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Ihde's Missing Sciences: Postphenomenology, Big Data, and the Human Sciences

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Abstract: In *Husserl's Missing Technologies*, Don Ihde urges us to think deeply and critically about the ways in which the technologies utilized in contemporary science structure the way we perceive and understand the natural world. In this paper, I argue that we ought to extend Ihde's analysis to consider how such technologies are changing the way we perceive and understand ourselves too. For it is not only the natural or "hard" sciences which are turning to advanced technologies for help in carrying out their work, but also the social and "human" sciences. One set of tools in particular is rapidly being adopted—the family of information technologies that fall under the umbrella of "big data." As in the natural sciences, big data is giving researchers in the human sciences access to phenomena which they would otherwise be unable to experience and investigate. And like the former, the latter thereby shape the ways those scientists perceive and understand who and what we are. Looking at two case studies of big data-driven research in the human sciences, I begin in this paper to suggest how we might understand these phenomenological and hermeneutic changes.

Key words: postphenomenology, big data, human science, Don Ihde, Edmund Husserl

For nearly four decades, Don Ihde has been urging philosophers to think seriously and rigorously about technologies. Not about Technology—singular and with a capital T—which is to say, not about technology as a kind of world-historical force, as someone like Martin Heidegger would describe it. Ihde wants us to think about *technologies:* the tangible, everyday tools we use, which mediate and shape

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our experiences of the world. In order to do so he has appropriated and refashioned phenomenology and hermeneutics to these ends, showing that doing philosophy need not only mean contemplating the abstract, invariant features of ourselves and the world; philosophy also offers tools for thinking through the nature and significance of new and concrete things (see Ihde 1979, Ihde 1998, Ihde 2009, Verbeek 2005).

In *Husserl's Missing Technologies* (2016) Ihde takes this program back to Edmund Husserl's doorstep—paying tribute, he says, to his "inspiration and forefather," while at the same time carrying out a much needed "critical reappraisal" (xvi). Of special interest to Ihde is what he calls the "recalcitrant modernism" of Husserl's conceptions of science and technology (25). For Husserl, Ihde argues, science is primary and technology secondary or "applied." Moreover, the tools and instruments scientists rely on for their experiments and investigations are, on Husserl's understanding, *incidental*—they do not alter the scientific enterprise in any fundamental way—and as such their use raises no significant phenomenological or hermeneutic questions. Yet as Ihde has shown time and again, nothing could be further from the truth. Science and technology are co-constitutive, understood better as technoscience. Tools and instruments have always mediated between scientists and their objects of interest, and the structures and materialities of those tools have shaped the way scientists understand the world (see Ihde 1979; 1991; 1998).

This kind of mediation becomes especially pronounced in the shift from what Ihde calls "modern" to "postmodern" science. In modern science the tools scientists used merely extended or amplified scientists' perception. Microscopes, for instance, made tiny things big enough for human beings to see. Telescopes brought far-away things closer. In spite of the mediation, however, the images perceived by scientists were *isomorphic* to the things being observed. With the shift to postmodern science this changes. The tools and instruments used by present-day scientists to observe and experiment on the world afford perceptions of things which are imperceivable by human bodily perceptual organs alone. Such perceptions and their use in scientific theory-construction exemplify technoscience—science which is, as Ihde says, "fully embodied in its technologies" (2016, 77)—and call out for phenomenological and hermeneutic analysis.

Ihde offers a variety of examples of scientists utilizing tools that do not merely extend the senses but rather constitute the very phenomena under investigation. Indeed, a whole chapter of *Husserl's Missing Technologies* is devoted to his prime example—"whole earth measurements"—which are the kind of measurements required in order to detect long-term, global phenomena like climate change (see

Ihde 2016, chap. 4). The examples Ihde presents are rich and worthy of postphenomenologists' attention, as they situate us in new and complex relationships with the natural world. The issue I want to raise in this paper, however, is that Ihde's examples are all drawn from the so-called "hard" sciences. They come from fields like ecology and climatology, physics, and neuroscience. Yet the tools of postmodern technoscience are being put to use outside those fields as well. Especially important is the role they are starting to play in the humanities and human sciences—in sociology, psychology, and economics, in history and literary criticism. It is important because in these cases the tools of postmodern technoscience are shaping the way we understand not just the world around us, but ourselves.

The set of technoscientific tools which fall under the general rubric of *big data* have taken on the most prominent role in contemporary humanities and human sciences, giving rise to research programs like Digital Humanities and Computational Social Science. In what follows I offer some examples of how these disciplines have become "embodied" in big data tools. I look at how such tools constitute the phenomena researchers investigate, and I ask what postphenomenological analysis can illuminate about this new approach to studying ourselves. I begin by looking in somewhat more detail at Ihde's critique of Husserl's modernist philosophy of science and his move to postmodern technoscience.

From Modern to Postmodern Technoscience

Ihde's tribute to Husserl in *Husserl's Missing Technologies* is straightforward: the phenomenological tradition that Husserl initiated was, for Ihde, a necessary step on the way to grasping our relationships with technologies. Without Husserl's insights into the structures of consciousness, and without the philosophical tools he used (especially variational analysis), Ihde's approach to philosophy of technology would never have gotten off the ground. The critical reappraisal is somewhat more complicated. It begins, as the book's title suggests, with the claim that Husserl failed to adequately analyze the many technologies he used in his everyday life—his eyeglasses, writing utensils, typewriters, and so on. Indeed, he failed to notice that such technologies even merited special attention. Husserl realized, as Ihde points out, that some of the experiences he was analyzing were technologically mediated. But he assumed that there wasn't anything phenomenologically interesting or important about that fact. "It is unlikely that Husserl gave attention, whether ordinary or phenomenological, to ordinary use-technologies," he writes, "So, in these ordinary senses Husserl is missing his technologies" (Ihde 2016, 14).

The reason he misses them, Ihde argues, the reason he thinks that there isn't anything significant about the fact that some of his experiences are technologically mediated, is that Husserl was stuck in what Ihde calls a modernist epistemology. Although it sometimes seems like Husserl is trying to move beyond his Cartesian heritage, when it comes to tools and technologies his intuitions remain stubbornly old fashioned. Technologies are, for Husserl, mere objects—dumb, lifeless, and therefore value-neutral *things*—available for us to use in advancing our own ends without any impact upon them. "What I am suggesting," says Ihde, "is that for Husserl, tools, technologies do not lose their *objectness*. It is as if one must first look at them as things, and then adapt them to praxis" (Ihde 2016, 25; emphasis in original). But as Ihde and others have shown, this picture is woefully inadequate. Our technologies aren't mere instruments; they shape the way we experience the world (see, for instance, Ihde 1979, Winner 1989, Verbeek 2005).

What's more, Husserl's epistemology—his "recalcitrant modernism" and "vestigial Cartesianism"—tracks a certain conception of the relationship between technology and science. Namely, the belief that science is the more fundamental endeavor of the two. As Ihde wrote in *Existential Technics* (1983), "In this interpretation, technology follows from science, both ontologically as an application of scientific knowledge and historically as the spread of this insight into ever-widening realms of material construction" (27). For modernists, in other words, science is possible without technology, but not the reverse.

As Ihde has demonstrated, however, even the earliest scientific endeavors were propped up by tools and technologies, and science "in its contemporary sense as an experimental science wedded to specific meanings of measurement, is *necessarily embodied* in its instrumentation" (Ihde 1983, 25; emphasis in original). The difference between early and contemporary science is that the tools and instruments of early science merely acted as extensions of our bodily perceptual organs. Microscopes magnified things too small for us to see and telescopes brought faraway things closer. But the things being magnified or brought closer were not transformed by the technologies which mediated scientists' experiences of them; the phenomena experienced remained, as Ihde says, *isomorphic* to the actual objects under observation. Contemporary science, by contrast, relies on tools and technologies which reveal things that are imperceivable by human bodily perceptual organs. They "reveal dimensions of reality no longer isomorphic or analogue to our bodily perceptual experience" (Ihde 2016, 33).

For these reasons Ihde insists that Husserl's modernist philosophy of science be replaced with what he describes as a *postmodern* philosophy of science.

On this picture, science is not understood as prior to and disconnected from the technologies it relies on and the lifeworld in which it is situated. Rather, science and technology are understood together, as technoscience. “In this sense,” he says, “not only will it be taken for granted that science needs instruments both for measurements and for observation, but for the very discovery or constitution of new phenomena” (Ihde 2016, 78). Only a postmodern philosophy of science can adequately explain how contemporary science—science that is “fully embodied in its technologies”—perceives and makes sense of the phenomena it does.

To illustrate such phenomena, Ihde revisits an example he explored at length in his earlier book *Expanding Hermeneutics* (1998): climate science and the problem of whole-earth measurements. “From what standpoint or perspective,” asks Ihde, “can the issue of whole Earth measurements be made” (1998, 51)? Detecting global climate change, he argues, requires taking the whole planet as one’s laboratory. It requires taking measurements from all over the world and recording them over long periods of time. It requires feeding those measurements into computer algorithms for processing. And only once all of that is done can scientists perceive the phenomena in question. Only then can they achieve the perspective required in order to make inferences about something like global climate change. Crucially, what connects that perception to the reality it represents are the tools and technologies which produced it. “Instruments,” writes Ihde, “maintain the connection of the sciences to the lifeworld. . . . Science is not disembodied, but is instrumentally embodied in an instrumental realism” (Ihde 2016, 82).

Interpreting the images such technologies produce involves navigating certain hermeneutical relationships. Postmodern technoscience produces images which are, again, non-isomorphic—they do not resemble their referents. Spectroscopes, for example, do not resemble the chemical signatures they represent. Functional magnetic resonance images (fMRIs) do not look like literal blood flowing through the brain. Postmodern science, Ihde argues, is “active, constructive, re-constructive from its sense of perception on. Instrumental perception is not receptive or passive in the early modern sense—it is actively constructive” (2016, 85–86). Beyond measuring mean global temperatures, Ihde offers a number of other examples of contemporary science operating as technoscience, actively constructing the phenomena under investigation. Particle colliders, “nano-sized laser tweezers,” measuring deforestation and the melting of glaciers, ultra-violet photography, tracking the “cascade effects” of predators on ecosystems (see Ihde 2016, chap. 4). In all of these domains, the tools and technologies used to explore the world or worlds in question do more than magnify something or bring something nearer; they make what was previously imperceptible perceivable at all.

Understanding this process requires phenomenological intervention. But classical phenomenology, as Husserl devised it, is ill-suited to describing the interpretive processes of contemporary technoscience. Just as Husserl's philosophy of science fails to grasp the embodied and embedded nature of technoscience, his phenomenology fails to grasp the praxis-oriented and multistable meanings its instruments produce. Where, using "imaginative variations," Husserl discovered fixed invariants or essences of experience, Ihde finds, using the same tools, "multistabilities" (2016, 85). The meanings derived from using technoscientific tools are contingent upon their materialities and cultural contexts.

To account for this, Ihde and others have developed what they argue ought to be classical phenomenology's successor: postphenomenology. As Ihde describes in the final chapter of *Husserl's Missing Technologies*, this postphenomenological research program came about after following Husserl's own instructions to do phenomenology by "going to the things themselves," and finding, surprisingly, that things were not as Husserl found them. Peter-Paul Verbeek has described the goals of postphenomenology this way:

> A postphenomenological 'turn toward things' in the philosophy of technology needs to consist of the analysis of the mediated role of technological artifacts in the relation between human beings and reality. Such an analysis can be carried out [along two dimensions]—hermeneutical and existential. . . . In hermeneutical terms, things can mediate the ways in which human beings have access to their world by the roles that such things play in human experience. . . . In existential terms, things mediate human existence. . . . Attention is paid [here] to the way in which the material environment of human beings shapes the way in which they realize their existence. (Verbeek 2005, 118–19)

Postphenomenology, in other words, asks about the world around us and about the tools we use to investigate it how they shape both our experience and our self-understanding.

In *Husserl's Missing Technologies* Ihde focuses on the former. The case studies he considers draw almost exclusively from what are often called the "hard sciences." Physics, chemistry, biology, climatology, and so on. He asks about the ways particle colliders and ultra-violet photography are changing our relationship to the world around us, but he neglects the fact that technoscientific technologies and instruments have come to mediate between us and what we know about *ourselves* too. Granted, he mentions fMRIs. But it is not only hard science—the humanities and human sciences are also being re-tooled, and that has implications which postphenomenologists ought to be investigating. In the next section I discuss two cases of research in the human sciences being mediated by a particular technoscientific tool: big data. I examine how big data constitutes the phenomena under investigation and ask how postphenomenology can help us understand what it means for our own self-understanding to be constructed in this way.

The Lens of Big Data

Big data is a concept from computer science that has made its way out both to the rest of academia and into the mainstream technology industry. Originally, it referred to datasets that were too large for existing computers and existing algorithms to extract meaningful information from them (Crawford, Milner, and Gray 2014). Now we have computers that are sufficiently powerful and algorithms that are sufficiently complex, so big data has come to represent a set of computational tools and techniques used to extract as much meaningful information as possible from the depths of vast datasets. These tools are transforming humanities and social science research (see Lazer et al. 2009; Oboler, Welsh, and Cruz 2012). It is the subject of so many research projects, the basis of so much grant funding, that some have called it "the megafauna of the academic landscape" (Crawford, Milner, and Gray 2014). There is so much hype around big data that Kate Crawford and danah boyd claim it has taken on a quasi-*mythic* stature. It is a "cultural, technological, and scholarly phenomenon," they argue, that in addition to offering a set of tools and methodologies, involves "the widespread belief that large data sets offer a higher form of intelligence and knowledge that can generate insights that were previously impossible, with the aura of truth, objectivity, and accuracy" (boyd and Crawford 2012, 663).

Big datasets can be "big" in different ways.[1] Some datasets index a massive number of individual records, wherein each record includes only a few variables. Netflix's user information database, for instance, probably only records a few pieces of information about each user, such as which titles they watch, how long they spend watching them, which they browse past, and so on. But it records this information about an enormous number of users. Other datasets contain fewer individual records, but many variables. As political scientist Rocío Titiunik writes, such datasets "may contain information on a person's preferred newspapers, political registration, recent travel history, fitness routine, social media contacts, campaign contributions, business transactions, and blog entries" (2015, 76). Some big datasets, such as Facebook's and Google's, are big in both senses: they record a great deal of information about a great number of people.

The source of all of this data is, of course, us. Nearly everything we do today in the course of our day-to-day lives leaves an enormous trail of data behind us. Using cell phones produces data about calls and text messages sent and received, apps used, websites accessed, and the location of the phone. Buying things with a credit or debit card produces data about what was purchased, for how much, when, where, and by whom. Researchers estimate that by the year 2020, 1.7 megabytes of data will be created for each human on the planet each second (Bansal 2014). That's the same as around 850 double-spaced pages of plain text *per person per second*.

It is on the basis of all this data that companies like Netflix and Hulu are able to predict which movies you'll want to watch next, Amazon can predict which books you'll want to read, companies like Target can figure out who is likely to get pregnant, and therefore ought to be sent maternity-related advertisements.[2] It is on the basis of all this data that companies are able to "customize" the prices at which they offer the same goods to different customers,[3] and governments are able to identify suspected terrorists (Stone 2012). On the basis of all this data researchers are using cell phone location information in Ivory Coast to optimize bus routes (Talbot 2013). Google has used search results to predict outbreaks of the flu (Lohr 2014).[4] And by analyzing tens of thousands of clinical records, drug regulators are discovering hidden risks in ordinary drugs and pulling them from the market (Tene and Polonetsky 2012).[5]

Incredibly though, despite all that has been learned from the troves of data we produce, only one half of one percent of the data that currently exists has ever been analyzed (Bansal 2014). As governments, private corporations, and research institutions all continue to spend more money developing new big data tools, both the amount of data that is analyzed and the amount of meaningful information that can be extracted from it will continue to grow. It is impossible to predict now what we will soon be able to know, about ourselves, each other, and the world. "If the last century was marked by the ability to observe the interactions of physical matter," says a recent report on big data, "—think of technologies like x-ray and radar—this century . . . is going to be defined by the ability to observe people through the data they share" (Regalado 2013).

If that's true, it bears asking what kind of vantage point all of that data offers. What *about* people is observable through the data they share? What about them is obscured? Echoing Ihde, Oboler, Welsh, and Cruz (2012) describe computational social science (i.e., social science driven by big data) as an "instrument based discipline":

> Through a key instrument, an instrument based discipline enables the observation and empirical study of phenomena. Whether the instrument is a microscope, radar, electron microscope or some other tool, the instrument serves as a lens making an otherwise invisible subject matter visible to the observer. In computational social science, the instrument takes the shape of computer systems and datasets; their availability and sophistication drives the development of theory, understanding and practical advances. (Oboler, Welsh, and Cruz 2012)

What phenomena are visible through the lens of big data? What perspective does it offer? How will the way we understand people—the way we understand *ourselves*—change in virtue of adopting and privileging that perspective? These are questions postphenomenology gives us tools to explore. And while answering them is beyond the scope of this paper, I hope at least to gesture in that direction.

Consider two cases. First, in the early 2000s, Google began a massive project to digitize[6] the world's books (Quint 2004; Roush 2005). By 2011, they had succeeded in digitizing over 15 million—around 12 percent of all books ever published—and researchers at Harvard and MIT started to play around with the data (Michel et al. 2011). They developed a tool, now called "Ngram," which charts the frequency of individual words or sets of words across time. And they argued that by analyzing n-grams (i.e., charts of frequencies of n-word-long sequences) one could make important discoveries about historical trends in human culture—what they call "culturomics" (ibid).

One of the culturomic discoveries they present is that the rate at which we as a society move on from the past seems to be increasing. In other words, today more than ever we are "focus[ed] on the present" (Michel et al. 2011, 179). The researchers arrived at this conclusion by analyzing how often individual years are mentioned in print in the years leading up to and following them. For example, the 1-gram "1951" rarely appeared in text until just before the year 1951, at which point its frequency "soared." After 1951 it continued to appear regularly for three more years before tapering off. This, they found, was the general pattern. Having run this sort of analysis on all of the years between 1875 and 1975, however, a subtle trend emerged: as time went by we put the past behind us faster. "'1880' declined to half its peak value in 1912, a lag of thirty-two years. In contrast, '1973' declined to half its peak by 1983, a lag of only ten years. We are forgetting our past faster with each passing year" (179).

Case Two: Social media networks have made it possible for social scientists to map huge networks of human relationships across space and time. In 2014 researchers at Facebook and Cornell University decided to see if they could figure out who amongst a group of Facebook friends were spouses or romantic partners by looking only at the abstract network of relationships. "Given all the connections among a person's friends," they asked, "can you recognize his or her romantic partner from the network structure alone?" (Backstrom and Kleinberg 2014). Other researchers had tried to accomplish this by looking for a network feature called *embeddedness*, which is the number of mutual friends two people share. The more deeply embedded two people are in each other's networks, the theory went, the stronger their "ties," and the stronger their ties, the likelier they are to be romantic partners.

In their widely publicized study, Lars Backstrom and Jon Kleinberg analyzed 1.3 million Facebook users who reported their significant others on the site. With each user having between 50 and 2000 Facebook friends, that meant analyzing 379 million nodes and 8.6 billion friend-relationships overall (Backstrom and Kleinberg 2014). What they discovered was that embeddedness is not the best indicator of romantic partnership after all. Such relationships actually track more closely with a different arrangement of social ties, which they call *dispersion*—a measure of the extent to which a couple's mutual friends are themselves *not* well-connected. Somewhat counter-intuitively, they found that romantic partners are likely to be highly dispersed. They not only have many friends in common, but share friends across many different contexts. For instance, I might be friends with both my partner's coworkers and his friends from high school, but the coworkers and high school friends are unlikely to know each other. "Certain important types of strong ties—including romantic and family relations—connect us to people who belong to multiple parts of our social neighborhood," the authors explain, "producing a set of shared friends that is not simply large but also diverse, spanning disparate portions of the network and hence correspondingly sparse in their internal connections" (Backstrom and Kleinberg 2014, 10).

What are we to make of these two studies? How does each constitute the subject matter under investigation? The big data imaging tools in each case make visible aspects of cultural history and the social world, which we would otherwise be unable to perceive. What does constituting the phenomena in these ways make apparent and what does it obscure? Both studies are cases of big data tools being used to investigate the social or cultural world, but each deploys those tools in different ways and to different effects. Taking the n-gram study first, one thing that is immediately obvious about the perspective it offers is that it is *diachronic*: what the researchers are interested in is how things have changed over long periods of time. It therefore privileges the temporal dimension of culture (how quickly people forgot the past then versus now), perhaps obscuring its geographic dimension (how quickly people in one place forget about the past versus people in another place), race, gender, and class dimensions (how quickly people from different social groups forget the past), and so on.[7] Second, since all of the data surveyed in this study comes from published books, it privileges the expression of cultural memory through written text over other forms of expression, such as music, monument, or architecture. One can imagine analyzing how frequently particular songs are played on the radio and uncovering different trends about how quickly people leave the past behind.

The phenomena under investigation in the Facebook study are rendered differently. Instead of a diachronic picture, the Facebook friend data is static or synchronic—there the researchers are interested not in how the objects of investigation change over time, but how they are shaped or arranged in one particular time-slice. This vantage point therefore obscures other facets of social networks, such as how long two nodes in a network have been connected. There is reason to believe that the strength of social ties is at least in part a function of how long those ties have lasted. The Facebook study also privileges the "shape" of social networks—how its nodes are arranged in the aggregate—over what we might call its "texture." Which is to say, the phenomenon it renders visible and subject to investigation is an abstract and impersonal one. It highlights the fact or existence of relationships rather than their particular character.

One could identify many more interesting features of these particular vantage points. And it's worth pointing out that there is nothing *wrong* with these perspectives. As Ihde and others have shown, scientific investigation is always theory- or perspective-laden. Researchers have to isolate variables that they suspect track and reveal interesting features of the world, whether they are using big data tools or not, and isolating those variables means ignoring or suppressing others. It is important to bring these perspectives to light, however, especially in the context of big data research, since many assume that having so much data at our disposal means we are no longer susceptible to perspectivalism and bias. As boyd and Crawford argue, again, there exists around big data an "aura of truth, objectivity, and accuracy" (2012, 663).

Despite their divergences, the perspectives in each case also have two important (and related) features in common—features which bring to light a crucial dimension of big data itself. First, the two research projects are both descriptive rather than explanatory in nature. The n-gram study aims to describe interesting or surprising trends in the written historical record. The Facebook study looks to describe a formal characteristic of social networks that might indicate when two nodes in the network are romantic partners. We can come up with theories to explain their findings, but the data itself won't confirm or deny them. This, it turns out, is no accident: big data is fundamentally a descriptive rather than explanatory technology. Machine learning and other data mining techniques work to detect subtle patterns in vast seas of information, to notice that disparate phenomena align. Which is to say, they detect *correlations* not *causes.* Big data can tell us that things happen to be arranged in a certain way, but it can't explain why they ended up like that.

This focus on correlation rather than causation leads to a second crucial feature of the perspective or vantage point constructed by big data tools: namely, a focus on behavior alone, rather than on the intentions behind it. We can see this in both case studies. Michel et al. have no interest in why any particular author wrote any particular word in any particular text. They don't care about the circumstances that led to the texts being written in the ways that they were, the details of the authors' lives, or the authors' assumptions about their audiences. They care simply that a word or group of words appears in some text at some time. Similarly, in the Facebook study, Backstrom and Kleinberg have no interest in why two people (or *nodes*) became friends in the first place. All that matters is that the connection exists. It is, as Geoffrey Bowker writes, a "Skinnerian psychology writ large—if all we care about is what goes in (stimulus) and what comes out (response), then to be effective we do not need to know what happens inside the mind/brain of the individual" (Bowker 2014, 1795–96).

Indeed, big data can't help but remain at surface level. Although an enormous amount of information might be collected about what we say and what we do, where we go and whom we interact with, the reasons or impulses that impel us are, at least for the moment, beyond the reach of even the most sensitive sensors. Unless we report what motivates us, investigators have to make do with empirically observable facts. (And even if we do report what motivates us we are oftentimes mistaken.) This might seem like a rather obvious point to make. But it is important because many of the disciplines and research programs being transformed by big data are disciplines and research programs which used to be interested precisely in why people think the way they do, what motivates them to act, why they organize themselves into different kinds of groups and so on. The fact that big data, in principle, has no access to our interiority means that the phenomena it constitutes for researchers to investigate are different from the phenomena researchers in many humanities and social sciences disciplines are used to.[8]

Some, like former *Wired* editor-in-chief Chris Anderson, don't think this new perspective is a problem. "Forget taxonomy, ontology, and psychology," he writes, "Who knows why people do what they do? The point is they do it, and we can track and measure it with unprecedented fidelity. With enough data, the numbers speak for themselves" (Anderson 2008). Similarly, Viktor Mayer-Schönberger and Kenneth Cukier argue that big data "challenges the way we live and interact with the world," orienting us with respect to "things one can do at a large scale that cannot be done at a smaller one" (2013, 6–7). "Most strikingly," they write, "society will need to shed some of its obsession for causality in exchange for simple correlations: not knowing *why* but only *what*" (ibid., emphasis in original). Others disagree. "To claim," write Crawford, Milner, and Gray, "that the dynamics of human interaction and the complexity of the social world can be reduced to a self-explanatory set of nodes and edges defies important insights from fields as diverse as machine learning, sociology, and economics. Data sets are not, and can never be, neutral and theory-free repositories of information waiting to give up their secrets" (Crawford, Milner, and Gray 2014, 1668).

Whether we should approach the changes big data heralds with worry or open arms is a question we must continue to reckon with. And as I hope to have shown, it is a question not only for the "hard" or natural sciences, but for the human sciences as well. Big data not only allows us to observe *more* about people, like the tools of postmodern technoscience that Ihde describes it allows us to observe things about people—about *ourselves*—that were previously impossible to observe. Just like whole-earth imaging, big data gives us access to information and measurements about human behavior and relations at a scale that was previously inconceivable. It mediates scientists' experiences of their subjects, and we have yet to fully grasp how the new vantage points it provides will alter not only our understanding of ourselves, but as Verbeek says, "the way in which we realize our existence." What will it mean for us to live in a world oriented toward "what" questions rather than "why" questions? Postphenomenology offers important tools for sorting these issues out.

Notes

1. For a more detailed and technical discussion of different kinds of datasets and the advantages and disadvantages of each, see Titiunik 2015.

2. Much to some people's chagrin. See Duhigg 2012.

3. I.e., to discriminate.

4. Though it has been argued that Google's predictions are not yet terribly accurate. See Lohr 2014.

5. This is what happened, for instance, in the case of Vioxx. See Tene and Polonetsky 2012.

6. "Digitizing" a book means scanning it to create an electronic copy and then using optical character recognition (OCR) software to render the book's text machine readable.

7. Indeed, since the data surveyed in the study comes entirely from published books, one wonders if it doesn't privilege the experience of those with access to the means of cultural production—i.e., published authors—over those who lack that access, and therefore obscures the fact that they are primarily surveying information about one particular economic class.

8. Reflecting on this point, Ekbia et al. write: "In the social sciences, this model may be rejected in favor of other explanatory forms that allow for the effects of human intentionality and free will, and that require the interpretation of the meanings of events and human behavior in a context-sensitive manner. Such alternative explanatory forms find little space in Big Data methodologies, which tend to collapse the distinction between phenomena and appearances altogether" (Ekbia et al. 2015, 1530).

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