside, who may speak, who may not, and who has authority and may be believed" (Marvin 1990, 4) depend on communication technologies that see some people as like or unlike others, despite variations the technologies cannot capture. Maps, newspapers, museums, and censuses help people see themselves as part of a common group, eliding differences and excluding those not represented in these media (B. Anderson 1983). Opinion polls and market surveys collapse contentious disagreements or subtle variations into binaries and predefined categories that underpin political action (Herbst 1995) and create commercial markets (Igo 2007). Such technologies efficiently align interests and enable a type of collective action—but they also have the power to artificially limit a group's size (Dahl and Tufte 1973), "compel" association where none is chosen (Rosenblum 2000), and aggregate people into groups without their consent (Salmon and Glasser 1995).

NIAs exercise this aggregative power by semiautonomously sorting data into categories and drawing inferences, through surveillance infrastructures that most people never encounter directly (McKelvey 2014). For example:

- The National Security Agency (NSA) uses cell GPS data to infer individual locations and relationships (Soltani and Gellman 2013) and Google's Advertising algorithmically labels people as potential terrorists (Soltani, Peterson, and Gellman 2013).
- Analyzing Facebook data, researchers at the Massachusetts Institute of Technology observed that "the percentage of a given user's friends who self-identify as gay male is strongly correlated with the sexual orientation of that user" (Jernigan and Mistree 2009, np), algorithmically inferring unrevealed orientations.
- Analyzing phone metadata of a relatively small population, Mayer and Mutchler (2014) correctly inferred caller identities,

relationships, occupations, medical conditions, religious affiliations, and political beliefs.

- An ethically controversial study automatically filtered Facebook users' content to be "positive" or "negative" to show that the emotional content of people's subsequent posts could be algorithmically influenced (Kramer, Guillory, and Hancock 2014).
- Computer scientists recently produced "images that are completely unrecognizable to humans, but that state-of-the art [deep neural networks] believe to be recognizable objects with 99.99% confidence" (Nguyen, Yosinski, and Clune 2014, 1).

Each of these examples entails algorithms deriving categories and creating associations by sensing and combining aspects of the world they have been programmed to see (Cheney-Lippold 2011). People who fail to leave data that can be categorized are effectively invisible to the database and algorithm (Lerman 2013), but those who leave few traces can still be categorized: reliable pattern-matching often does not require "big data" but small amounts of densely connected metadata that an algorithm is programmed to see as related.

A *deontological* critique would ask how much such algorithmic samples look like broader demographic categories: Does Twitter's distributions of genders and ethnicities match those of the United States? How do Facebook's 1 billion-plus users align with global population patterns? Do high-frequency trading algorithms simply speed up the transactions people would have made anyway? A *teleological* critique of algorithmic convening is rooted in pragmatism. It asks whether the algorithms of Facebook, Twitter, the NSA, or high-frequency trading produce "satisfactory relations with other parts of our experience" (James 1997, 100) without worrying whether algorithms recreate the existing demographic patterns. A *virtue-based* critique of convening would ask how designers think people *should* be aggregated, what comparison and association they build into their designs, and how audiences interpret the associations algorithms present them. Deontologically acceptable NIAs correspond with how standards *outside* the assemblage have already sorted the world, teleologically acceptable NIAs produce associations that people see as efficacious, and acceptable virtue-based algorithms align with designers and users' local, idiosyncratic hopes for and expectations of the world.

Algorithmic convening thus poses a complex ethical challenge. It is difficult to criticize algorithmic convening on deontological grounds because the inner workings of algorithms are proprietary and thus hard to compare to other types of associational technologies (like the census or opinion polls). It is difficult to criticize algorithmic convening on teleological grounds since the effects of a single assemblage are not universally distributed—different people experience different algorithmic assemblages differently. Finally, it is difficult to criticize the virtue of algorithmic convening because we can usually only evaluate what algorithms *produce*, with little insight into the dynamics of the cultures that created them. Most insights we have into the priorities, values, and compromises that determine how an algorithm convenes groups come from corporate self-reporting (Facebook 2013; Google n.d.), post hoc analyses (Bucher 2012), auditing (Sandvig et al. 2014), or reverse engineering (Seaver 2014).

An ethical critique of an algorithmic assemblage that convenes people could be multidimensional, analyzing how well its aggregates adhere to external standards, how its affiliations are interpreted and deployed, and what kind of assumptions and values underpin the cultures that create such associational technologies.

Governing Action by Judging the Probability of Similarity

The second aspect of understanding how NIAs govern "what we ought to do" rests upon understanding how they judge similarity and probability. How closely and confidently do they see a situation resembling a previous one?

Recommendations based on probable similarity raise ethical concerns because when unobservable and seemingly objective computational logics equate two or more instances, people see "resemblances between certain acts" as "completely natural and self-evident." This makes it harder for them to recognize "genuine differences," generate alternatives, defend unsuggested actions, or argue for exceptions to similarity (Hofstadter and Sander 2013, 10). Many search algorithms organize their outputs by relevance, but the ethical provenance or significance of such judgments is often unclear. For example, Facebook can help "lenders discriminate against certain borrowers based on the borrower's social network connections" (Sullivan 2015) and online advertisers can use racial stereotypes to create targeted ads (Sweeney 2013)—but to criticize or resist such predictions means understanding how algorithms create and associate *categories* like "friends with," "credit risk," "black-identifying names."

Categories give people "the feeling of understanding a situation," helping them "to draw conclusions and to guess about how a situation is likely to evolve" (Hofstadter and Sander 2013, 14-15). They are shared impressions of the world and shortcuts that reduce the risk of misinterpreting new data or situations. But categories are also evidence of the power to strip "away the contingencies of an object's creation," to put "the thing that does not fit into one bin or another ... into a 'residual' category" that signals marginality, impurity, or an outlier accident (Bowker and Star 1999, 299-300). Algorithmic categories raise ethical concerns to the extent that they signal certainty, discourage alternative explorations, and create coherence among disparate objects—categorically narrowing the set of socially acceptable answers to the question of what ought to be done. Consider the following examples:

- Google's Autocomplete (Garber 2013) algorithm finishes people's search queries by comparing them to content and people it sees as similar, reinforcing cultural stereotypes (Baker and Potts 2013) and dissuading people from unpopular searches (Gannes 2013).
- Facebook algorithms track users across the web, watching what they click on, read, share, and comment on to create a personal preference history that organizes Facebook's News Feed and suggests actions (Gerlitz and Helmond 2013). It recommends purchases it sees as similar to users' profiles and suggests news it sees as consistent with past reading behavior (Nielsen and Schrøderb 2014).
- Amazon.com product recommendations are primarily based on how similar an *item* is to those that others have purchased, rated, or viewed (Linden, Smith, and York 2003). This "item-to-item" approach makes it easy to make recommendations to customers who have purchased little, overcoming the lack of "transactional data" (Beer and Burrows 2013) to suggest purchases consistent with similarities among products. Recommendations for what ought to be purchased come not from the similarities among people or consistency with past behavior but from categorical resemblances among objects.

These examples raise ethical concerns because each case—recommending a search, standardizing a user's online behaviors, and suggesting a purchase—involves unseen, categorical, computational judgments about which searches, articles, or purchases should *probably* come next. Users are not offered limitless options but are, in fact, given a narrowly construed set that comes from successfully fitting other people, past actions, and inanimate objects into categories—using categories to discipline action.

Such algorithmic assemblages are simply the latest version of computational systems disciplining users within a narrow set of actions the computer expects (Suchman 1994). Efficient and scalable systems *require* stable categories of people who have learned to say certain words, click certain sequences, and move in predictable ways. This is the ethical power of algorithms: to create a disciplined *network* of humans and machines that resembles and recreates probabilities, making the set of possible outcomes the *model* anticipates likely and reasonable (Mackenzie 2015). Efficient—but not necessarily ethical—algorithmic assemblages use such probabilities to suggest what ought to be done.

Such similarity systems can fail and be resisted, though. Targeted advertisements, for example, made people "uncomfortable if [they] seemed to know too much of their past behavior" but were acceptable again if they "perfectly aligned" people's interests (Wohn and Sarkar 2014, 577). The discomfort with such "uncanny valleys" (Mori 1970) of similarity may not only be the evidence of failed algorithms but starting points for investigating the *ethical* limits of similarity. That is, algorithms that produce results judged as too similar—or the "wrong" kind of similar—may represent moments when people find algorithms' ends, means, or values as too inconsistent with personal codes, too unhelpful for navigating social relationships, or too misaligned with their ethical idiosyncrasies. For example, my Facebook connections may indeed reliably predict my credit risk, but the algorithm driving this prediction may be ethically dubious if it simply accepts similarities between social connections and financial behaviors without seeing structural racism and socioeconomic discrimination as mediators—judgments, categories, and similarities that may be hard to computationally encode.

The *ethics* of a probabilistic system cannot only be judged by "the degree of belief warranted by evidence" it provides (how much it can be trusted) or its ability to "produce stable relative frequencies" (how often it should be trusted; Hacking 2006, 1). What is *also* required is a sensitivity to the categories it uses and a sufficiently creative imagination able to envision other, *better* types of similarity that might produce more "satisfactory relations with other parts of our experience" (James 1997, 100).

Setting Deadlines and Governing Rhythms

Algorithmic assemblages can also suggest *when* action should be taken, but such suggestions depend on how quickly and confidently an assemblage produces results with an acceptable risk of error. Computer scientists use "big-O" notation to indicate "whether a given algorithm will be able to run in a reasonable amount of time on a problem of a given size," suggesting how much error might be tolerated at any moment in the algorithm's operation (Skiena 1998, 16).[1] Such notation is a shared language for analyzing the temporal dynamics of code, a way to quantify the risk of interrupting an algorithm. If slow and fast algorithms are stopped after the same amount of time, the slow algorithm may have produced *more* error-prone results than the fast algorithm (because its conclusion is based on fewer pieces of data), or it may have produced *less* error-prone results (because it has more confidence in the answers it did have time to give). If you know how a code works, you can calculate the probability that an algorithm's results are correct at any point in time.

It is harder, though, to time an *assemblage's* results—to understand how long a mix of code, people, practices, and norms requires to produce meaningful, trustworthy results. For example:

- Twitter's "Trends" algorithm "identifies topics that are immediately popular, rather than topics that have been popular for a while or on a daily basis" (Twitter 2014). A small number of users who frequently tweet is responsible for most of these trends (Asur et al. 2011) and Twitter staff sometime intervene to hand-curate trends (Gillespie 2012). A trend's ethical significance—how its patterns might suggest action at any particular moment—depends on momentary confidence in the trend, on actors' power to interrupt the algorithm, freeze its results, act on answers, or wait for more data. The Twitter assemblage's preference for immediacy (sensitivity to frequent tweeters, the code's design, staff interventions) makes it less useful for taking action supported by longer-term views.
- News organizations frequently use algorithms to list the "most e-mailed" or "most read" articles on their websites. But, unlike the rhythms that have traditionally organized news publishing (morning and evening newspapers, six-o'clock newscasts; Schudson 1986), the actions of distributed users determine which list items persist or decay. The rhythms that produce clicks, forwards, tweets, likes, and posts from other parts of the web are beyond the control of news organizations and susceptible to third-party algorithms that surface stories (e.g., Twitter trends, Facebook News Feed, Google News), making it impossible to reassemble an online audience (Lehmann et al. 2013). If networked news organizations earn their democratic legitimacy, in part, from convening and sustaining conversations with distributed audiences, they have an ethical imperative to break news, update audiences, issue corrections, and give a historical

context. But implementing this imperative depends upon an algorithmic assemblage of networked news time: people, code, practices, and norms extending far beyond the newsroom that create the networked press's rhythms and timeliness.

- Algorithms can also anticipate future actions. Police departments in Los Angeles (Berg 2014) and New York use "predictive policing" algorithms to combine historical crime data with real-time, geolocated tweets, deploying officers "where and when crime is most likely to occur" (Morrison 2014). And Pennsylvania is considering allowing judges to use statistical estimates of future offenses to determine an inmate's current sentence—punishing them not only for crimes they have committed but crimes that algorithms think they *might* commit (Barry-Jester, Casselman, and Goldstein 2015). Algorithmic ethics resemble actuarial ethics: a prediction's legitimacy is based not only on the probable correctness of a current calculation but on the risk of applying that calculation in the future. If "risk is a product of human imaginations disciplined and conditioned by an awareness of the past" (Jasanoff 2010, 15), predictive algorithms are a key element of disciplining and conditioning ethical imagination—of envisioning what might or ought to be done.
- Algorithms can also influence memory. The Internet Archive (2001) lets sites opt out of its index by including the following lines of code in its webserver's "robot.txt" file:

```
User-agent: ia_archiver

Disallow: /
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- The *Washington Post* (2014) uses this code to prevent the archive from indexing its site, while the *New York Times* (2014) uses similar code to prevent the Associated Press and Reuters from archiving its site. Even without these blocks, Thelwall and Vaughan (2004) show how the Internet Archive algorithmically narrows its own archive: since its crawler algorithm privileges sites that already have links to them, countries with less densely linked websites can fail to appear in the archive altogether. Similarly, researchers collecting tweets using Twitter's own Application Programming Interface report having incomplete data sets compared to accessing the full archive through the Twitter's exclusive data "firehose" (Driscoll and Walker 2014)—the same moment can be remembered differently

> depending on the sampling algorithm used. If data-based decisions about what *should* happen are to align with—or purposefully differ from—records of what *has* happened, then we need to understand how algorithms organize the past and thus influence memories.

Unlike algorithmic convening (when algorithms construct the "we") or algorithmic similarity (when algorithms create the space of probable action), algorithmic *timing* entails prediction, interruption, and anchoring—using algorithms to suggest when an event will likely happen, the relevant time frames, the memories to recall. What does it mean if public attention assembled by an algorithm appears only briefly and dissipates before it can be understood? If public attention no longer exists, does it need to be accounted for? If there is no record of public attention, how can it be recreated or prevented from reoccurring? Since Google Search, Facebook News Feed, and Twitter Trends continually change their algorithms without public oversight, which *versions* of an assemblage should be held responsible for ethically questionable outcomes?

Answering these questions requires seeing how algorithmic assemblages create what Durkhein called a consensus on "temporal orientation'" (Durkheim [1912] 1954, 440). Consensus is not necessarily agreement but, rather, the product of forces battling to mark time, to define stops and starts, to make interruptions, to say that enough is known to act. For example, understanding contemporary, networked "news time" means tracing how the power to structure time is distributed among news organizations, social media companies, and their respective practices, code, actors, and norms. Part of holding the media ethically accountable for its organization of people's time and attention means appreciating how algorithmic assemblages order events, suggest causes, orient attention, recall memories so that some actions might be taken over others, some consequences secured and others avoided. (Dewey 1954, 12)

Conclusion

Starting from an admittedly simplistic notion of ethics as "the study of what we ought to do," my aim has been to sketch an ethics of NIAs. Specifically, how algorithms convene a "we," judge similarity, and create time—all in order to suggest which actions are likely to happen, and when.

My definition of NIAs as *assemblages* of institutionally situated code, human practices, and normative logics may seem overly broad, but it is intended to narrow the empirical study of algorithmic ethics to the linkages *among* empirical sites. I unpacked the simple definition of ethics as "the study of what we ought to do" into its conceptual constituents—convening, probability, time—to create concepts that can only be fully appreciated in relationships among algorithmic code, practices, and norms. The assemblages governing the question of "what we ought to do" might, therefore, be seen as a three-by-three matrix of concepts (convening, probability, time) and actants (code, practices, norms)—potential actions and their ethical significance exist at this matrix's intersections. To be sure, the concepts and actants might change or be reformulated in response to different ethical theories and new empirical contexts. The framework offered here is meant only as a step toward analyzing the empirical and normative dynamics at play in NIAs.

Such frameworks are urgently required because media are increasingly susceptible to algorithmic assemblages. Algorithms are created by professionals with shifting boundaries (software designers move among social media, ecommerce, and networked news platforms), algorithmic technologies have unpredictable outcomes (outputs cannot be understood by any single programmer or controlled by any one organization), and algorithmic ecosystems are increasingly personalized (media reaches consumers through myriad and opaque rules and values). The existing approaches to media accountability that assume stable technologies and clear questions are outstripped by the dynamic and contested nature of algorithmic assemblages. Some see accountability existing as code transparency, others seek state regulation of companies with algorithmic monopolies, and others aim to build algorithmic literacy among end users. Each unit of analysis is important but considering the ethics of each on isolation misses appreciating the full power of algorithmic assemblages.

Unlike other media technologies whose ethical dynamics might be evaluated when they are designed, deployed, or interpreted, NIAs and their ethical dimensions are moving targets. A purely deontological approach might be applied to the entire assemblage—asking whether its rules and policies adhere to ethical principles—but it may be difficult to trace which parts of an assemblage adhere to or deviate from deontological guidelines. A strictly teleological approach focused on ends and consequences may be the most effective for large-scale, complex assemblages, but it begs questions about who is inside or outside of an assemblage—who is the maker and who is its target when algorithms dynamically adapt to the users they encounter?

Should users be held partly accountable for an algorithm's output if they knowingly provided it with data? A virtue model seems promising since it questions the seemingly idiosyncratic sociotechnical dynamics of assemblages—seeing each as a particular ethical arrangement—but this approach is difficult to scale in the context of fast-moving, algorithmic assemblages with myriad, unseen code, actors, and norms. A combination of all three approaches is likely needed.

My aim has been to show that even though algorithms are unstable objects of study, their ethics might still be investigated systematically by redescribing an ethical framework in terms of traceable, operationalized concepts and then looking for evidence of such concepts among the elements of algorithmic assemblages. This approach does not require—but nor does it eschew—code transparency. Seeing inside a black box is sometimes necessary, but never sufficient, for holding an algorithmic assemblage accountable. Rather, this framework focuses on the pragmatic question of how an entire assemblage *acts*. Its code may be transparent, its designers may have good intentions, and its institution may be well regulated, but an algorithmic assemblage might only be considered ethical if some combination of its means, ends, and virtues helps "us get into satisfactory relation with other parts of our experience" (James 1997, 100).

While this might seem like a hedge or ethical relativism—what does "satisfactory" mean, which parts, and are all experiences to be considered equally valid?—this approach is meant to connect the lived, relational dynamics of algorithmic assemblages (code, practices, norms) to an operationalized conception of ethics (convening, probability, time) so that any approach to accountability might answer the question: how are groups, similarities, and time lines governed by algorithmic assemblages creating (un)satisfactory relations? This is an argument against equating the ethics of algorithmic assemblages with the transparency of algorithmic code—an argument *for* a more expansive model of algorithmic ethics, taking up Dewey's (1891, 196) observation that "to do truly is to regard the whole situation as far as one sees it, and to see it as far as one can."

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Note

1. For example, if the time, **T**, an algorithm requires to work on a data set of size ***n*** is **2*n***, then the time required to complete the algorithm increases *linearly* with the size of the data set (the algorithm is said to have linear big-O time, written as $\mathbf{T}(\boldsymbol{n})=\mathbf{O}(\boldsymbol{n})$).

References

Anderson, B. 1983. *Imagined Communities*. Revised ed. London, UK: Verso.

Anderson, C. W. 2011. "Deliberative, Agonistic, and Algorithmic Audiences: Journalism's Vision of Its Public in an Age of Audience Transparency." *International Journal of Communication* 5:19. Accessed September 8, 2015. http://ijoc.org/index.php/ijoc/article/view/884.

Arnuk, S. L., and J. C. Saluzzi. 2012. *Broken Markets: How High Frequency Trading and Predatory Practices on Wall Street Are Destroying Investor Confidence and Your Portfolio*. New York: FT Press.

Asur, S., B. A. Huberman, G. Szabo, and C. Wang. 2011. "Trends in Social Media: Persistence and Decay." Paper presented at the AAAI Conference on Weblogs and Social Media, Association for the Advancement of Artificial Intelligence, Barcelona, Spain, July 17–21, 2011.

Baker, P., and A. Potts. 2013. "'Why Do White People Have Thin Lips?' Google and the Perpetuation of Stereotypes via Auto-complete Search Forms." *Critical Discourse Studies* 10 (2): 187-204. doi:10.1080/17405904.2012.744320.

Barry-Jester, A. M., B. Casselman, and D. Goldstein. 2015. "The New Science of Sentencing." *The Marshall Project*. Accessed August 10, 2015. https://www.themarshallproject.org/2015/08/04/the-new-science-of-sentencing.

Beam, M. A. 2014. "Automating the News: How Personalized News Recommender System Design Choices Impact News Reception." *Communication Research* 41 (8): 1019-41. doi:10.1177/0093650213497979.

Beer, D. 2009. "Power through the Algorithm? Participatory Web Cultures and the Technological Unconscious." *New Media and Society* 11 (6): 985-1002.

Beer, D., and R. Burrows. 2013. "Popular Culture, Digital Archives and the New Social Life of Data." *Theory, Culture and Society* 30 (4): 47-71.

Benjamin, S. M. 2013. "Algorithms and Speech." *University of Pennsylvania Law Review* 161 (6): 1445-94.

Berg, N. 2014. "Predicting Crime, LAPD-style." *The Guardian*. Accessed August 20, 2014. http://www.theguardian.com/cities/2014/jun/25/predicting-crime-lapd-los-angeles-police-data-analysis-algorithm-minority-report.

Bijker, W. E. 1995. *Conclusion: The Politics of Sociotechnical Change of Bicycles, Bakelites, and Bulbs: Toward a Theory of Sociotechnical Change*. Cambridge, MA: The MIT Press.

Bowker, G. C., and S. L. Star. 1999. *Sorting Things Out: Classification and Its Consequences*. Cambridge, MA: The MIT Press.

Brunton, F., and H. Nissenbaum. 2011. "Vernacular Resistance to Data Collection and Analysis: A Political Theory of Obfuscation." *First Monday* 16 (5): 1-16.

Bucher, T. 2012. "Want to be on Top? Algorithmic Power and the Threat of Invisibility on Facebook." *New Media and Society* 14 (7): 1164-80.

Calo, M. R. 2015. "Robotics and the New Cyberlaw." *California Law Review* 103 (4): 101-46.

Carey, J. W. 1989. *Communication as Culture: Essays on Media and Society*. New York: Routledge.

Carlson, M. 2015. "The Robotic Reporter: Automated Journalism and the Redefinition of Labor, Compositional Forms, and Journalistic Authority." *Digital Journalism* 3 (3): 416-31. doi:10.1080/21670811.2014.976412.

Chadwick, A. 2013. *The Hybrid Media System: Politics and Power*. Oxford, UK: Oxford University Press.

Cheney-Lippold, J. 2011. "A New Algorithmic Identity: Soft Biopolitics and the Modulation of Control." *Theory, Culture and Society* 28 (6): 164-81.

Christians, C. G., T. L. Glasser, D. McQuail, K. Nordenstreng, and R. A. White. 2009. *Normative Theories of the Media*. Urbana: University of Illinois Press.

Computer Ethics Institute. 2011. *The Ten Commandments of Computer Ethics.* Accessed May 1, 2013. http://cpsr.org/issues/ethics/cei/.

Cummings, M. L. 2006. "Automation and Accountability in Decision Support System Interface Design." *The Journal of Technology Studies* 32 (1): 23-31.

Dahl, R. A., and E. R. Tufte. 1973. *Size and Democracy*. Stanford, CA: Stanford University Press.

DeLanda, M. 2006. *A New Philosophy of Society: Assemblage Theory and Social Complexity*. New York: Bloomsbury Academic.

Dewey, J. 1891. "Moral Theory and Practice." *International Journal of Ethics* 1 (2): 186-203.

Dewey, J. 1954. *The Public and Its Problems*. New York: Swallow Press.

Diakopoulos, N. 2015. "Algorithmic Accountability: Journalistic Investigation of Computational Power Structures." *Digital Journalism* 3 (3): 1-18. doi:10.1080/21670811.2014.976411.

DiMaggio, P. J., and W. W. Powell. 1991. "Introduction." In *The New Institutionalism in Organizational Analysis*, edited by W. W. Powell and P. J. DiMaggio, 1-38. Chicago: The University of Chicago Press.

Driscoll, K., and S. Walker. 2014. “Working within a Black Box: Transparency in the Collection and Production of Big Twitter Data.” *International Journal of Communication* 8:20. Accessed September 8, 2015. http://ijoc.org/index.php/ijoc/article/view/2171.

Durkheim, E. (1912) 1954. *The Elementary Forms of the Religious Life*. Translated by J. W. Swain. Glencoe, IL: Free Press.

Edelman, B. 2011. “Bias in Search Results? Diagnosis and Response.” *The Indian Journal of Law and Technology* 7 (1): 16-32.

Facebook. 2013. “News Feed FYI: A Window into News Feed.” *Facebook*. Accessed April 1, 2014. https://www.facebook.com/business/news/News-Feed-FYI-A-Window-Into-News-Feed.

Flanagan, M., D. Howe, and H. Nissenbaum. 2008. “Embodying Values in Technology: Theory and Practice.” In *Information Technology and Moral Philosophy*, edited by J. van den Hoven and J. Weckert, 322-53. Cambridge, UK: Cambridge University Press.

Friedman, B., P. H. Kahn, and A. Borning. 2006. “Value Sensitive Design and Information Systems.” In *Human-computer Interaction in Management Information Systems: Foundations*, edited by P. Zhang and D. Galletta, 348-72. London, UK: M.E. Sharpe.

Galloway, A. 2011. “Are Some Things Unrepresentable?” *Theory, Culture and Society* 28 (7-8): 85-102.

Gannes, L. 2013. “Nearly a Decade Later, the Autocomplete Origin Story: Kevin Gibbs and Google Suggest.” *All Things D*. Accessed January 29, 2014. http://allthingsd.com/20130823/nearly-a-decade-later-the-autocomplete-origin-story-kevin-gibbs-and-google-suggest/.

Garber, M. 2013. “How Google’s Autocomplete was … Created / Invented / Born.” *The Atlantic*. Accessed March 3, 2014. http://www.theatlantic.com/technology/archive/2013/08/how-googles-autocomplete-was-created-invented-born/278991/.

Gerlitz, C., and A. Helmond. 2013. “The Like Economy: Social Buttons and the Data-intensive Web.” *New Media and Society* 15 (8): 1348-65. doi:10.1177/1461444812472322.

Gillespie, T. 2012. “Can an Algorithm be Wrong?” *Limn: Crowds and Clouds*. Accessed January 2, 2014. http://limn.it/can-an-algorithm-be-wrong/.

Gillespie, T. 2014. “The Relevance of Algorithms.” In *Media Technologies: Essays on Communication, Materiality, and Society*, edited by T. Gillespie, P. Boczkowski, and K. A. Foot, 167-94. Cambridge, MA: MIT Press.

Glasser, T. L. 1989. “Three Views on Accountability.” In *Media Freedom and Accountability*, edited by E. E. Dennis, D. M. Gillmor, and T. L. Glasser, 179-93. New York: Praeger.

Goffey, A. 2008. "Algorithm." In *Software Studies: A Lexicon*, edited by M. Fuller, 15-20. Cambridge, MA: MIT Press.

Google. n.d. *How Search Works: From Algorithms to Answers*. Accessed January 6, 2014. http://www.google.com/insidesearch/howsearchworks/thestory/.

Hacking, I. 2006. *The Emergence of Probability: A Philosophical Study of Early Ideas About Probability, Induction and Statistical Inference*. Cambridge, UK: Cambridge University Press.

Herbst, S. 1995. *Numbered Voices: How Opinion Polling Has Shaped American Politics*. Chicago: The University of Chicago Press.

Hofstadter, D., and E. Sander. 2013. *Surfaces and Essences: Analogy as the Fuel and Fire of Thinking*. New York: Basic Books.

Hursthouse, R. 1999. *On Virtue Ethics*. Oxford, UK: Oxford University Press.

Igo, S. 2007. *The Averaged American: Surveys, Citizens, and the Making of a Mass Public*. Cambridge, MA: Harvard University Press.

Internet Archive. 2001. *Removing Documents from the Wayback Machine*. Accessed March 1, 2014. https://archive.org/about/exclude.php.

James, W. 1997. "What Pragmatism Means." In *Pragmatism: A Reader*, edited by L. Menand, 93-111. New York: Random House.

Jasanoff, S. 2010. "Beyond Calculation: A Democratic Response to Risk." In *Disaster and the Politics of Intervention*, edited by A. Lakoff, 14-41. New York: Columbia University Press.

Jernigan, C., and B. F. T. Mistree. 2009. "Gaydar: Facebook Friendships Expose Sexual Orientation." *First Monday*. Accessed September 4, 2015. http://firstmonday.org/article/view/2611/2302.

Kant, I. [1785] 2002. *Groundwork for the Metaphysics of Morals*. Translated by A. W. Wood. Binghamton, NY: Vail-Ballou Press.

Kleinnijenhuis, J., F. Schultz, D. Oegema, and W. van Atteveldt. 2013. "Financial News and Market Panics in the Age of High-frequency Sentiment Trading Algorithms." *Journalism* 14 (2): 271-91. doi:10.1177/1464884912468375.

Kramer, A. D. I., J. E. Guillory, and J. T. Hancock. 2014. "Experimental Evidence of Massive-scale Emotional Contagion through Social Networks." *PNAS* 111 (24): 8788-90. doi:10.1073/pnas.1320040111.

Kushner, S. 2013. "The Freelance Translation Machine: Algorithmic Culture and the Invisible Industry." *New Media and Society* 15 (8): 1241-58. doi:10.1177/1461444812469597.

Latour, B. 2004. "Why Has Critique Run Out of Steam? From Matters of Fact to Matters of Concern." *Critical Inquiry* 30 (2): 225-48.

Latour, B. 2005. *Reassembling the Social: An Introduction to Actor-network-theory*. Oxford, UK: Oxford University Press.

Lehmann, J., C. Castillo, M. Lalmas, and E. Zuckerman. 2013. "Transient News Crowds in Social Media." Paper presented at the ICWSM 2013. Accessed September 4, 2015. http://chato.cl/papers/lehmann_castillo_lalmas_zuckerman_2013_transient_news_crowds.pdf.

Lerman, J. (2013). "Big Data and Its Exclusions." *Stanford Law Review*. Accessed September 4, 2015. http://www.stanfordlawreview.org/online/privacy-and-big-data/big-data-and-its-exclusions.

Levine, C. 2007. "Analyzing Pandora's Box: The History of Bioethics." In *The Ethics of Bioethics: Mapping the Moral Landscape*, edited by L. A. Eckenwiler and F. G. Cohn, 3-23. Baltimore, MD: Johns Hopkins University Press.

Lin, T. C. W. 2013. "The New Investor." *UCLA Law Review* 60 (3): 678-735.

Linden, G., B. Smith, and J. York. 2003. "Amazon.com Recommendations: Item-to-item Collaborative Filtering." *IEEE Internet Computing* 7 (1): 76-80.

Mackenzie, A. 2015. "The Production of Prediction: What Does Machine Learning Want?" *European Journal of Cultural Studies* 18 (4-5): 429-45. doi:10.1177/1367549415577384.

Mager, A. 2012. "Algorithmic Ideology." *Information, Communication and Society* 15 (5): 769-87.

Marres, N. 2007. "The Issues Deserve More Credit: Pragmatist Contributions to the Study of Public Involvement in Controversy." *Social Studies of Science* 37 (5): 759-80.

Marvin, C. 1990. *When Old Technologies Were New: Thinking About Electric Communication in the Late Nineteenth Century*. Reprint ed. New York: Oxford University Press.

Maurer, B., T. C. Nelms, and L. Swartz. 2013. "When Perhaps the Real Problem Is Money Itself!: The Practical Materiality of Bitcoin." *Social Semiotics* 23 (2): 261-77. doi:10.1080/10350330.2013.777594.

Mayer, J., and P. Mutchler. 2014. "MetaPhone: The Sensitivity of Telephone Metadata." *Web Policy*. Accessed April 1, 2014. http://webpolicy.org/2014/03/12/metaphone-the-sensitivity-of-telephone-metadata/.

McKelvey, F. 2014. "Algorithmic Media Need Democratic Methods: Why Publics Matter to Digital Media Research." *Canadian Journal of Communication* 39 (4): 597-613.

McQuail, D. 2003. *Media Accountability and Freedom of Publication*. Oxford, UK: Oxford University Press.

Merrill, J. C. 2011. "Theoretical Foundations for Media Ethics." In *Controversies in Media Ethics*, 3rd ed., edited by A. D. Gordon, J. M. Kittross, J. C. C. Merrill, W. Babcock, and M. Dorsher, 3-32. New York: Routledge.

Mori, M. 1970. "The Uncanny Valley." *Energy* 7 (4): 33-35.

Morrison, K. 2014. “The NYPD Will Use Twitter to Predict Street Crime.” *Social Times*. Accessed December 1, 2014.https://socialtimes.com/nypd-twitter-predict-crime_b147775.

Napoli, P. M. 2014. “Automated Media: An Institutional Theory Perspective on Algorithmic Media Production and Consumption.” *Communication Theory* 24 (3): 340-360. doi:10.1111/comt.12039.

Nguyen, A., J. Yosinski, and J. Clune. 2014. “Deep Neural Networks are Easily Fooled: High Confidence Predictions for Unrecognizable Images.” *arXiv - Computer Vision and Pattern Recognition*. Accessed December 12, 2014. http://arxiv.org/abs/1412.1897

Nielsen, R. K., and K. C. Schrøderb. 2014. “The Relative Importance of Social Media for Accessing, Finding, and Engaging with News: An Eight-country Cross-media Comparison.” *Digital Journalism* 2 (4): 472-89. doi:10.1080/21670811.2013.872420.

Orlikowski, W. 2010. “Technology and Organization: Contingency All the Way Down.” *Research in The Sociology of Organizations* 29: 239-46. doi:10.1108/S0733-558X(2010)0000029017.

Pasquale, F. 2011. “Restoring Transparency to Automated Authority.” *Journal on Telecommunications and High Technology Law* 9 (235): 235-54.

Pinch, T. J., and W. E. Bijker. 1984. “The Social Construction of Facts and Artefacts: Or How the Sociology of Science and the Sociology of Technology Might Benefit Each Other.” *Social Studies of Science* 14 (3): 399-441.

Rosenblum, N. L. 2000. *Membership and Morals*. Princeton, NJ: Princeton University Press.

Salmon, C. T., and T. L. Glasser. 1995. “The Politics of Polling and the Limits of Consent.” In *Public Opinion and the Communication of Consent*, edited by T. L. Glasser and C. T. Salmon, 437-58. New York: The Guilford Press.

Sandvig, C., K. Hamilton, K. Karahalios, and C. Langbort. 2014. “Auditing Algorithms: Research Methods for Detecting Discrimination on Internet Platforms.” Paper presented at the Data and Discrimination: Converting Critical Concerns into Productive: A preconference at the 64th Annual Meeting of the International Communication Association, Seattle, WA.

Schiller, D. 1979. “An Historical Approach to Objectivity and Professionalism in American News Reporting.” *Journal of Communication* 29 (4): 46-57.

Schudson, M. 1978. *The Ideal of Objectivity Discovering the News: A Social History of American Newspapers*. New York: Basic Books.

Schudson, M. 1986. “Deadlines, Datelines, and History.” In *Reading News*, edited by R. K. Manoff and M. Schudson, 79-108. New York: Pantheon Books.

Seaver, N. 2014. "On Reverse Engineering: Looking for the Cultural Work of Engineers." *Medium*. Accessed April 3, 2014. https://medium.com/anthropology-and-algorithms/d9f5bae87812.

Shilton, K. 2012. "Value Levers: Building Ethics into Design." *Science, Technology, and Human Values* 38 (3): 374-97.

Skiena, S. S. 1998. *The Algorithm Design Manual*. Berlin, Germany: Springer.

Soltani, A., and B. Gellman. 2013. "New Documents Show How the NSA Infers Relationships Based on Mobile Location Data." *The Washington Post*. Accessed April 2, 2014. http://www.washingtonpost.com/blogs/the-switch/wp/2013/12/10/new-documents-show-how-the-nsa-infers-relationships-based-on-mobile-location-data/.

Soltani, A., A. Peterson, and B. Gellman. 2013. "NSA Uses Google Cookies to Pinpoint Targets for Hacking." *The Washington Post*. Accessed January 2, 2014. www.washingtonpost.com/blogs/the-switch/wp/2013/12/10/nsa-uses-google-cookies-to-pinpoint-targets-for-hacking/.

Star, S. L., and K. Ruhleder. 1996. "Steps Toward an Ecology of Infrastructure: Design and Access for Large Information Spaces." *Information Systems Research* 7 (1): 111-34.

Steen, M. 2014. "Upon Opening the Black Box and Finding it Full: Exploring the Ethics in Design Practices." *Science, Technology, and Human Values* 40 (3): 389-420. doi:10.1177/0162243914547645.

Striphas, T. 2015. "Algorithmic Culture." *European Journal of Cultural Studies* 18 (4-5): 395-412. doi:10.1177/1367549415577392.

Suchman, L. 1994. "Do Categories Have Politics?" *Computer Supported Cooperative Work* 2 (3): 177-94.

Sullivan, M. 2015. "Facebook Patents Technology to Help Lenders Discriminate Against Borrowers Based on Social Connections." *Venture Beat*. Accessed August 6, 2015. http://venturebeat.com/2015/08/04/facebook-patents-technology-to-help-lenders-discriminate-against-borrowers-based-on-social-connections/.

Sweeney, L. 2013. "Discrimination in Online Ad Delivery." *Communications of the ACM* 56 (5): 44-54. doi:10.1145/2447976.2447990.

Thelwall, M., and L. Vaughan. 2004. "A Fair History of the Web? Examining Country Balance in the Internet Archive." *Library and Information Science Research* 26 (2): 162-76.

The New York Times. 2014. *Robots.txt.* Accessed April 15, 2014. http://www.nytimes.com/robots.txt.

Twitter. 2014. "FAQs About Trends on Twitter." *Twitter Help Center*. Accessed April 20, 2014. https://support.twitter.com/articles/101125-faqs-about-trends-on-twitter#.

Wallach, W., and C. Allen. 2008. *Moral Machines: Teaching Robots Right from Wrong*. Oxford, UK: Oxford University Press.

The Washington Post. 2014. *Robots.txt.* Accessed April 15, 2014. http://www.washingtonpost.com/robots.txt.

Webster, J. G. 2010. "User Information Regimes: How Social Media Shape Patterns of Consumption." *Northwestern University Law Review* 104 (2): 593-612.

Winner, L. 1986. *The Whale and the Reactor*. Chicago: Chicago University Press.

Winner, L. 1993. "Upon Opening the Black Box and Finding it Empty: Social Constructivism and the Philosophy of Technology." *Science, Technology, and Human Values* 18 (3): 362-78.

Wohn, D. Y., and C. Sarkar. 2014. "The Uncanny Valley Effect in Behavioral Targeting and Information Processing of Peripheral Cues." Paper presented at the iConference 2014, iSchools Organization, Berlin, Germany, March 4–7, 2014.

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