Big Data And Changing Concepts of the Human

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Abstract. Big Data has the potential to enable unprecedentedly rigorous quantitative modeling of complex human social relationships and social structures. When such models are extended to nonhuman domains, they can undermine anthropocentric assumptions about the extent to which these relationships and structures are specifically human. Discoveries of relevant commonalities with nonhumans may not make us less human, but they promise to challenge fundamental views of what it is to be human.

Introduction.

Humanistic discussions of the implications of Big Data for people have largely focused on ethical and legal issues raised by the gathering, control, and use of the data generated when people use information technology. Controversy over the gathering and use of telephone metadata from ordinary U.S. citizens is a case in point (Mayer et al. 2016). The issue raised by this paper is more foundational: what does Big Data imply for our conception of what it is to be human? This issue arises from the combination of the new availability of real-world data from human social networks with new developments in network science. The interaction makes more likely the discovery of unexpected similarities between humans and nonhumans at the social level, raising in vivid new form the problem of understanding what makes us human beyond having *Homo sapiens* DNA.

Part 1. Big Data and Human Behavior

Big Data is voluminous data – so much data that standard data management tools cannot be used to create, capture, store, search, analyze, and visualize it in ways that are useful, relevant, accurate, and timely (Gantz and Reinsell 2011).[1] The Big Data of interest here is that generated by or about people and their social relationships. For example, we create such data when we count our steps using wearable personal technology (Stahl et al. 2010) or make a purchase, tweet, or search online using interactive or networked technology. We also have a "digital shadow" – information created about each of us based on the information we create (Gantz and Reinsell 2011).

However, mainstream definitions of Big Data don't always capture its importance. When considering the implications of Big Data, size is relative. A dataset can be much bigger in breadth and depth (or detail) relative to the size and scope of the datasets that a potential user usually has access to. An inability to manage such datasets may a relevant problem for the purposes of monetization or business efficiency, but not for other purposes. In particular, Big Data enables social scientists to explore social interactions in previously unavailable ways. For example, digital shadows provide "outstandingly large" samples of real behavior to which social scientists have not previously had access (Bentley et al. 2014). Social network analysis is not new, but the availability of data harvested from or experimentally induced in enormous real-world social networks is. This availability makes possible a transition from sociological network theory based on one-time, often self-reported, data from dozens of people, to a “computational social science” based on massively longitudinal datasets of millions of people that offer “a qualitatively new perspective on collective human behavior” (Lazer et al. 2009: 722). Social scientists can now run randomized experiments involving millions of people and

[1]This mainstream definition (e.g. Wikipedia https://en.wikipedia.org/wiki/Big_data) is one of many (Press 2014). However, nearly all emphasize size (without specifying size quantitatively) and the difficulty of managing it.

their relationships to test hypotheses of social behavior – for example, hypotheses about the roles of influence and susceptibility to influence in social contagions and the individual and local-network features associated with influence and susceptibility to influence (Aral and Walker 2012; Salganik et al. 2006). Running a social science experiment with even 14,000 participants, as in Salganik et al. 2006, is completely intractable in a physical lab.

Social scientists can also study behavior in large real-world social systems without having to rely on sampling – for example, analyzing patterns in downloads of apps by 50 million Facebook users (Onnela and Reed-Tsochas 2010), the dynamics of collective attention as measured by 1 million users rating stories at a user-contributed news website (Wu and Huberman 2007), or the interplay of structural constraints and individual preferences in homophily (the tendency of like to associate with like) in a 30,000-member university community, as measured by over 40,000 time-stamped emails (Kossinets and Watts 2009). Exploration of social networks via technological means is considered the tip of the iceberg in terms of socially-relevant data of interest to social scientists, given the growth in mobile devices, wearable technology, and brain-computer interfaces (Roesch et al 2014: 97). In short, for the social sciences, Big Data is data of "unprecedented breadth and depth and scale" generated by real-time, real-size social networks and the individuals in them (Lazer et al 2009).

At the same time, computer scientists and other quantitative researchers are exploring network behavior at a more abstract level of analysis (Baronchelli et al. 2013; Bullmore and Sporns 2009; Barabasi and Albert 1999). In the emerging interdisciplinary network science, researchers are finding that similar network behavior arises at multiple scales – from the Internet to the brain to metabolic reactions to scientific collaborations. Networks within individuals (e.g., brains) and networks between individuals (e.g., social networks) exhibit deep similarities. In addition, human social networks share at least a basic structure with other large-scale networks in different domains, such as having a few highly connected nodes (hubs) and many nodes with very few connections. Structural features even this basic can have important social effects, such as whether information is communicated through a network in ways that facilitate or hinder decision-making (Mason et al. 2008). Quantitative network models have also been developed to reveal basic features of the formation and structure of collaborative networks in the arts and sciences (Guimera et al. 2005) and to demonstrate the possibility of self-organization in the formation of a complex polity (Froese et al. 2014). These studies do not involve Big Data, and network science also applies to small groups (Katz et al. 2004) as well as individual psychological phenomena. However, uses of quantitative models in social science are expected to vastly increase as network science and other tools for manipulating Big Data are developed (Watts 2007; Lazer et al. 2009).[2]

It is the intersection of socially generated Big Data and network science that generates the conceptual issue raised here. Big Data may make a similar impact elsewhere, but this specific area of overlap can make the problem for our concepts of the human particularly clear. To date, it is relatively sparsely populated by published

[2] Social connectionism involves the use of connectionist models for social psychology – for example, connectionist models of how individuals form prejudices (Van Rooy et al. 2003). The focus here is on social structures (e.g., a racist society) rather than individual cognition (e.g., a racist individual). That said, the morals of this paper also apply to psychology (Figdor forthcoming).

studies.[3] In one such study, for example, Mateos et al. 2011 used network analysis of an online database of 300 million names from 26 countries and 4 continents (as well as a local naming network in Auckland, New Zealand) to reveal how cultural, ethnic, and linguistic communities can persist even after geographical dispersal. Still, the potential problem can be foreseen just given how quantitative models are used throughout science.

Part 2. The Conceptual Problem

In its essence, the problem is a familiar one of whether and how to revise old categories in the face of new similarities. As an intuitive example, if advanced computing devices are able to do much of what human minds can do, are they really intelligent or do they only simulate intelligence? Answers to this question are a matter of categorization, which we capture in words ("intelligent") or concepts (INTELLIGENT).[4] Not all conceptual border disputes are significant. Whether a particular new item of furniture counts as a chair (falls under the concept CHAIR) doesn't matter to most of us, although it can matter to some of us (e.g., if you are a furniture importer, and chairs are subject to

[3] That said, the Santa Fe Institute (https://www.santafe.edu/research/projects/hidden-laws-in-biological-and-social-systems) comprises one group of researchers dedicated to this sort of cross-domain research. Regardless, the field is in its infancy.

[4] I adopt the convention of using all capital letters to denote concepts (e.g. FISH) and mention quotes to denote predicates (e.g., "fish", "pesce"). The differences between concepts (FISH), predicates ("fish"), and categories (which are denoted by either) won't matter here. Also, a standard distinction in philosophy of language is drawn between sense and reference – the meaning of a term and what it refers to. For example, "the morning star" and "the evening star" are names with the same reference – the planet Venus – but different meanings. For predicates, a corresponding distinction holds between extension (a set of entities) and intension (a property shared by the members of the set). For example, the extension of "fish" is the set of all individual fish, and its intention is the property shared by fish (call it Fishness). As before, predicates with different intensions (meanings) can have the same extension (reference). My focus here is on the reference (or extension) of predicates or concepts. For some theorists, reference exhausts meaning anyway.

import tariffs). Social categories, however, matter to almost everyone. Is marriage only between a man and a woman? What is it to belong to the black race – if there is such a thing? Can an Alzheimer's patient's relationship with a robot caregiver be a real friendship, or is the patient being exploited? (Sparrow and Sparrow 2006). If humans have legal standing because they have advanced cognitive capacities, does a chimpanzee whose cognitive capacities are more advanced than those of a cognitively disabled human have legal standing (The Nonhuman Rights Project)? Of course, a single case that conflicts with implicit assumptions about category boundaries (e.g. one gay couple that wants to marry) may not suffice to raise the question of the adequacy of those boundaries, let alone their revision. But individual cases can be very influential, and it is hard to ignore many cases of the same type. It is thus likely that at least some studies in computational social science (to borrow Lazer's label) will at least raise the problem.

To see how, consider some general features of mathematical models and modeling practices.[5] A mathematical model has two basic elements: a structure, and an interpretation or construal. For example, without an interpretation or construal to link the mathematical equations to the world, the equations are not *about* anything at all. Similarly, networks have nodes and edges as their structural features, but what the nodes and edges represent is a matter of their interpretation. Following Weisberg 2013, the construal includes the modeler’s specification of which real-world system the model is

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[5] Not all models are mathematical (e.g. scale models, animal models). However, I am construing "mathematical" models all those which can be described using equations or other mathematical tools (e.g. connectionist networks or computational models). In philosophical terms, mathematical equations are descriptions of models, although scientists often call the equations themselves models. Mathematical models can also be depicted in various ways – i.e. by standard graphs with x- and y-axes, and by network graphs with nodes and edges.

intended to represent, along with specification of which aspects of the target the modeler will focus on and the criteria used to evaluate the goodness of fit between the model and the target system. These criteria establish how much the model can vary from the target in the specified respects without ceasing to be a model of it. A simple illustration of these concepts is the Lotka-Volterra model of the dynamical relation between the sizes of populations of predators and prey. This is often presented as a set of linked equations:

$$\frac{dV}{dt} = rV - (aV)P, \qquad (1)$$

$$\frac{dP}{dt} = b(aV)P - mP. \qquad (2)$$

The equations were developed with populations of fish in the Adriatic sea as the intended assignment, focusing on their relative sizes. In the standard construal, **V** represents the size of the prey fish population (e.g., cod), **P** the size of the predator population (e.g., sharks); the parameter **r** represents the intrinsic growth rate of the prey population, **m** the intrinsic mortality rate of the predators, **a** the capture rate of prey, and **b** the birth rate of predators.[6] The model is typically described as a model of predator-prey relations. Lotka and Volterra intended the variables **V** and **P** to represent certain populations of fish (as captured in the concepts SHARK and COD) and the concepts PREDATOR and PREY characterize the relationship between these fish populations.

It is a common modeling practice to use mathematical models for systems other than the ones for which they were initially developed. For example, the Lotka-Volterra

[6] Equation (1) equates the change in prey population over time to the difference between its intrinsic growth rate and the rate at which prey are captured by predators. Equation (2) equates the change of predator population over time to the difference between the birth rate of predators and the predator mortality rate. The equations are linked in that the conversion of dead prey into baby predators in equation (2) is a function of the capture of prey by predators in equation (1).

equations were quickly used by others to capture the relative sizes of populations of wolves and moose. This switch in construal from populations of fish to populations of land mammals is permissible (indeed, unremarkable) because wolves are already in the extension of PREDATOR and moose in the extension of PREY. But the Lotka-Volterra equations have been used to capture relationships between plant species, wage levels and jobs, and capillary tips and chemoattractant in wound-healing angiogenesis (Arora and Boer 2006; Goodwin 1967; Pettet, McElwain, and Norbury 2000). Unlike the prior extension to wolves and moose, these cases are conceptually problematic. Are plants, wages, and capillary tips predators? What evidence is relevant to our decision? The point here is not to answer these metaphysical and epistemological questions, but to show how they arise due to ordinary modeling practices in science. The intuitive examples given above of marriage, caregiving, and legal standing are simpler examples, but the basic problem is the same. In fact, with models in science it is arguably worse. Mathematical models provide scientifically grounded insight into important structural similarities that can cross-cut pre-existing categories. They also don't have *a priori* restrictions regarding the domains to which they may be fruitfully applied.

Enterprising scientists have long taken advantage of these features. For example, Ratcliff's (1978) drift-diffusion model of decision-making explains differences in response times and accuracy in making simple decisions depending on the quality of the relevant information. For example, subjects who must decide whether a test picture matches a sample can decide more quickly and with greater accuracy if the test picture is sharp rather than blurred. This cognitive model was originally developed based on data from human subjects. But it has also been used, inter alia, for macaque monkeys and fruit flies (Shadlen and Newsome 1996; Dasgupta et al 2014). Again: do macaques and fruit flies really make decisions? What evidence is relevant in making this determination?[7]

The intersection of socially derived Big Data and network science promise to raise these same questions for social concepts. As a result, when models of human social interactions are extended to nonhuman domains, the assumption that these social interactions are specifically human can no longer be taken for granted. As noted, such models need not be based on Big Data, although they may subsequently be tested and revised using Big Datasets from larger, real-world human social groups. For example, Guimera et al. 2015's model of the assembly of creative teams is based on counting the numbers of collaborators in Broadway musicals and selected academic journal publications. Their model predicted team member selection based on three parameters: team size, the fraction of newcomers in new outcomes, and the tendency of team incumbents to select past collaborators. This model could be tested with much larger populations and revised or elaborated in various ways as a result. Plant biologists have already considered that the concept of facilitation should be employed for plants, in addition to competition (Bruno et al. 2003). If Guimera et al.'s model or some revised version of it is successfully extended to plant populations, should we also consider some plants as newcomers and others as incumbents, and consider whether plant collaboration promotes creative innovation and formation of group knowledge? If the model is robust with Big Datasets from much larger scale human groups, and it is then extended to large nonhuman groups, such as bacteria, do these same concepts apply to them as well?

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[7] Elsewhere (Figdor forthcoming) I argue that they really do make decisions. In this paper, my goal is not to defend an interpretation of social concepts bur rather to show what the overlap of Big Data and network science implies for the likelihood that we will be facing a lot more of these sorts of conceptual issues in very short order.

Similarly, Froese et al.'s (2014) computational (connectionist) model of a self-organizing decentralized system of government may eventually be tested using Big Datasets from real-world complex political organizations. The social categories of rulers, elites, priests, coalitions, and representatives are all implicated in the model. If the same model turns out to have real-world application to some bacteria colonies, it suggests that we might conceptualize these colonies as political entities, and that relationships of social influence and collaboration naturally extend to many nonhuman groups. Mateo et al. 2011's study of naming networks in dispersed human populations brings in concepts of cultural, ethnic and religious affiliations that persist through dispersion. We don't usually label nonhumans with names (other than pets or particularly outstanding members of wild species). But given some analogous labeling schema, the same networks might be found in nonhuman populations, with the corresponding question of which of the associated cultural, ethnic or religious categories might also be extended.

Finally, to explore the issue in detail, consider a hypothetical case of a single business and the complex relations between the individuals who work in it, the other organizations with which it competes, cooperates, and compares itself to, the institutional and regulatory structures in which it operates, and the interactions between these factors (Watts 2007). The Big Data generated by this business might be used to formulate a network model that captures the dynamical changes in social relationships within businesses that grow from two founders to dozens of employees as well as their relationships with other businesses. It reliably predicts which businesses are more likely to adjust to changing internal social dynamics and which are not, holding constant other features that affect success at any specified rate of financial growth. It distinguishes the formal positions as well as the major characteristics of and informal relationships (the "unwritten rules" and patterns of influence) between the people that fill them. Some individuals are influential, some marginalized; some are mentors, others malingerers. The model provides deeper understanding of the interplay of character and informal relationships in organizational success and failure. It might show how individual features and social relationships of people occupying formally identical roles in closely-matched businesses have very different outcomes.

An enterprising microbiologist might well take this model and use it successfully to predict the growth and survival of bacteria colonies in a dynamic ecosystem that – like an economy – is sometimes favorable and sometimes harsh.[8] The model is able to predict which colonies will thrive and which will not, holding constant other features that affect success (such as amount of available nutrients). Assume the biologist is able to distinguish bacteria within the colony (or perhaps small clusters of them) and assign them to various roles with different responsibilities within the colony in such a way that (ceteris paribus) the survival of the colony can be explained by the different ways in which the bacteria filling these roles interact with each other. The microbiologist adopts the same concepts for the roles and the personal characteristics to describe the various bacteria clusters. For example, some bacteria are senior mentors of junior-level bacteria. Her ability to use the model licenses (but does not establish) the extensions of these social concepts to the new domain. The equations establish a formal similarity between

[8] Note that some bacteria colonies are already considered predatory (e.g. Velicer et al. 2000), while others are described as communicating linguistically and making collective decisions (Ben Jacob et al. 2004).

humans and bacteria at a social level. Does it make sense to say that some bacteria really are mentors of junior members of the organization? How do we decide?

We tend to think of the behavior of nonhuman groups in purely evolutionary terms. We explain their behavior in terms of biological fitness. The applicability of social science models of real-world human social networks and relationships to nonhumans would suggest that this reductive attitude is as mistaken for nonhumans as we think it is for humans. We would be missing an important level of analysis of nonhuman behavior that corresponds to the social level in humans. The more we are able to model the features and relationships that underlie social concepts using socially derived Big Data, the greater the potential for social conceptual extension.

Perhaps right now it intuitively seems too much of a stretch to extend social concepts to nonhumans. But usage can change. Witness the term "computer" (or the concept COMPUTER): now it is debated whether humans are computers, when originally humans were the *only* computers. So the immediate conceptual shock of thinking of a cluster of bacteria as a senior mentor of a junior-level cluster does not decide the matter. From the point of view of Big Data-driven models, the bacteria fill the formal roles and establish informal relationships in such a way that the whole colony and its growth and survival can be seen as instantiating a form of social complexity that we formerly associated just with humans. There are obvious differences between bacteria and humans, but the question is whether these differences matter for understanding the relationships between humans in a business and between bacteria in a colony.

Of course, there is no guarantee that quantitative models developed from real-world human social data will apply elsewhere. It may be that the only models that do are so abstract that they do not raise significant conceptual puzzles. For example, we already know that human social networks are like many others in that they contain hubs with many more connections than average, yet this fact is hardly cause for conceptual concern. Still, if computational social science is just around the corner, so too is the possibility of social conceptual extension and revision.

Part 3. The Disruptive Potential for Traditional Humanistic Concerns

What counts as a real social relationship, a real social role, a real social emotion? As noted, it is often far from trivial whether we either exclude something from or include something in a social category. However, social categories of mentor or incumbent and social relations of having influence or collaborating may not be considered particularly humanistic even if they paradigmatically involve humans. In this section, I'll consider briefly the potential problem in relation to two traditionally humanistic concerns: the nature of personhood, and the nature of moral standing. For any theory in which standing in a social relationship is constitutive of being a person or having moral standing, changes in social category boundaries have important ethical implications. We may consider ourselves downgraded by recognizing a similarity to something we consider inferior, and may fear how we might be treated as a result given our own treatment of other animals. By considering two such theories, I can illustrate how the extension of social concepts to nonhuman domains has the potential to affect our conceptions of what it is to be human. We may not care much if bacteria are mentors. But what if a detailed social network model that also fits bacteria-colony behavior suggests that we should extend the concept of personhood to them as well?[9]

Baker (2015), building on earlier work (e.g., Baker 2000) argues that individual human persons are social entities, because human persons have robust first-person perspectives, acquiring such perspectives requires acquiring a language, and language is social – it requires a linguistic community. Persons could not exist in a world without social or linguistic communities. On her view, there are both rudimentary and robust first-person perspectives (more precisely, stages of development of first-person perspectives). The rudimentary stage involves a nonconceptual capacity for intentional behavior that requires consciousness and intentionality – for example, avoiding pain. Nonhuman mammals can develop this perspective, but for them it is "the end of the first-person line" (op.cit.: 79). The robust stage involves developing a capacity to conceive of oneself as oneself from the first-person. This capacity for self-conception is acquired by acquiring a natural language. Persons have self-concepts, which requires having concepts, which requires having language. Without this capacity, "there would be no significant distinction between human persons and nonhuman primates" (op.cit.: 79):

> Robust first-person perspectives enable us to realize we are agents, to take responsibility for things that we do, to recognize that we are subjects of experience, to care about the future, to change our habits in the light of rational assessments of our goals. These abilities – made possible by our robust first-person perspectives – are unique (as far as we know) in the universe. …[O]ur robust first-person perspectives set us apart from everything else in the natural world. (op.cit.: 80).

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[9] I am not endorsing these theories, and they are not the only ones in which social relationships play a critical role. For example, Brandom (1994) makes social relations constitutive of conceptual thought and language; Schechtman 2014 defines persons in terms of social interactions and structures; and Kittay 2005 argues for the importance of social relationships in moral standing. I use them to illustrate the general point.

The potential for disruption is entailed by the final sentences – the idea that this suite of capacities derived from a capacity to acquire natural language, is unique to us as far as we know. Because our specialness is closely linked to the uniqueness of possession, any change in the boundaries of the relevant concepts is highly threatening, even though extending a category to nonhumans is not a zero-sum game. (If fruit flies make decisions, it does not follow that we no longer do.)

Unfortunately, the origins and extent of language capacities are a thriving research area, and will only grow given network science and Big Data derived from linguistic networks (e.g. Mehler 2007, Baronchelli et al. 2006). Some in microbiology already argue that bacteria communicate linguistically (Ben Jacob et al. 2004). Animal researchers have reported that chimpanzees in an immigrant troop learn to change the pitch of their food calls to converge with those of a host troop, and that the change in vocalization coincided with greater social integration and the formation of strong social ties between members of the original subgroups (Watson et al. 2015; see also Harms 2004). If language is not unique to humans, Baker's theory of what makes humans persons fails to restrict personhood to humans.

A second (although related) humanistic concern involves moral standing, the status one possesses for being subject to moral consideration. If an entity has moral standing, either directly or indirectly, we may not treat it any way we please (Warren 1997: 3). For example, a human being cannot be killed for food, while a cow can, because the human has moral status that the cow lacks. On Jaworska and Tannenbaum's (2014) view, higher moral status accrues to humans above nonhumans because the former can participate as rearees in person-rearing relationships and thus potentially attain the status of being a self-standing person ("SSP"). On this view, certain social relationships confer moral standing.

Jaworska and Tannenbaum agree that sophisticated cognitive capacities, such as the capacity to reason, to be self-aware, and to care, ground the higher moral status that accrues to humans or anything that has them. However, on their view, moral status can also be conferred by a capacity that is "deeply relational" in that its exercise requires active participation of another. The paradigm is a parent-child relationship between non-cognitively impaired humans. In these relationships, the child learns by practice to do the activities that characterize self-standing persons (for example, doing simple rule-abiding activities that are models for practical deliberation at a later age). The parent engages with the child in these activities with the end in mind of raising a self-standing person. Importantly, even if the child does not or cannot complete the process, she is already participating in the form of life of SSPs – there must be some non-zero probability of the rearee's becoming a SSP, but her activities can fall short of completion.[10] This kind of person-rearing relationship suffices to confer on the rearee the higher moral status, even if she is too cognitively impaired to ever achieve self-standing personhood and even if the rearer is a guardian or an institution. Most animals are omitted because few animal owners engage with them with the aim of raising self-standing persons, but also because engaging in the activities with them has zero probability of turning them into SSPs. As they put it, "evidence abounds that turning cats and dogs into SSPs is impossible" (2014:

[10] On their view (op.cit.: 254, fn. 23), "a form of life is given by the practice or activity manifested in that life; the end informs (and forms) what the activity is, and so constitutes that kind of life."

258) – they do not have the capacities to engage in the kinds of activities that a rearer can transform into those characteristic of SSPs.

Jaworska and Tannenbaum's account makes standing in certain social relations necessary if not sufficient to confer moral standing. In this case, the social relations are paradigmatically small – one rearer and one rearee – but the possibility of institutions as rearers, as well as multiple rearees, shows that the relevant relations can in fact be many-many. It follows that the sorts of conceptual extensions discussed above could expand the range of entities that have moral standing beyond what we currently envision. As we saw with Baker, their disclaimer about evidence showing what is impossible for nonhumans is telling. The age of computational social science has barely begun. It is not impossible that real-world social systems of the rearer-rearee sort (e.g., a communal nursery on an Israeli kibbutz) may generate Big Data about those relationships (from personal devices as well as networked technology) that can be used to develop models for predicting various successful outcomes for rearees, including severely impaired rearees. If the relationships are constitutive of moral standing, rather than the normal cognitive capacities, then it is an empirical issue as to whether these social relations are restricted to humans. These models extended to nonhuman groups would provide evidence of what nonhumans are capable of, as rearees or rearers.

Conclusion.

Although much current controversy over Big Data-driven research deals with pressing ethical and legal issues, fundamental conceptual issues are just around the corner. Once we have used socially-derived Big Data to elaborate, develop, or test mathematical models of human social relationships and their dynamics, it is predictable that scientists will use these models to understand relationships in other real-world complex systems. If they are successful, these nonhuman domains would have important structural similarities to our own that raise the question of whether human social concepts extend to them. There is no one answer to this problem, nor have I advocated for one. My goal has been to show that and how such conceptual issues will arise given the new social science research possibilities afforded by Big Data and network science. If these social relationships and catogories are not uniquely human, what is it to be human?

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