Mixed [M] eth (ics | ods): Thoughts on Ethics at the Intersection of Ethnography and Machine Learning

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Abstract
This essay proposes three areas of ethical discussion related to mixed method research of digital data: conflict between dissimilar methods; interpretation of mixed methods results by researchers; and interaction with and comprehension by the research subjects. The paper considers the overlap and conflict between ethnography and machine learning as an emerging set of mixed methods for behavioral trace data analysis.

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Introduction: Mixed Methods, Mixed Ethics?

While discussions of research ethics – particularly related to studies of the internet and digital data – abound, few conversations focus on the intersection of ethical considerations when researchers synthesize methods in particular projects. Questions related to mixed method ethics are becoming more and more important, as new types of methods continue to evolve (such as the increasing popularity of "trace ethnography” [5] and recent trends toward data-science-related analyses). If at all, researchers have noted that ethical considerations should merely fall in place with both sides of the methodological approaches, such as avoiding deceptive practices, reducing risk, and maintaining confidentiality. For example, [9] argues that a proper mixed methods study, where there is “fluid integration of the findings across methods,” must include “ethical vigilance that transcends both the quantitative and qualitative component” (p. 47). Mixed methods studies draw from different backgrounds, skills, and especially values, and ethical considerations differ for each side.

These recommendations for mixed-method research, though, usually fall within studies that do not involve digital data or online information ecosystems, which present new challenges for researchers developing cross-methodology projects. In a digital landscape, traditionally separate and distinct methods can be particularly useful when combined and synthesized: for instance, ethnography working on concert with machine learning to study populations in online communication platforms. But challenges in mixed methods become particularly astute as 1) datasets and tracking become increasingly large and complex, and 2) computational methods advance far beyond the grasp of traditional qualitative approaches. For example, traditional ethnographic methods like participant observation and interviews both inform and draw from quantitative studies and have been shown to synthesize well with so-called data science [4]; still, advanced computational techniques currently run up against ethnographic insights due to their complexity, even though machine learning techniques have developed in directions that are both greatly quantitative (supervised prediction approaches, like neural network classification) and greatly qualitative (e.g., multidimensional unsupervised clustering).

While synthesizing research findings remains as complex as it is in mixed-method research, is it also even possible for a mixed-methods study – especially one with distinct sides like ethnography and machine learning – to have an ethical approach that is “fluidly integrated” across the disparate sides of the research? Or do some mixed-methods approaches introduce complex ethical considerations that may not coalesce? Below, I explore three aspects of digital mixed methods research to examine evolving opportunities for researchers to engage in necessary discussions about ethics: overlap and conflict between disparate methods; interpretation of mixed methods results across disciplines; and interaction with and comprehension by the subject population. I ground these discussions by considering the intersection of data science and ethnography, though the same considerations could be made for other large-scale, computational methods, like online experimental designs, quantitative surveys, etc.

What could big data ethnography be? From Practical to Ethical Conflicts Between Methods

First, are the ethical considerations taken in quantitative computational studies any different from those of ethnographic studies? How do these considerations overlap and/or conflict, and what further ruminations need to be made at their intersection?

Mixed methods like ethnography and machine learning are not very similar. The practical fundamentals of these two methods are distinct and dichotomous: ethnographic methods rely on interpreted data driven by immersion within a collective or community, while quantitative approaches rely on modeled data derived from a sample (or a population). Ethnographic methods tend to work on the level of specifics; quantitative, computational methods tend to work on the level of aggregates. This is not to say, though, that the two cannot work together, nor that they are completely separate. For example, quantitative data can be gathered given the context of informal qualitative research (even though the final report might disregard it), and qualitative studies can derive insights and trajectories from quantitative findings. The foundations of both methods can look familiar too: ethnography and machine learning share many inductive, exploratory, and "gut feeling" approaches to finding evidence and producing frameworks and models for behavior [3].

The ethics of mixed methods like ethnography and machine learning still depend the basic tenets of ethical research: minimization of harm, maximization of benefits, safety of and respect for participants, etc. (see various ethical guidelines from scholarly organizations, e.g., [1, 8]). Every researcher attempting a mixed-methods framework should consider how the respective approaches to these tenets shift when moving from one method to the next. Further, these considerations – for each method too – will change throughout various stages of the research; for example, "decisions about gaining access to a site for data collection are different from decisions about how to interact with participants or whether or not informed consent is needed." [8, p. 6].

Since all methods deal with some formation of data at some point, one cross-methodological issue is how each method represents the data to be analyzed and any ethical considerations at the points of overlap. Methods can complement each other and provide richer context for various findings: for instance, interviews showing people's personal expressions about participation in online groups that are analyzed with clustering algorithms to detect types of behaviors. But is there an ethical concern in linking methods? For instance, researchers may need to consider the extent to which they can and should place observations about particular individuals within the context of a larger, holistic social network, potentially providing too much context about the individual. Another example could be conducting natural language processing on people's online communication patterns that, linked with other qualitative data, could potentially reveal specific traits of those people. Sometimes these approaches may reveal additional data that could de-anonymize a user or provide information about a research participant's at-risk status. These types of edge cases may only exist in the linking of methods, but researchers must be additionally careful in combining methodological approaches instead of solely considering the ethical questions of each method separately.

Is my neural network racist? Interpretation and Comprehension Across Methods

Second, how do researchers understand each other's work, and how can mixed methods navigate gaps in methodological literacy for members of different disciplines? Ethical considerations do not stop at data collection: data processing and analysis also involve rigorous deliberations about what the data can and should show, as well as how to present the data in an appropriate, understandable way.

Given the complex nature of computational approaches, some methods, their processes, and their results may be out of the grasp of more qualitative researchers. Few ethnographers know how quantitative results are derived from a k-nearest neighbors or support vector machine algorithm. Further, some advanced computational scientists do not entirely know how particular algorithms (ie., deep learning) generate given results [7, 2]. This type of gap introduces ethical concerns: namely, how does a mixed method researcher represent their data, know the implications of their method(s), interpret the data properly, and help other scholars comprehend the results.

Simple machine learning algorithms may aid ethnographic work, by for instance identifying suitable individuals for interviews from a massive dataset of digital logs or showing high-level aggregate trends within a population that can be further investigated in the field. But with more complex approaches, like with neural networks in deep learning, it becomes more difficult to say what features actually produced the results and whether or not those features should be questioned. This uncertainty leads to some provocative questions: e.g., How is it possible to know whether an advanced neural network is racist? The contentious question needs more time beyond the scope of this paper to be unpacked, of course, but if a researcher, such as one studying race representation online, does not know the underlying features that their algorithmic approach is generating in the performance of a classification task of particular marginalized individuals, how would she know if a given output were “defined” inside the algorithm in an appropriate manner? Methodological choices generally come down to practicality, but researchers must consider the values that they put into all analytical approaches, as well as those approaches’ inherent functions and biases.

Also related to interpretation, the issue of error remains particularly salient within mixed methods research. Considering marginalized populations, it is vitally important to consider how labels are applied to at-risk individuals within the group under analysis. Parallel to common approaches to spam, cheater, and fraud detection, the researcher should want to reduce false positives and false negatives as much as possible. In cases of at-risk people, mislabeling could have drastic ethical conundrums. For example, a social network clustering algorithm could place particular individuals into groups that they don’t belong or don’t identify with, and it must be up to the researcher to ensure that mislabeling doesn’t fail these individuals when reported in the research. This can be a difficult task, especially at the scale of studying millions of people with machine learning techniques (and still remains something that ethnographers grapple with on the scale of dozens) [10]. Usually, when data scientists encounter overlaps or outliers, these cases are seen as too complicated to deal with, introducing error to models. Throwing these cases out as potential errors, though, introduces an additional ethnical question of representation, especially for marginalized peoples.

As digital data becomes increasingly available, we will encounter more and more instances when this data is adopted in mixed method studies; therefore, it will be increasingly critical to know how computational methods are producing results, not just that results have been produced. Additionally, those employing computational techniques need to be able to learn from ethnographers in how insights are interpreted from observatory and interview-based data, in order to properly adapt those takeaways into and alongside algorithmic approaches. Computational social scientists interpret context from data on a daily basis, as they need to understand the situations within which their datasets have been generated (especially for digital, behavioral trace data); however, few researchers recognize this as a critical moment in their algorithmic processes. Frequently, though, ethnographers struggle with ethical questions at the exploratory stages of their fieldwork, and it is thus important for data scientists to recognize that these periods in their early work do set the foundation for ethical considerations to be made later.

Am I in that social network visualization? Speaking With, Back To, and For The Population

Finally, how do people – especially people in the population of study – interpret mixed methods results? How can mixed method researchers engage with communities to inform but also represent them ethically?

As with all public-facing research, general consumers of information should be able to understand the final work produced. Researchers should note how comprehensible the results of mixed methods are to the general public, as well as how members of the population studied will interpret the work. These issues are not new: for instance, some studied communities in ethnographic work do not feel as if the research represents them appropriately. As digital data becomes adopted in mixed methods studies, scientific literacy and data literacy – not to mention inverse issues like readability – remain potent problems as academics continue to engage with the general public. As conventions around research (e.g., a community understanding the role and behaviors of an embedded ethnographer) become challenged by dichotomous research methods (which, in the eyes of the public, appear sometimes conflicting or confusing), how should researchers engage with the publics they study?

Not all scholars agree on the necessity of working with or speaking back to the population of study. However, it is an ideal. As Kurzman [6] explains, "It is absurd for social scientists to debate the subjects' situation without letting the subjects speak up for themselves" (p. 267), though he recognizes that sometimes academic writing is incomprehensible to the subjects of study, and further, situations occur where social-scientific arguments are justified at the expense of offending the community of study. Even by striving for closeness to the community, a "social silencing" can occur where "social forces systematically [prevent] subjects from properly understanding their situation" and expressing it to the ethnographer (p. 251). As digital data becomes integrated into mixed methods research, researchers must have a core ethical argument about how "public" and even company-owned data might be used in a way that reveals insights about a community without that community being able to speak back to the research findings or its initial methodological decisions.

In addition to working with or alongside communities of study, the perceptions of produced research matter as a final ethical concern. In a personal example, I encountered pushback on a project I was assisting on that adapted trace ethnography with social network analysis using publicly-available data: some individuals expressed distrust at being observed and studied in a public forum (ethnography) with the additional threat of perceived surveillance (social network analysis). There are many issues to tease out around public-ness, consent, etc. here, but one initial takeaway is that the added element of computational method provoked contempt (regardless of ethical measures taken in collection and processing of data). Whether or not a study produces risk for individuals, the perception of risk must be addressed.

Conclusion

This paper has introduced three areas for ethical concern regarding mixed method research involving digital trace data: conflict between dissimilar methods; interpretation of mixed methods results by researchers; and interaction with and comprehension by the research subjects. While mixed method research with digital trace data continues to emerge, IRBs – while knowledgeable about particular methods – are likely unprepared to acknowledge the ethical concerns at the intersection of disparate methods. Given the few discussions about mixed method research and ethics, I hope to see more scholars engage with this topic in the near future.

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