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Reflexivity, Positionality and Rigor in the Context of Big Data Research

B. Ricker

In this robust unstructured era of big data, neopositivistic empiricism asserts strict objectivity when manipulating data, yet big data are riddled with the subjective positions of those entering the data, those creating and maintaining the storage and retrieval mechanisms and those sifting through the data. Big data offer unique analytical opportunities to reveal patterns that may have gone unnoticed otherwise. The sheer amount and variety of data being generated by a seemingly heterogeneous population and then collected primarily by businesses is a relatively new phenomena, and it is tempting to assume data do not lie and are truths.[1] The experiences of those who enter the data that then become amalgamated into big data, the experiences or subject positions, often referred to as positionality, of those manipulating and handling the data shape their understandings of the world, their epistemology. Positionality (in terms of race, age, socio-economic status, ethnicity) of a researcher, scientist, database administrator and other actors influence what questions are and are not asked in data science. Knowledge is mediated and constructed through interactions with the world. The meanings extrapolated, the knowledge built from big data is limited by the questions that are asked.

Here I impose a social constructivist critique, or rather a reflectivist theoretical stance,[2] echoing the postulation of Thatcher inferring that that the questions we ask, the analysis we conduct, and in turn, the patterns we find in big data are heavily influenced by our epistemologies, the lenses by which we view the world. Epistemologies describe the background, the perspective or lenses from which we study the world.[3] We must consider not only the perspectives of individual researchers but also those of other individuals, such as the computer scientists and database administrators who maintain the data.[4] The so-called black box is made up of a disconnected stream of bureaucracies, not a conspiring individual, but countless groups of individuals limited by their own knowledge, positionality, time and other constraints including those associated with actors up stream. Thus I ask: (how) do identities and experience (dis)appear from big data? This overarching question can be help understand research design choices and what meaning is extracted from big data based on the identities and experiences of the researchers who enter the data and the database administrators who maintain them. This can be also applied to the identities and experience of the subjects whose data have been amalgamated into big data. As critical theorists, moving past positivistic assumptions, we understand that even the choice of mathematical methods by which researchers query, analyze, and display data are influenced by their positionality. While big data may seemingly be overtly quantitative, the data are also overwhelmingly qualitative in nature, necessitating methodology distinctive to qualitative research.

In an effort to identify social and spatial implications hidden (or not) within big data, lessons learned from qualitative Geographic Information Systems (GIS) and previous GIS critique can provide useful insight when investigating ways in which to productively utilize big data particularly for social benefit beyond existing neoliberal initiatives.[5] In the tradition set by Baxter and Eyles, England and others who have set the standard for rigor and qualitative methods, I suggest that we enter into a discussion considering how rigor applied to qualitative research could be beneficial for the analysis and manipulation of big data.[6] Theories and reflexive methodologies associated with feminist geography are becoming richly diverse (Rose, 1997) and should be creatively applied to the study of big data. Otherwise we risk continuing to serve the agendas of the technocratic elite, rather than the needs of the underprivileged, those who could benefit most from sharing their personal information.

Big Data in a Spatial Context

Big data is known as data that are high in volume, velocity, and variety; are highly flexible and exhaustive. Often containing associated locational and temporal information.[7] Big data is seen as perplexing due to the sheer amount of data and also because of the recurring and unspecified filtering imposed on them.[8] Data that previously went (digitally) undocumented are now being collected via the big data movement. These data are frequently diverse including time stamps, documenting not only such things as a phone user's most recent activity, movement patterns, buying habits, call logs, but wide range of ambiently collected data. Other data being collected are qualitative full of rich information such as opinions typed into a restaurant review application. All of these activities can be and often are documented by someone and something. While these data are new in that they are being collected digitally in volumes that were once considered infeasible, the idea of collecting this type of data are not entirely new. Mathematicians of the past have encountered some of the same challenges being faced today by big data engineers.[9] This form of digital data offers social scientists, particularly social spatial scientists, and new opportunities to collect and access qualitative data through the utilization of massive amounts of unstructured data.[10] At present, while excessive amounts of digital information are being collected and hoarded, the goal of harnessing their full potential has yet to be realized. Utilizing big data is a significant challenge because they are largely unwieldy. Businesses and researchers alike are still figuring out how to interact with this form and volume of data. big data has the potential to reveal and link spatial contexts, meaning, and processes. However they are noisy and cumbersome making it difficult to yoke their strengths for social good.[11] Kitchin clearly identifies opportunities, challenges and risks associated with big data and spatial science research. Opportunities are afforded in the sheer amount and diversity of data being collected while the risks and challenges associated include the assumption that these data can "speak for themselves" and theory is dead.[12]

The data entry process associated with big data may inform experience in place. These are the context in which the data are collected. They are often the location of the qualitative observations most valuable to human geographers and social scientists. The data being entered and then aggregated as location based services (LBS) is a cyclical process.[13] Early research suggests that many voices and experiences (particularly those of the underprivileged and underserved) are missing from big data currently being collected.[14] Big data collection risks infringing on individual's privacy while also exhibiting social unevenness.[15] Experience from the past could help inform how big data can be used in productive purposes.

While the focus of this chapter is not on the makeup of big data infrastructure, I see it relevant to point out that there are multiple levels of data collection, storage, aggregation, manipulation, introducing many opportunities to insert personal bias in one stack. Broadly speaking, the stack refers to the combination of elements, typically software and hardware components, required for a database or system going and usable and useful. If you were to search images for the term "big data stack" you would find thousands of versions of different data structures. The configuration of the stack dictates what information can be collected, how it is combined or not with other data, each of these seemingly minute decisions influences how data can be used in the future. It is these seemingly objective tasks and steps where it is possible to insert bias by those who interact with the data themselves and the decisions about the receptacles and organizational structures in which it is housed. Descriptions of these stacks include a storage location often in distributed data centers, file systems, data warehouses, and databases. There are seemingly endless ways to configure a big data stack. Like research more broadly, analyzing and organizing this stack associated with (big) data is a recursive, and hopefully reflexive process. Technical and theoretical research is being conducted to best identify relationships between data-centric and operation-centric approaches to computationally intensive geographic data and analysis methods.[16]

To retrieve data collected and stored a search needs to be conducted using a query language. Conducting such a query across distributed databases and data centers is no easy task. This process is constantly being improved and much research is being done to optimize this process specialized for GIS processing and big data.[17] Once data are retrieved they must be aggregated. There is no one industry standard software package available at this time that can retrieve the data, run statistical analysis and provide visualization capabilities, since at present there are three or more software systems required to fulfill all of these tasks. I consider the software package de jour for data retrieval to be Oracle NoSQL, statistics would be R, and for visualization the presently popular choice is Tableau (depending on the circle). Hadoop is presently a popular open source big data software framework for setting up hardware clusters. The workflow vaguely described here varies dramatically from project to project and company-to-company. This is an evolving process which influences who handles data and in turn who may modify it. Data provenance is a formal area of research.[18]

When big data are described as passing through the black box of software and data aggregation, it is important to understand the black box can be thought of as a bureaucracy in that many actors are involved to set up and maintain "the stack". The stack refers to the organizational and flow structure of the data, where it is stored and the flow in which it travels and is housed until called upon. Each of these actors has their own positionality, their own educational background and understanding of the technology available and accessible. These perceptions include views and experience with proprietary versus open source software systems, which will in turn have implications on storage, access, retrieval and visualization of information down the line. Each of these actors has different time constraints, which will also influence how they decide to set up and maintain a big data stack. This is the description of but one of many other potential stacks. As Thatcher (2014) points out, the "data fumes" from one stack could pass through several other stacks before they reach an end user or researcher, leaving endless opportunities to taint the data.

The technical architects associated with a project largely dictate big data stack construction and decision making, which influences the structure and maintenance of a data stack. These decisions are influenced by the goals of the individual project, the funding agency, and the experience of those on the development team. These decisions have long-term ramifications including if and how spatial data are collected, stored and used. Each actor associated with the stack hold power as seen in this popular internet comic (Figure 1). In this comic, one colleague is asking another to pull data from a database. It becomes clear in this comic that the person who is asking to pull data from the database does not know how to do so from a big data stack based on the terminology being used in the exchange. It can also be inferred that the person being asked does not want to complete the task.

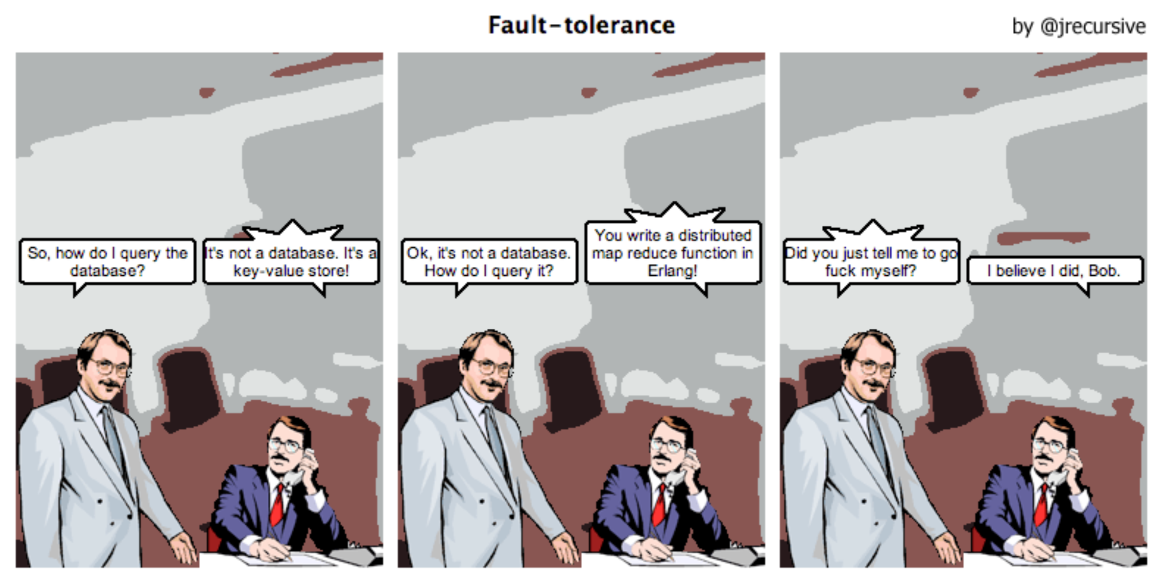

Figure 1. Example of Power relations. Illustration courtesy of John Muellerleile (@jrecursive).

In an effort to demystify big data to the researcher approaching this data from the Geoweb, Thatcher's research revealed the actors who control the black box by illuminating the positionality, and the thought process of those creating the structure of the data- not only the data collected or the output, but also the way in which the data are housed and queried as well. His work has provided a fundamental understanding of the decision-making processes and structure associated with big data collection and distribution.[19] Dalton & Thatcher[20] and Thatcher[21] provided a rare glimpse of what is inside the black box. Their efforts can be used to inform future efforts to utilize big data for social improvement.

Lessons from qualitative research and rigor within the context of big data

While qualitative geographers and social scientists call attention to how their work cannot and should not be evaluated in the same manner as positivist/quantitative research, they rarely described how their research *should* be evaluated.[22] Feminist poststructuralist call for ethical research, challenging the so-called objective research paradigm, by challenging researchers to be more reflexive and inclusive of methods that reveal sensitive power relations between the researcher and those being researched.[23] As researchers of big data, it is necessary to locate ourselves in our work, and show how this location influences the questions we ask and how we conduct and write up our research.[24] We need to identify ourselves as an insider or outsider in relation to the subject in an effort to help us interpret the meaning of the data collected.[25] How much are we participating in the big data process and at what point of the process do we as researchers have experience?

Human and feminist geographers challenge us to be suspicious of objectivity and move past looking only at spatial patterns by looking at other types of relationships within our research.[26] This is not to say that qualitative methods are not scientific or rigorous. In quantitative research, methodological rigor refers to the validity, reliability and objectivity of the research process. Within the field of qualitative research this includes the researcher's responsibility to be reflexive and honest about their position in relation to the research being conducted.[27] Rigor in both qualitative and quantitative research helps indicate to what level the research is believable and worthy of attention.

To establish rigor in qualitative research, Baxter and Eyles suggest a set of criteria rather than a fixed set of rules. Criteria include credibility, transferability, dependability and confirmability of one's research.[28] While these authors were evaluating and speaking largely to qualitative research in which the researcher had direct contact with the subject in the form of collecting data through interviews and other forms of direct contact with a community, these ideas can and should be applied to the study of big data. Baxter and Eyles conducted an extensive literature review in which they identified the presence or lack of presence of: rationale for methological choices, multiple methods, description of respondents, direct quotations from subjects, interview practices, procedures for analysis, immersion and length of fieldwork, revisits, verification by subject, appeals to interpretative community, and rationale for verification as indicators for rigor in research.[29]

Debates from GIS critique as they apply to big data

The aim of critical GIS is to illuminate ways in which positivist practices associated with GIS and knowledge production generate hierarchies of power that produce social, economic, and cultural inequity (Pavlovskaya & Martin, 2007). Critical GIS and qualitative GIS scholarship have extensively covered the debates associated with the critique of GIS research, questioning quantitative versus qualitative approaches to the use of the technology and extending this critique to the Geoweb.[30] It is not my intention here to provide an extensive literature review of these ideas or debates but rather to echo Graham and Shelton's call to look to experiences in related disciplines to highlight ideas and arguments that could be relevant to the critique of big data in a spatial research context.[31] Debates that occurred primarily in the 1990's regarding epistemological approaches to research in GIS are well documented,[32] yet still unresolved.[33]

We risk replicating epistemological debates documented in critical GIS literature in the context of big data and the Geoweb, because like GIS, big data is seen as a positivistic and objective. Quantitative ways of knowing and represented as maps associated and produced with GIS are given more weight and seen as authoritative compared to other representations of knowledge. GIS has been critiqued particularly for affording scientist a disembodied view of the world often referred to as the 'god trick' referring to the ability to see the whole world while being distant from it (Haraway already cited and Pickles, Pavlovskaya & Martin 2007, Rose, 1997). Historically, GIS and cartography have not commonly featured minority subject positions or objects thus the aim of the critical GIS movement has been to eradicate socially constructed inequalities through maps (Pavlovskaya & Martin, 2007). Increasingly, significant efforts have been made to utilize GIS for feminist endeavors.[34] Recent research harnessing big data on the Geoweb displaying a similar phenomenon that was documented with traditional GIS in that women and underprivileged populations' views are not being equally represented using traditional forms of GIS.[35] Similar debates and findings are likely to continually arise in the context of big data and the Geoweb.

Referring to the data being collected, GIS are socially produced creating a case to research this process from multiple epistemologies.[36] As Elwood and Cope postulate, it is valuable to utilize multiple epistemologies, through diverse modes of analysis and forms of knowledge to transcend levels of agency and authority through different forms of data, representation and analysis in research. Epistemology is closely intertwined and influenced by positionality.[37] Positionality influences epistemologies and the data collected and consequently information which becomes knowledge generated therefrom (Rose, 1997). Critical reflexive engagement challenges quantitative and positivist approaches closely held by traditional research in GIS.[38] Knowledge is situated and not objective (Haraway 1991 and Pavlovskaya & Martin, 2007). Feminist scholars acknowledge that situated knowledges add diversity to our understanding of the world providing an opportunity to engage in dialogue with those possessing other positionalities (Rocheleau 1995). Recognizing that knowledge is situated requires the researcher to reveal their positionality which in turn reveals the origin of the truth being documented, which gives the researcher ownership and responsibility of that truth. This process has been termed 'strong objectivity' acknowledging that positionality influences worldview, and by acknowledging this is a step towards objectivity in that neutrality in science is impossible (Harding 1992). It has also been recognized that knowledges are not fixed, they are fluid and evolve, and can pool to create shared bodies of knowledge and need not be considered distinct experiences which influences who counts in a GIS, groups or individuals (Rocheleau, 1995).

With situated knowledge in mind, "GIS scholars work with a mixed epistemological toolkit that varies from positivism to pragmatism."[39] It is necessary to acknowledge that methods and epistemology can be related but are not fixed; multiple epistemologies can be utilize a single method.[40] Critical cartography has taken steps to acknowledge and celebrate inclusive mapping practices that are occurring outside of corporate and government agencies who typically are responsible for managing spatial data and cartography (Crampton and Krygier 2006; Leszczynski and Elwood, 2015). By advancing non-normative claims to power, it becomes possible t to advocate for those who are typically marginalized by bringing attention to seemingly inevitable dominant positionalities typically associated with power (Takacs 2003).

At present, the manipulation of big data is most commonly collected and analyzed to push corporate agendas. These agendas have been masked and defended by claims that data are objective. Quantitative ways of portraying information are given more value than qualitative information that is often equated with anecdotes. When GIS was originally gaining popularity within the field of geography, GIS was critiqued for serving technological elitist agendas (Schuurman, Elwood see citation #5), much like big data is now being critiqued in this book. Feminist post-structural critiques recognize that multiple perspectives and methodologies can be inserted into GIS (Rocheleau, 1995; Pavolovskaya & Martin 2007). Similar observations and transitions will likely be observed for big data, as the subject positions of those involved in the process of knowledge production resulting from big data are increasingly revealed. Much like GIS, we risk reproducing inequalities observed in reality on maps (Elwood 2008; Hecht & Stephens, 2014), in our big data. The medium used to collect, analysis, and aggregate data will influence who participates in the process of knowledge production (Chambers, 2006). It is hoped that as more people identify the utility in big data and the skills required to harness the utility, more will participate in the analysis thereof making the possibility for more and diverse epistemological representations to exist in the future.

Structure of big data: Inserting reflexivity through positionality

Bringing the discussion back to the promise of 'big data,' Graham and Shelton call for use of big data to identify ways to reduce social inequality and environmental injustice.[41] A critical first step is to induce rigorous qualitative research, including data collection, analysis and dissemination associated with the big data utilization process.

Wilson calls to question how and who gazes into the (Arc)toolbox? The same question can be posed in terms of 'big data,' who can see and reach into the black box?[42] As researchers we need to explicitly state our positionality. Are we insiders or outsiders in our relationship with the technology in question. Wilson clearly describes this spectrum as borderland in terms of GIS researchers, the insiders who practice GIS and the outsiders who do not.[43] When we consider this idea in terms of 'big data,' what is missing is the mechanisms associated with collecting, storing, retrieving, and analyzing the (big) data. While big data is a seemingly technological challenge, technology is never utilized outside of social constructs. Thus it is necessary to discuss epistemological approaches to technological utilization associated with big data.[44] Considering these new processes associated with qualitative data collection, using new methods associated with 'big data,' need to be considered so we can work toward a more inclusive big data horizon.

Inserting reflexivity into our own research, but also considering the positionality of those we cannot see or meet, who are actors in the supply chain of 'big data,' may insert rigor into our research in 'big data.' The aim of reflexivity is to remind the researcher that they are not a machine. Context and subjective perspectives shape the meanings shared by the subject with the researcher.[45] Here it is important to remember that individuals, who maintain epistemological individualism, program the machines.

Big data is made up of seemingly invisible processes,[46] yet it is possible to visualize the invisible, to apply qualitative rigor by considering the positionality associated with those who are programming the cyborg.[47] While it is not possible to connect with each of the individuals involved in collecting, storing and retrieving, organization 'big data,' it is possible to contemplate their positionality. Consider not only those who input the data and then analyze the output, but also those that create and construct the data infrastructure in which the data are stored. They may inadvertently provide an opportunity to insert bias, to reflect the positionality of the developer, the data infrastructure engineer and cyber construction worker. The position of the researcher and the programmer (and those maintaining the big data) may influence the access to information to which others may not have access.[48] These individuals have unique constraints including time, money, expertise and previous experience (including epistemology). What can and cannot be collect in each data field, what data can be collected by a sensor, or by a query. For research to be replicable the positionality of those involved in the data collection storage and analysis procedures needs to be revealed or at least considered, because those with different positionality may collect different data, or seek patterns in data that have been horded. Also part of the invisibility is the positionality of the programmer. What technical training have they received? Why did they choose open source vs. proprietary software?

Discussion

In the tradition of Baxter and Eyles, England and others who have set the standard for rigor and qualitative methods, I suggest that we enter into a discussion regarding how to apply qualitative rigor when analyzing, manipulating and critiquing big data.[49] There is a need to be reflexive as researchers while we develop and pose our research questions and assert our positionality as it applies to both the collection and analysis of big data.

Inserting qualitative rigor into an inanely quantitative field not only introduces reflexivity but also reifies the inclusion of more voices in the data set, meeting the goal of using ‘big data" for social good. Baxter and Eyles suggested criteria to establish rigor in qualitative research in a different context[50] and I suggest that we find ways to apply them to the analysis of big data. These criteria include consideration of the credibility, transferability, dependability and confirmability of one's research. In addition to the consideration of methodological rigor itself, particularly making explicit the rational for methodological choices, indicators for rigor in research include multiple methods, description of respondents, direct quotations from subjects, interview practices, procedures for analysis, immersion and length of fieldwork, revisits, verification by subject, appeals to interpretative community, rationale for verification are indicators for rigor in research.[51]

It is clear that social spatial researchers see much hope in big data for helping underprivileged populations; however we have yet to see this use come to fruition.[52] These spatial social scholars are echoing England's recommendation to conduct research with integrity especially with marginalized populations.[53] Feminist poststructuralist call for ethical research, challenging the so-called objective research paradigm, by calling researchers to be more reflexive and inclusive of methods that reveal sensitive power relations between the researcher and those being researched.[54]

While the process of interacting with big data is opaque and the researcher is commonly far removed from those entering the data or even organizing and storing it, qualitative rigor could be incorporated by simply considering the positionality of all of the actors involved in the process, not only the researcher but also considering the positionality of those who control other points in the big data process.

Perhaps if we overtly acknowledge that the research relationship, including the big data stack, is hierarchical, reflexivity alone cannot resolve the issue but it will make others more aware.[55] While the researcher holds power (in the case of big data, the powers that own the data or those with the skills to interact with the data), she can also give it away (Rose, 1997; Nast 1994). There is a need to be reflexive as researchers while we develop and pose our research questions, and assert our positionality as they apply to both the collection and analysis of big data.

Acknowledging the multiple positionalities involved in big data assemblage used in qualitative research may help the researcher gain access to new information. The same consideration can be applied to those building the infrastructure for big data.[56] Those who pose the query to the key-value store pair may (not) gain access to information based on their positionality, their understanding of the world and what they can offer the data contributor in return.

It is the researcher who decides which voices will be heard and what will be written up in the final project to be shared with a wider audience, reflexivity and acknowledging the researchers position in the research is an example of rigor (England 1994; Rose, 1997). In the era of big data there are so many actors involved that they all have had some hand in determining what data are included into a data set that may then be analyzed by a researcher or analyst. No longer is it only the researcher who decides which voices are heard, which data are collected, which data are queried, are stored, and are aggregated.[57] Today big data are stored within large bureaucracies. To be considered, individual data must make it through several steps before it reaches a researcher. No data are truly raw.[58]

Conclusion

Here I described ways in which feminist and poststructuralist approaches could be applied to research challenges from a qualitative perspective that are associated with big data research.

Moving forward, identifying ways to use big data to reveal (spatial) patterns and qualitative experiences that previously went unnoticed, established qualitative research methods could be used to impose rigor and to identify valuable patterns within the big data. How big data is interpreted are informed by individual experience with it in the world and epistemologies of everyone who touches it. It is hoped that big data utilization can go beyond number crunching, toward the discovery and display of spatial patterns of behaviors or needs; however we must acknowledge that the mathematical methods by which we choose to analyze and display data are influenced by our positionality. Guidance offered by Baxter & Eyles, England and others have informed us of the utility of rigor in qualitative research methods, and here I displayed how these ideas can be used to investigate big data.[59]

By attempting to illuminate individual positionalities within the black box, the stack, could be considered an effort to mitigate positivistic assumptions and call to question how subjectivities are inserted in the data collection, storage, retrieval, and analysis phases of big data, inserting rigor. Each facilitator of each step within a stack has an opportunity to insert their subjective bias, their positionality influences the data. By acknowledging the positionalities of those working within the stack, this is one step closer to 'strong objectivity.' Understanding this relationship will help inform how we approach big data as qualitative researchers. The data cannot speak for themselves as they have passed through many hands, many boxes, and many fields prior to reaching the hands of the researcher or analysts.[60] The black box, these stacks, are made up of disconnected streams of bureaucracies, not necessarily conspiring individuals, but a group of individuals limited by their own knowledge, positionality, and time constraints and those of others up stream.

Much can be learned from other disciplines who critique similar technological approaches to research.[61] Here I presented how feminist and poststructuralist challenges associated with big data including guidance towards establishing qualitative rigor as it could be applied to big data. By illuminating the subject positions of those who control the black box forming big data, hopefully another step towards infiltrating the cyborg can be taken. [62]

Endnotes

[1] Kitchin, “Big Data and Human Geography.”

[2] Smith, “"Social Constructivisms.”

[3] *Ibid.*

[4] Thatcher, “Big Data, Big Questions.”

[5] Elwood and Cope, ""Introduction: Qualitative GIS;" Schuurman and Pratt, "Care of the Subject;" Schuurman, "Trouble in the Heartland;" Schurrman, *GIS: A Short Introduction*; Schuurman, "Database Ethnographies;" Schuurman, "Formalization Matters.”

[6] Baxter and Eyles, " Evaluating Qualitative Research;" England, “Getting Personal.”

[7] Kitchin, “Big Data and Human Geography.”

[8] Graham and Shelton, “Geography and the Future of Big Data.”

[9] Barnes and Wilson, "Big Data, Social Physics;" Barnes, "Big Data, Little History."

[10] Kitchin, “Big Data and Human Geography.”

[11] Graham and Shelton, "Geography and the Future of Big Data.”

[12] Kitchin, “Big Data and Human Geography.”

[13] Ricker, Hedley, and Daniel, "Fuzzy Boundaries.”

[14] Haklay, "Neogeography;" Hecht and Stephens, "A Tale of Cities;" Kelley, "Urban Experience;" Stephens, "Gender and the GeoWeb;" Zook and Graham, "Mapping DigiPlace."

[15] Crampton *et al.*, "Beyond the Geotag;" Graham and Shelton, “Geography and the Future of Big Data;” Leszczynski and Wilson, "Guest Editorial;" Zook and Graham, “Mapping DigiPlace."

[16] Wang and Armstrong, "Theoretical Approach.”

[17] See the work resulting from NSF Grant #1047916 SI2-SSI: CyberGIS Software Integration for Sustained Geospatial Innovation.

[18] Buneman, Khanna, and Tan. "Data Provenance."

[19] Thatcher, "Big Data, Big Questions."

[20] Dalton and Thatcher, "What Does a Critical Data Studies Look Like."

[21] Thatcher, "Big Data, Big Questions."

[22] Baxter and Eyles, "Evaluating Qualitative Research."

[23] Baxter and Eyles, "Evaluating Qualitative Research;" England, "Getting Personal."

[24] England, "Getting Personal."

[25] Baxter and Eyles, "Evaluating Qualitative Research;" Schuurman and Pratt, "Care of the Subject;" Wilson, "Towards a Genealogy."

[26] England, "Getting Personal."

[27] Baxter and Eyles, " Evaluating Qualitative Research."

[28] *Ibid.*

[29] *Ibid.*

[30] Leszczynski and Wilson, "Guest Editorial;" Schuurman and Pratt, "Care of the Subject;" Schuurman, "Trouble in the Heartland;" 2009; Schuurman, "Formalization Matters." Wilson, 2011; Wilson, "Towards a Genealogy."

[31] Graham and Shelton, "Geography and the Future of Big Data."

[32] Elwood and Cope, ""Introduction: Qualitative GIS;" Schuurman and Pratt, "Care of the Subject;" Schuurman, "Trouble in the Heartland;" Schurrman, *GIS: A Short Introduction*; Wilson, "Towards a Genealogy."

[33] Schurrman, *GIS: A Short Introduction*.

[34] Elwood and Cope, ""Introduction: Qualitative GIS;" Elwood and Leszczynski, “Privacy, Reconsidered;" Harvey, "To Volunteer or to Contribute;" Kwan, "Gender and Individual Access;" Leszczynski and Wilson, "Guest Editorial."

[35] Haklay, "Neogeography;" Hecht and Stephens, "A Tale of Cities;" Stephens, "Gender and the GeoWeb."

[36] Schuurman and Pratt, "Care of the Subject;" Schuurman, "Formalization Matters."

[37] Takacs, “HOW DOES YOUR POSITIONALITY.”

[38] Elwood and Cope, ""Introduction: Qualitative GIS;"

[39] Schurrman, *GIS: A Short Introduction*, 30.

[40] Elwood and Cope, ""Introduction: Qualitative GIS;"

[41] Graham and Shelton, "Geography and the Future of Big Data.”

[42] Wilson, “Towards a Genealogy.”

[43] *Ibid.*

[44] Schurrman, *GIS: A Short Introduction*.

[45] England, “Getting Personal.”

[46] Graham and Shelton, "Geography and the Future of Big Data.”

[47] Haraway, *Cyborg Manifesto*.

[48] England, “Getting Personal.”.

[49] Baxter and Eyles, "Evaluating Qualitative Research;" England, “Getting Personal.”

[50] Baxter and Eyles, "Evaluating Qualitative Research;"

[51] *Ibid.*

[52] Graham and Shelton, "Geography and the Future of Big Data;” Kitchin, “Big Data and Human Geography.”

[53] England, "Getting Personal."

[54] *Ibid.*

[55] *Ibid.*

[56] *Ibid.*

[57] *Ibid.*

[58] Dalton and Thatcher, "What Does a Critical Data Studies Look Like."

[59] Baxter and Eyles, "Evaluating Qualitative Research;" England, "Getting Personal."

[60] Kitchin, "Big Data and Human Geography;" Thatcher, "Big Data, Big Questions."

[61] Elwood and Cope, "Introduction: Qualitative GIS;" Schuurman and Pratt, "Care of the Subject;" Schuurman, "Trouble in the Heartland;" Schurrman, *GIS: A Short Introduction*; Wilson, "Towards a Genealogy."

[62] Haraway, *Cyborg Manifesto*.

[1] D. Takacs, "HOW DOES YOUR POSITIONALITY BIAS YOUR Epistemology," *NEA High. Educ. J. Thought Action*, no. Summer, pp. 27–38, 2003.

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