The Role of Niche Signals in Self-organization in Society

by

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For Rebecca, my love and partner in it all.

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Abstract

This dissertation is concerned with the emergence of social patterns. The ability of groups of humans to bring order to both the physical and abstract realms may be our species' most distinguishing characteristic. It is dependent upon our willingness to cooperate and otherwise coordinate, yet willingness alone is not sufficient for achieving coordinated outcomes on a large-scale because the informational demands of bottom-up organizing are high. Understanding the emergence of social order then requires, in part, understanding how information flows are structured in ways that allow groups to meet the informational demands of self-organization. Of particular importance in this regard are the patterns of person-to-person interactions. In contemporary social network research these interactions are often described as the conduits through which information flows, but person-to-person interactions are also the site and source of the coordination problem needing to be solved. To resolve this tension, network interactions must be patterned in ways that allow for the free flow of information, yet social networks most often exhibit high degrees of clustering, a characteristic which can impede the free flow of information and, thus, large-scale coordination.

Does this mean bottom-up processes do not drive coordination within large groups? Is resolution by fiat the only way? Many have made the argument we create and tolerate authorities for precisely this reason, but is that the only viable mechanism for the establishment of large-scale coordination? Inspired by stigmergy, a form of communication used by social insects to coordinate hive activities, this dissertation explores the value of signals occurring outside or alongside of the person-to-person interactions studied using social network analysis. Social life features an abundance of small signals—often in the form of verbal or written communication, but also physical objects and even sounds and smells—potentially freighted with meanings or embedded knowledge. Several research traditions have regarded these signals as part of the fabric of social life, but is the information these signals yield patterned in a way that can help overcome the challenges of large-scale coordination?

To begin to answer whether these signals can play a role in mass coordination, this dissertation takes three distinct approaches. The first analyses coupled differential equations describing a system in which a common resource environment is structured by the ongoing actor-to-actor interactions. This system is a modification of a canonical model of molecular self-organization, the hypercycle, and succeeds in organizing vastly more complex sets of interactions than the original. This confirms the information embedded in the environment can indeed be a powerful source of information for coordination. The second paper takes this formal insight into the lab to test whether the addition of a small number of extra-network signals can enable the emergence of conventions in a large, networked group of human participants. It can, and the probability of it happening depends on the strength of the extra-network signal and the topological features of the network. The final paper uses a unique dataset and topic modeling in an attempt to track the emergence of consensus around the themes in works of fiction. While there can be movement in the direction of consensus, the path lengths of the underlying network are too long to support large-scale consensus, a finding consistent with results of the experiment. Implications of these three findings are discussed in the conclusion.

Chapter 1: Introduction

The ability of groups of humans to bring order to both the physical and abstract realms may be our species' most distinguishing characteristic. We have a great deal in common with our evolutionary next-of-kin physiologically, yet zoologically our propensity and capacity to organize our collective enterprises and experiences is unrivaled. We have succeeded in shaping much of the natural world around our needs, created highly complex economies, and produced tremendously rich systems of communication and meaning. The processes that gave rise to these outcomes are rife with tensions, but nonetheless require large-scale coordination at their core. Humans have thrived because of our manifest ability to coordinate from the bottom-up to create well-ordered symbolic and economic systems, that is, to self-organize societies.

This sense of how deeply cooperative our species is has emerged after centuries of a more pessimistic view of social life. Hobbes' state of nature coupled with a narrow reading of Darwin helped paint a picture of insuperable conflict among the members of our species. Yet, from genes up to the level of societies, it is clear that that view does not do the facts justice. Epigenetics, evolutionary developmental biology, and powerful critiques of sexual selection (Bar-Yam 2000; Roughgarden 2009; Sober and Lewontin 1996) have undermined the primacy of genes as the selfish motors of evolution in the sense popularized by Richard Dawkins (Dawkins 1976, 1978). While the proper unit of selection is not clear, it is not selfish genes. Furthermore, the evolutionary strengths of reciprocity and cooperation are analytically clear (Axelrod 1984; Gintis and Bowles 2011) and have vital empirical support (Fehr, Fischbacher, and Gächter 2002; Henrich et al. 2001; Henrich and Henrich 2007; Ostrom 1990). The dual inheritance model of evolution (Boyd and Richerson 1985; Cavalli-Sforza et al. 1982) and its focus on the coevolution of genes and culture has done much to explain how and why our tendency to coordinate activities has benefitted us (Boyd, Richerson, and Henrich 2011; Enfield 2006; Kendal, Tehrani, and Odling-smee 2011). This dissertation, however, does not study the ways in which coordinated and cooperative behaviors are deeply constitutive of human societies. Instead, it takes the human tendencies toward coordination as given and asks what else is necessary for those tendencies to deliver the desired result. In particular, it explores whether a class of signals—stimuli that may yield actionable information—often treated as analytically unimportant is in fact instrumental for large-scale coordination and, therefore, in part responsible for our species' ability to self-organize.

While recent research on coordination problems has very reasonably focused on information gained from direct interaction between individuals, the public spaces we construct also carry a wide range of signals that can yield information that drives a group toward a particular collective outcome. Consider the ongoing attempts to adopt a mobile phone-based payment system. As a network good—one that is more valuable as more users opt-in—with little in the way of a top-down push for adoption, if it does become widely used, it will very likely be because a crucial wave of new users adopt it after seeing others use the method in public. The signal that is seeing a stranger do something may not even rise to the level of consciousness for the observer, yet multiple signals carry crucial information about the behavior of others that individuals can use to coordinate activities. Adopting a payment system is an example of coordination in the usual sense of all doing the same thing, but small signals from unidentified others can also drive processes of coordinated differentiation, like how subtle physical cues can help determine individuals' choice of housing, which gives rise to distinctive neighborhoods, or how public signaling via sartorial choice creates identifiable personal styles. This sort of differentiation can be an important form of coordinated behavior, especially economically, where the division of labor enables the creation of more complex products.

The above examples are of coordination in the physical realm, but public signals likely play an important role in ordering the realm of cognition and abstract thought, from language to ideas about what is possible. The pairing of the word *phishing* with a set of practices for stealing personal information was a gradual and public process of coordination that resulted in a new word, a conceptual category of practices, and, for many, new understandings of what is possible. But while successful coordination can create anew, coordination via public signals likely also reinforces otherwise outdated patterns. It is easy to imagine that highly gendered professions like nursing or plumbing remain so because impressionable children come to think of them as gender-specific occupations over years of casual public observation and thus create implicit ideas about occupational suitability that have no basis but nonetheless maintain the pattern.

The role of signals emanating from the public spaces we construct is underappreciated in today's networked world, but has been noted and even figured prominently in the past. Public signals clearly occupied an outsized role in Bentham's design of the Panopticon (Bentham 1787; Chwe 2001; Foucault 1977); Durkheim saw the public nature of rituals as integral to their effects (Durkheim 2001); Simmel worried the overwhelmingly public nature of life in cities dampens our emotive capacities (Simmel 1903); Walras's public price-sharing mechanism (the auctioneer) was thought necessary to reach equilibrium prices (Walras 1954); The popular Bass model of product diffusion (Bass 1969), Schelling's model of residential segregation (Schelling 1971), and Granovetter's threshold model of collective behavior (Granovetter 1978) all implicitly rely on public signals about behavior. Beyond these well-known examples involving the public observation of others, several research programs highlight the importance of nonhuman objects as signals. Material-semiotic approaches (Callon 1998; Latour 2005; Law and Mol 1995) assert the importance of manmade objects and other nonhuman entities in social life. Likewise, the theory of distributed cognition argues that cognitive processes are spread across individuals through the externalized products of cognition (i.e. physical objects) (Hutchins 1995). The material culture tradition focuses on the rich cultural meanings and messages that can be embedded in objects (Tilly et al. 2006). Ecological psychologists argue that affordances—assumptions about possibilities of behavior vis-à-vis objects—are instrumental to cognition and action (Barker 1968; Gibson 1977; Rietveld and Kiverstein 2014; Withagen et al. 2012).

Suffice it to say that my assertion of the social importance of such public signals is not novel. Indeed, others have even already argued that an extreme form of them is instrumental for coordination (Chwe 2001). My goal, rather, is to provide more analytical clarity about the origins and structure of such signals and explore whether they alter social processes. In particular, I argue these signals can push processes of self-organization toward coordinated equilibria. To help unpack this claim, I develop the concept of *niche* signals. Biologists and ecologists have long used the term niche to refer to the environment a species is adapted to, but there is a renewed interest in the concept stemming from the development of the theory of *niche construction,* the evolutionary process by which the inhabitants of an environment (i.e. a species) structure it in ways that alters evolutionary fitness (Odling-Smee, Laland, and Feldman 2003). The classic example of niche construction is a beaver dam. Beavers build a physical structure and are adapted to the unique environment it creates. Importantly, the dam changes the whole local ecology and can alter the fitness of species that played no part in the construction of the dam. A dam is a large and obvious altercation to the environment, but most species structure their local environments in ways that other species in the same environment adapt to. This is so pervasive that it might simply be called co-evolution (Laland et al. 2014), but niche construction highlights the mediating role of the local environment. This sense of niche then refers to the broad context for action and something produced by those actions, and evokes the existence of important endogeneity in the evolutionary process.

Humans are the exemplar niche constructing species, to the point that little of our daily life exists in environments not fundamentally of our own making. At this point, our fitness as individuals has little relation to the natural environment Darwin had in mind and is almost wholly determined by our ability to navigate and exploit social niches we have constructed. To navigate these complex niches, humans can use information obtained directly from other actors, but, I argue, indirect signals from within the niche can also be vital sources of information. Signals from a niche can lead to knowledge about the state of niche, but importantly often also knowledge about the social value of particular behaviors or beliefs. Observing others in the niche, or the traces they leave behind in the niche, can create or reinforce beliefs. For example, seeing lots of hybrid vehicles parked in one's neighborhood would likely reinforce beliefs about their social desirability, reliability, or practicality in addition to the basic information about their prevalence.

Other sources of information can do the same, but signals from the niche can have a distinct structure compared to other potential sources. Within-network signals can provide a heavily biased sample of the broader system, aggregate information is most often too expensive or impractical to gather, and broadcast mechanisms can be nonexistent or too weak. Niche signals, however, have the potential to yield less biased information about the state of the whole system because the space in which social networks reside is often folded over on itself when mapped to the physical and digital niches in which social life resides space. This means socially distant persons, who are more likely to have access to different information, can be in the same physical space and niche signals can quickly traverse long social distances. The same can be said in the digital realm, where websites create "networked publics" (Boyd 2010; Ito 2008), which can have both public and private subspaces. Because so much of social life is now digital, I generally do not refer to physical space and instead use niche to encompass both physical and digital spaces.

Niche signals can be distinct from within-network signals in ways other than potentially being less biased. First, they can be qualitatively different than the often-conversational signals from acquaintances; there is no conversational equivalent to seeing hundreds of cars over the course of a day. Second, they can be received without rising to the level of consciousness; one rarely consciously observes the cars of a neighborhood, but can often report a sense of the population when prompted. Unconscious processing is likely necessary because, thirdly, the signals are incredibly abundant. An implicit awareness of many of these signals is a part of the everyday tasks of navigating social spaces, but often not a part of higher order cognition.

These features suggest niche signals are an area ripe for more theorizing and research. Before undertaking that task, however, it is advisable to first explore whether these signals, in any number forms, can be shown to have an impact on social processes So while niche signals can quickly travel long social distances, the question remains whether the signals yield useful information. I argue that they do and therefore have been undervalued. In the era of "big data," that signals like these have been undervalued might be the consequence of an elision of the terms *signal* and *information*. It is common in the social sciences to use the term information to refer to content of some sort, whether a conversation, an article, or a video. This shorthand is natural but can be misleading. Reading the same syndicated article on the websites of two different newspapers does not yield twice the information. Information theory separates the concept of information from the signal or message that delivers it by emphasizing what receiving a signal does to reduce the receiver's uncertainty about some state of the world. So receiving the same message again does nothing to increase information. Furthermore, one reader might learn a great deal more by reading an article than another reader does in virtue of the differences in the readers' backgrounds. This highlights the fact that a strict definition of the information yielded by a signal or message requires contextualizing in a history of signals received. This distinction relates to why weak ties (Granovetter 1973) spanning structural holes (Burt 1992) are beneficial; the signals gained through these ties yield a great deal of information relative to non-brokers. On the other hand, for most social ties there is a high level of redundancy, with very similar messages coming from the same alters. While redundancy may reinforce some aspects of cognition, it can fail to yield new information. However, niche signals can cumulatively yield a great deal of information even though each is by itself a weak signal.

The informational redundancies in social networks highlight a tension common to dynamical systems; local order prevents the emergence of a global order. A classic example is that of ferromagnetics: a ferrous material becomes magnetized when the dipole spins of its atoms are oriented in the same direction. The spins naturally want to align, but because an individual atom's orientation is constrained by the local order of the often-conflicting orientation of neighboring atoms, a collection of atoms in a disordered state will remain there. In order to break this symmetry—the conflicting forces holding the system in a disordered global state—additional fluctuations or noise need to be added to the system. For ferrous materials this can be achieved by either heat or an external magnetic field. In social systems, the high degree of clustering endemic to social networks can lead to similar failures to "break symmetry." This dissertation explores whether the addition of niche signals can convey the information necessary to break those symmetries. The papers that follow study that effect with three distinct approaches.

The first paper stems from work done with John Padgett and takes the hypercycle model of autocatalysis (Eigen and Schuster 1979), a mathematical model of the self-organization of molecules into a reciprocal role system, and adapts it to allow the acting elements to have information about the activities of others not immediately adjacent in the role structure. This information is present in the common environment as the inputs/outputs of the reactions (or interactions) in the cycle. The original model exhibits a barrier to self-organization for even modest levels of complexity (i.e. the number of possible molecules or roles able to chain together) (Hofbauer and Sigmund 1988). A numerical analysis of the modified system of differential equations shows, however, that interactions with an environment formed by the activities of others allows for the emergence of significantly more complex hypercycles. It does so by inhibiting the rate of reactions that have success early but ultimately undermine the viability of the whole system. This result depends on the strength of the feedback from the environment. While this highly formalized and stylized approach necessarily misses important aspects of social interactions, we believe it offers a strong deductive basis for the claim that niche signals can be critical to processes of self-organization.

The second paper puts this claim to the test with a behavioral experiment. A recent paper by Centola and Baronchelli (Centola and Baronchelli 2015) explored experimentally the emergence of conventions (e.g. calling unwanted email SPAM) within large networked groups of individuals and found the puzzling result that a single convention for the whole group emerged only if interactions were randomized across the whole group (i.e. homogeneous mixing). Groups embedded in random and lattice networks never converged to a global convention. While these networks and interaction topologies are all stylized, that a convention would emerge only in the absence of meaningful network structure does not square with what we know about the world; conventions do exist and the social networks in which people are embedded exhibit clustering. This paper explores whether niche signals can resolve this puzzle. Participants are simply shown the behavior of random and unidentified group member(s). The results for 32 trials show that the presence of niche signals can indeed break the symmetry in networks with clustering and lead to the emergence of conventions. The effect, however, is mediated by the average shortest-path-length of the network. The longer it is the more niche signals are required. These results offer strong support for the importance of public signals in the emergence of coordinated "goods" like conventions. Experiments however must greatly simplify behaviors and contexts in order to be tractable. Can this type of self-organization be observed in action?

The third and final paper seeks to identify and understand the process of self-organization in the reception of new works of literary fiction. Literary fiction is a genre rich with themes and meaning but full of ambiguity. Yet a book's audience often comes to focus on a particular theme or attribute to the text a specific meaning. Using a rich data set from an online literary community, the paper uses the method of topic modeling in a novel way to seek evidence of a convergence within the readership toward an accepted set of meanings for a work of literary fiction. In spite of anecdotal evidence of this happening, my analysis reveled only weak evidence of such a convergence. A supplementary analysis of the network in which readers are embedded revealed a possible reason no widely accepted meaning emerged; the average shortest-path-length for the network of readers of each book was very high (roughly 4.5 on average). The experiment showed networks with high path lengths need more niche signals for consensus to be achieved and suitable amounts are not likely to be consumed by readers using the site.

This work is undertaken with one eye toward understanding our species' past successes at coordination and the other eye toward the future. As economic life and technologies have changed the ways in which people associate and communicate, many have worried we are losing public spaces and public discourse (Arendt 1948; Etzioni 1994; Fukuyama 2000; Putnam 2000; Simmel 1903). While my research agrees that public spaces and the information they yield can be integral for the emergence of coordination, it also suggests that the loss of full-throated public discourse (if we ever had it) does not spell ruin for efforts at coordination. A relatively small number of niche signals can have beneficial effects by breaking the symmetries that prevent coordination across clusters. Furthermore, in a world in which exposures to signals are often controlled by the proprietary algorithms of websites and apps, tweaks to those algorithms could have significant positive effects.

Chapter 2: Niche Construction by Hypercycles: A Powerful Means of Self-organization

Abstract

The emergence of complex organizations and industries requires that the self-interested behavior of individuals be sufficiently interdependent and that the whole be robust in the face of the steady churn of individuals. The hypercycle, an abstract system of chemical reactions believed to be necessary for the emergence of life, offers an insightful framework for understanding the reconciliation of these issues by describing a cycle of mutualisms among a set of roles that reproduce their own occupants. Unfortunately, the basic hypercycle is limited in how complex a set of reactions it can sustain. This paper's numerical analysis of a system of coupled differential equations shows that by explicitly describing the population dynamics of what the role-occupants produce, already implicit in the application of hypercycle theory to social settings, and coupling those dynamics to the reproduction of role-occupants, the resulting hypercycles can become significantly more complex. The precise degree of complexity this "niche construction" mechanism supports depends on the amount of feedback available from the product environment.

Introduction

The robustness of a complex network of social or economic interactions depends on its ability to integrate individual interests and continually reconstruct and reconfigure itself in the face of destructive and otherwise transformative forces. Communities and cultures lose individuals, organizations lose skilled workers, industries lose businesses, and economies lose industries. And more than offsetting those losses are the newcomers, from children and businesses to technologies and industries, which need to be integrated without disrupting the balance of interests. What is necessary for complex patterns of interactions to persist and even flourish in the headwinds of constant flux? Drawing on work by Eigen and Schuster (Eigen 1971a, 1971b; Eigen and Schuster 1977) on self-organization in prebiotic chemistry, Padgett and collaborators (Padgett 1997; Padgett, Lee, and Collier 2003; Padgett and Powell 2012) propose a *hypercycle* approach to social organization to understand first how interaction networks arise and then how novelty can emerge therefrom; when a reaction is the catalyst for itself or another, the reaction is *autocatalytic,* and if there exists a set of reactions for which each catalyzes exactly one other within the set, it is referred to as an *autocatalytic set* or *hypercycle*.

The theory of hypercycles originated as an explanation for how diverse self-replicating macromolecules (e.g. RNA and DNA) could arise on prebiotic Earth (Maynard Smith 1979; Szostak, Wasik, and Blazewicz 2016). Such molecules produce both other macromolecules (e.g. proteins) and copies of themselves. The existence of life depends on such molecules, and the hypercycle framework arose to explain more specifically the origin of RNA, a process many have argued is necessary for the emergence of life[1]. In spite of their importance, explaining the origin of such molecules is not easy because self-replicating RNA molecules faithfully replicate themselves using a complex protein created itself by RNA (RNA replicase). Without this protein, if the naturally occurring mutation rate in replication were too high, any nascent species (a population of identical molecules) of RNA would quickly return to a random collection of protein sequences. But even if the mutation rate were lower, a single, less complex and less

[1] This account has challenges in the details (Boza 2015; Martin and Russell 2003; Maynard Smith 1979; Orgel 2004) and alternatives exist (Shapiro 2006; Wächtershäuser 1988, 1990). Nonetheless, it is widely-accepted, if not hegemonic (Bartel and Unrau 1999; Copley, Smith, and Morowitz 2007; Joyce 2002; Martin and Russell 2003). The status of this debate, however, has no bearing on the basic insights of the hypercycle model (Padgett and Powell 2012).

useful species of molecule would come to dominate through selection induced by the need for common resources (Eigen and Schuster 1977; Maynard Smith 1979). These related problems have been referred to as an "information crisis" (Hofbauer and Sigmund 1988) because natural forces appear to select against the amount of information contained in complex macromolecules. Thus, there was a need to explain how the errors intrinsic to replication would not be fatal while simultaneously ensuring a single, simple molecular species did not come to dominate. The hypercycle solves this problem by positing a self-replicating cycle of molecular *quasi-species*. The quasi-species sequentially catalyze the replication of the next in a complete cycle. The mutual dependency overcomes the two problems of the information crisis; it allows the quasi-species to be shorter and less complex than the whole cycle, which significantly reduces the problem of replication errors,[2] and it balances the competition between the quasi-species by ensuring each species' success replicating (or lack thereof) has a corresponding impact on the replication of the other species. A sudden loss or gain of a particular molecule type will ripple forward through the cycle as the rates of the subsequent reactions in the chain slow down or speed up until balance is restored.

These features of the hypercycle framework make it an enticing approach for understanding the emergence of complex social entities. The knowledge and knowhow embedded in a product like a car or computer did not originate in a single person or even firm. Instead, it was the result of the bringing together of individuals or firms with particular skills and knowledge bases for more than just one moment in time. Fruitful interactions encourage and facilitate the reproduction of the associated skills and knowledge, thereby transferring the weight of the collective enterprise from individuals to roles new actors can be trained to fill. In this sense, a role in a complex production network is like one of the quasi-species in the hypercycle; individuals may come and go, but as long as a role's function is being fulfilled and remains in balance with the others, the network of roles is maintained and will become a cohesive whole. This dynamic, while fairly conservative in isolation, importantly also provides explanatory purchase for understanding the origins of novelty social forms and products. The rebalancing dynamic will produce a new hypercycle when two or more existing hypercycles are brought into

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[2] If the error rate is .01, the typical replication of a molecule with 100 nucleotides will contain an error. However, a molecule with 25 nucleotides will successfully replicate 3 out of 4 times. The combination of four of the shorter molecules can contain the same sequence of 100 nucleotides as the larger one.

contact, given that a new autocatalytic set exists in the union of the originals. This second, re-configurative feature of the hypercycle model makes it a particularly rich metaphor for understanding the evolution of social organization (Baron 2014; Page 2013; Zuckerman 2014). It can explain how a network of actors and practices can stabilize in the short run, but also how those actors and practices can be fundamentally transformed as different networks are brought into contact with each other.

The potential explanatory power of the theory of hypercycles for both prebiotic chemistry and social science is great as long as the hypercycles can emerge spontaneously, but there are some serious challenges in that regard. Setting aside the decades of unsuccessful attempts to grow RNA in a controlled experiment (Anastasi et al. 2007; Szathmáry 2013; Szostak et al. 2016), there are several problematic entailments of Eigen's original mathematical model. For one, a hypercycle is vulnerable to parasites, quasi-species that benefits from a catalyst produced by the hypercycle but does not contribute its own catalyst to the cycle (Maynard Smith 1979). A hypercycle also needs to be localized (compartmentalized) to allow for the evolution of population (Bresch, Niesert, and Harnasch 1980; Michod 1983). Furthermore, even when assuming away these first two issues, the number of quasi-species that can spontaneously assemble into a hypercycle is at most four (Hofbauer and Sigmund 1988); the feedback mechanism is fatally weakened if it must be transmitted through more than four quasi-species, meaning the hypercycle largely fails to deliver on its promise of being an information "integrator" (Küppers 1983). Subsequent research has shown the first two of these issues can be simultaneously addressed by spatializing the model (Boerlijst and Hogeweg 1991, 1995; Padgett 1997; Padgett et al. 2003; Szathmáry and Demeter 1987) and the length of the cycles can be increased by enriching the environment (Padgett et al. 2003; Padgett and Powell 2012). This paper presents formal results showing this latter issue can also be addressed to great effect by including the dynamics of product formation. Just as RNA produces proteins, the occupants of social roles create products, whether durable physical objects or more abstract results like an accounting ledger. By coupling the dynamics of this product space to the dynamics of the skills space, we show the hypercycle model can yield significantly larger cycles. Furthermore, the number of skills that can co-exist in a cycle is no longer predetermined and instead becomes a function of the amount of feedback from the product space. These results are shown through the numerical analysis of coupled differential equations.

The upshot of this analysis is a strong argument for a particular ecological approach to understanding the emergence of social organization. There is no shortage of ecologically informed approaches to social science, but, as one of us has argued elsewhere (Padgett and Powell 2012), these approaches excel at explaining selection from among species but neglect the emergence of the species selection happens to. Failing to link emergence and selection should be problematic in social settings because humans excel at constructing niches, environments that define the fitness landscape on which selection happens (Kendal et al. 2011; Odling-Smee et al. 2003). Said differently, the particular species or forms of social organization that exist today are endogenous to the environments they themselves created, and selection cannot be decoupled from the effects a species has on the local environment. As it happens, our analysis suggests this fact can do much to explain the relative complexity of social organization; niches can carry a great deal of information that actors can use and the result is the ratcheting up of complexity (Taylor 2004). Versions of this argument have been made previously and in a number of ways (Boyd et al. 2011; Hutchins 1995; Kendal et al. 2011; Pinker 2010; Taylor 2004), and this paper explores this process mathematically.

The results and interpretations are directed at a social science audience and not the literature on chemical autocatalysis for the simple reason that the present model makes two assumptions that, while defensible, if not called for, in the description of social interactions, are not readily justifiable in known chemistries. The model we present in fact has important similarities to the lesser-known hypercycles-with-translation model of Eigen and Schuster (Eigen and Schuster 1978). We re-conceptualize that model's persistent catalysts as mutable or intermediate products being transformed by the RNA templates. However, self-replication occurs when a template *donates* a product (enzyme) to another template, not when it receives one. This better matches the flow of rewards in social and economic transactions, but is at odds with the forward-looking mutualisms of how the original hypercycle equation was first defined (but not the general idea of autocatalysis (Szathmáry 2013)) . Nonetheless, our findings largely agree with those of Eigen and Schuster in that modeling of a second class of molecules increases the number of molecular species that can co-exist in a metastable cycle.

The Basic Hypercycle Model

Before detailing the model we analyze, we review the original model of the hypercycle proposed by Eigen and Schuster, discuss its social science interpretation and review key relevant results from previous analyses of it. While not known when the model was first proposed, the hypercycle equation is a special case of a general class of equations called the replicator equation (Hofbauer and Sigmund 1998; Schuster and Sigmund 1983; Szathmáry 2013), familiar to many through its use in the modeling of evolutionary processes, from population dynamics to game theory. As is the case with the replicator equation, the hypercycle equation is a differential equation that deals with species, here molecular species. A species is a classification scheme for individual molecules based on the sequences of nucleotides that make it functionally distinct. While in principle replicator equations could count the individuals of a type, it is customary to track the population percentages instead. In chemistry, this percentage is referred to as the concentration of the species, a terminology we adopt. Equation 1 is simplified version of the original for *n* molecule types .[3]

$$\dot{r_i} = r_i r_{i-1} - r_i \sum_{j=1}^{n} r_j r_{j-1} \qquad (1)$$

$\dot{r_i}$ is the rate of change in the concentration of molecule type r_i. Contributing to that rate is the first term of the right-hand side, the probability with which molecules of type *i* and *i-1* interact in a well-mixed solution, which is equal to the concentration of the first, r_i, multiplied by the concentration of the second, r_{i-1}. By the assumption of the "chemistry" involved, if type *i* molecules encounter molecules of types other than *i-1*, nothing happens. While more complex chemistries can exist and have been analyzed (Padgett et al. 2003; Padgett and Powell 2012), equation 1 describes a chemistry in which a single potential hypercycle exists—molecules of type *i* catalyze molecules of type *i*+1, type i+1 catalyzes type i+2, and so on until type *n* catalyzes type 1. This cycle is depicted in Figure 2.1.

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[3] The original included reaction rate and dissipation rate constants. These can be removed by a barycentric coordinate transformation (Hofbauer and Sigmund 1988) without changing the results of the stability analysis.

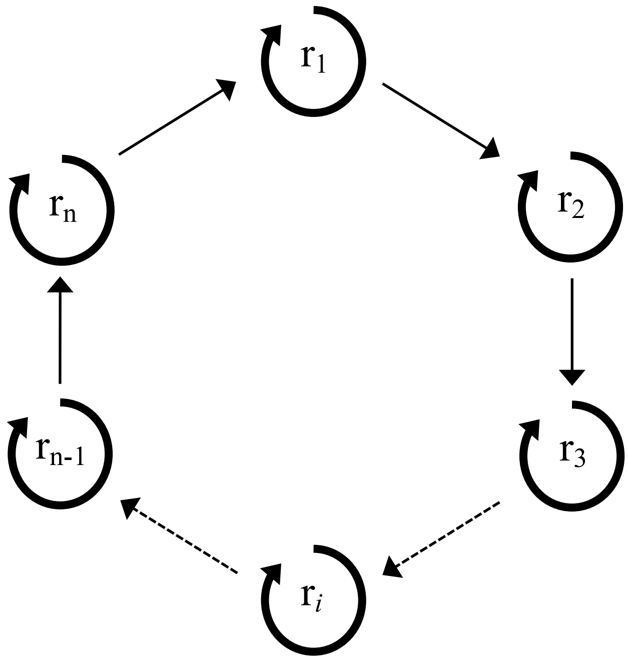

Figure 2.1: The Basic Hypercycle: The basic hypercycle is compromised of *n* molecule types that sequentially catalyze each other's replication. The molecule types are labeled from r_1 to r_n and have a circular arrow around them indicating replication. The arrows between molecule types indicate the direction of the catalyzing reaction (i.e. molecules of type r_1 catalyze molecules of type r_2). The dashed arrows indicate the possibility of additional (or fewer) reactions existing.

In a system of unlimited size, population growth could be unbounded, but to make the system mathematically tractable, a second, dilution flux term is added. It maintains a constant population of molecules by removing the same number of molecules just created in the growth terms of all *n* molecule types (the summed terms), but removing molecules in proportion to that molecule's current concentration, r_i.

The social interpretation of the system this equation treats the species of molecules as *skilled* roles filled by individuals. Similar to the molecules in the chemistry interpretation, the individuals use a skill unique to their role type to affect some change, but instead of creating a catalytic enzyme, they are creating or transforming a product, providing a service, or otherwise adding something of social value. When this skill leads to a successful interaction with another role or skill type, the interaction prompts the replication of a skill. As written in equation 1, the replicated skill would be the one receiving the product or service. This direction has a clear interpretation in chemistry, as does the other (Szathmáry 2013). While certainly one can imagine a successful service or product "creating" new customers, we prefer the interpretation of the replication occurring in the provider of the product or service; a successful forward-facing transaction will often induce further investment in the associated skill. As it happens, which skill is replicated after a transaction does not alter the outcome of the dynamics of Equation 1. (The same cannot be said for the equation we introduce below).

Stability Analysis of Equation 1

In order to understand how complex (i.e. long) a cycle the system described by equation 1 can support, we turn to the stability analysis of the equation. The dynamics of a system of differential equations can exhibit a variety of behaviors. Stability is a property of the behavior of the system around its fixed points—any set of values that yield themselves when the equation is applied to them (i.e. an equilibrium or rest point). The hypercycle equation has a unique inner (i.e. all values are positive) fixed point when concentrations are all exactly equal, $r_i = 1/n$ for all i (Hofbauer and Sigmund 1988). However, the stability of that rest point depends on *n.* For n=2,3,4, the fixed point is globally stable, meaning the concentrations can start out at any positive fraction and the system will converge to equal concentrations. For $n \geq 5$, however, the inner rest point is unstable. Thus, unless the concentrations start at exactly even, at least one of the molecule types will approach zero and the hypercycle will effectively die. Because positing even concentrations is to assume the order the hypercycle seeks to explain, this means the basic hypercycle model cannot account for the emergence of cycles containing more than four molecule types. These results have been shown formally.[4] The panels in Figure 2.2 give the visual intuition of the outcomes for initial conditions in which a single molecule/skill type dominates the population in the beginning. The stability of the equation is not altered by the initial conditions as long as the system is not at its precise equilibrium point and the choice of initials conditions here is to highlight the ability of the hypercycle (for N=2,3,4) to not only maintain diversity but to amplify it. Nonetheless, these plots help make it clear that the basic hypercycle equation does not support particularly complex cycles.

Perhaps not immediately clear is that Equation 1 describes an aspatial system. The molecules exist in a "well-mixed" solution, meaning the reaction rates are only dependent of their current concentration (this is the result of the law of mass action). Locating reactions in

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[4] Hofbauer and Sigmund (Hofbauer and Sigmund 1988) in fact show that the hypercycle is permanent for all *n.* This means no concentration hits zero in spite of the fixed point being unstable. However, the local minima are some very small delta away from zero, which is traditionally interpreted as failure of the hypercycle.

space has the potential to alter reaction rates because suitably reactive molecules can become spatially separated. Boerlijst and Hogeweg (Boerlijst and Hogeweg 1991, 1995) have shown that spatializing the basic model in fact changes the reaction rates in beneficial ways; it induces a wave-like structure of replication that prevents the emergence of parasitic molecule types and supports the emergence of more complex cycles. This finding is mirrored in the work of Padgett (Padgett 1997; Padgett et al. 2003; Padgett and Powell 2012), which shows more complex cycles are possible if the model is spatially embedded. However, in addition to adding space, this hypercycle model adds an external resource environment to reflect the more transactional nature of social settings. The complexity of the resulting hypercycles depends crucially on the nature of this environment, and we now turn to explicating and analyzing the role of such an environment.

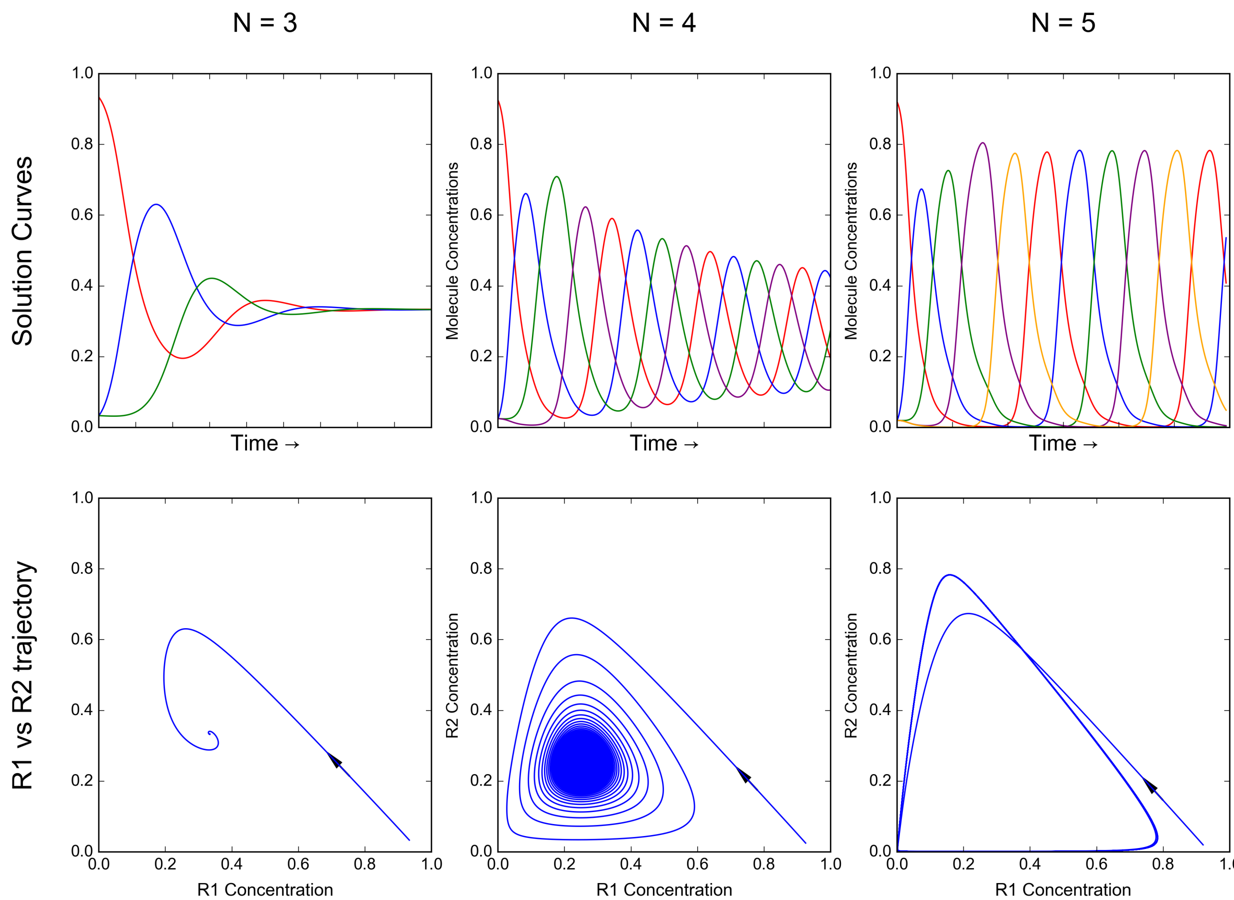

Figure 2.2: Basic Hypercycle Solution Curves: Solution curves and trajectories for N = 3, 4, 5. The first row plots the concentrations of the molecule types over time. The second row plots the projection of a trajectory in the N-dimensional space onto the R1 and R2 plane. The initial conditions for all trajectories are r_1=.9, $r_{j\neq i}$= .1/(n-1). The system asymptotically approaches equal concentrations quickly for N=3. For N=4, the sinusoidal oscillations also converge to the fixed point. For N=5, the concentrations reach a stable periodic orbit.

The Environmentally-dependent Hypercycle Model

The hypercycle of equation 1 models autocatalytic reactions as two suitable molecules bumping into each other, hence the probability of replication being exclusively dependent on the molecules' concentrations. In reality, one molecule would not catalyze the replication of the other directly by bumping into it, but rather through the addition of a catalyst molecule it produced. But because this product is always assumed to be collocated, it can be safely omitted. However, social interactions are not chemical reactions, and in applying the concept of a hypercycle to social life, Padgett and collaborators adapt the framework to be more clearly social in nature. The self-replicating molecules are individuals with a specific skill (referred to as a rule) that takes an input, transforms it, and later releases it. These outputs are referred to as products and are the "catalysts" for the work done later by other skilled individuals. To start a series of transformations, a rule needs a product to transform and attempts to find a suitable one in the common resource environment. Using an agent-based model, Padgett and collaborators have found that when the environment contains all inputs in constant and equal probabilities, the resulting hypercycles can be up to 9 types long, more than twice as long as the original hypercycle. Furthermore, if the product environment is endogenously produced by the rules, it also supports more complex cycles. Of particular interest is the fact that this result holds when the environment starts out with a single product type instead of assuming diverse and plentiful products are already available. This suggests the endogenous construction of the product environment is indeed a powerful mechanism aiding the emergence of more complex hypercycles. However, the model is spatialized and these results could largely be driven by the well-documented ameliorative effect space has on the hypercycle. To explore the effect of the endogenous structuring of the product environment, a process we refer to as niche construction because of its similarity to the well-studied evolutionary phenomenon of the same name, we modify the equation for the original hypercycle. This removes space from consideration, allowing us to study the mechanism in isolation. We analyze the new system's stability using numerical techniques below.

Niche Constructing Hypercycles

To make the role of products explicit, we modify equation 1 such that the replication of a rule, r_i, occurs when it encounters a product it can transform, p_i, transforms it, and finds a suitable rule to pass the product to, r_{i+1}. The fact that replication occurs after passing on a product instead of upon receiving it differs from the original equation. Reversing the order allows for a more natural correspondence to social and economic interactions; a skill is reinforced when its application results in a successful interaction or transaction. The probability of such a replication event is simply the product of the three relevant concentrations, $r_i p_i r_{i+1}$. As before, the growth rate of each rule type is offset by a dilution flow equal to the rule-type's current proportion in the population times the total number of replication events, in other words, the sum of the growth terms for all rule types. Equation 2 captures these micro-dynamics.

$$\dot{r_i} = r_i p_i r_{i+1} - r_i \sum_{j=1}^{n} r_j p_j r_{i+1} \qquad (2)$$

To account for the dynamics of the concentrations of products, which can be thought of formally as a second class of molecules, a second equation is needed to capture both the growth and loss terms for each product type. When a product is a part of a successful transaction (as in equation 2), it is not immediately included in the growth or loss terms because it is participates in a chain of transformations until a rule fails to find a compatible rule to pass the transformed product to.[5] Upon failure to find a compatible rule, the product is released back to the environment in whatever state it is currently in. Returning products to the environment is how it becomes endogenously structured. The probability of a new instance of a product type p_i being returned to the environment is the probability of it being transformed into its current state, $r_{i-1}p_{i-1}$, but also failing to be passed to a rule of the type that can transform it (i.e. r_i). The probability of such failure is just the probability of encountering any other rule type instead, or $1 - r_i$. Thus, the growth term is $r_{i-1}p_{i-1}(1 - r_i)$. There is no dilution term for the product types because there is no replication of products, just the transformation of already existing products. Instead, products of type *i* are lost as they are transformed into the next product type in the cycle,

[5] These chains of transformations are not included in Equations 2 and 3 but the versions of the equations with the chaining terms included appear in Appendix 2A. Our analysis here does not address this expanded form for several reasons. First, it is standard practice to ignore these higher order terms in chemical kinetics because the law of mass action renders them inconsequential. They are relatively rare and the terms for each rule/molecule type often cancel each other out. However, our main justification for omitting them is that our analysis of them showed the dynamics to be, for all intents and purposes, identical.

i+1. Thus the second, loss term is equal to the growth term of the next product type. This yields equation 3a.

$$\dot{p_i} = r_{i-1}p_{i-1}(1 - r_i) - r_i p_i(1 - r_{i+1}) \tag{3a}$$

The coupled nature of equations 2 and 3a introduces feedback between the populations of rule types and product types, but the strength of the feedback depends on the relative size of the populations because each transformation is applied to a single product. Thus, if the population of products consists of a single product, the probability of each transformation would always be either zero or one. If the population were infinite, however, a single transformation would have no effect on probabilities of replication or transformation events. One way to think about the relationship between the environment and the strength of feedback is as the ratio between the number of rule instances and the number of product instances. If there are twice as many products as rules, the feedback will necessarily be less for each transformation. However, differential equations do not count discrete units, just the percentages of the total population. Thus equations 2 and 3a assume a ratio of 1 if the rule and product concentrations are defined in terms of independent populations. But because we are interested in the effects of the endogenous structuring of the environment, we need an expression that allows for the control of the amount of feedback from the environment. We accomplish this with the introduction of a *capacity* factor *C*. This factor effectively controls the ratio of rules to products, but can be more directly thought of as the *capacity* of rules to alter the environment. The larger the capacity, the larger the impact on the population of product types and the larger the corresponding change in the probabilities of finding suitable product types. Thus, a larger capacity is associated with stronger feedback. The addition of the capacity factor *C* results in equation 3b. Equation 2 remains unaltered. The dynamics of these coupled differential equations correspond to an aspatial hypercycle model in which individuals with skills alter inputs into outputs usable by others. For related specifications, see Appendix 2B. We now turn to the stability analysis of the system defined by equations 2 and 3b.

$$\dot{p_i} = r_{i-1}Cp_{i-1}(1 - r_i) - r_i C p_i(1 - r_{i+1}) \tag{3b}$$

Stability Analysis of the Niche Constructing Hypercycle

The niche constructing hypercycle equations may be tractable for a formal approach to stability analysis, but given that our primary goal is illustrating the power of the niche construction mechanism, we use a numerical approach instead. Figure 2.3 shows the solution curves for N = 10, 15, and 25 and for capacity factor $C = 1$, 2, and 4. All products start as type p_1. Figure 2.4 shows the projection of the trajectory from the N-dimensional space onto the $r_1$and r_2-plane. These two figures make it clear that the niche-constructing hypercycle model supports the emergence of significantly more complex (i.e. long) hypercycles than the original model does. The curves in Figure 2.3 correspond to the concentrations of rule types and exhibit a sinusoidal form with decreasing amplitude, suggesting each rule type is orbiting around the equilibrium fixed point of all concentrations being equal to 1/N. Examples of these orbits can more readily be seen in Figure 2.4. This strongly suggests this version of the hypercycle is stable for all values of N analyzed. While the analysis of yet larger N is possible, a hypercycle of length 25 is already very complex and evidence of its stability is ample ground for concluding the niche construction mechanism significantly alters the prospects for self-organization, even when the system starts from a state of being dominated by one rule type and has only a single product type.

Figures 2.3 and 2.4 also make clear that the rules' capacity to alter the environment can speed the time to convergence, but in principle does not alter the stability of the system. However, various concentrations can approach zero before beginning to converge and this would likely presents an issue in a stochastic version of the system. Small and random accumulations of errors could easily completely extinguish a rule type and therefore kill the hypercycle. (Koopman et al (Koopman et al. 2002) argue all stochastic systems will die off given enough time).

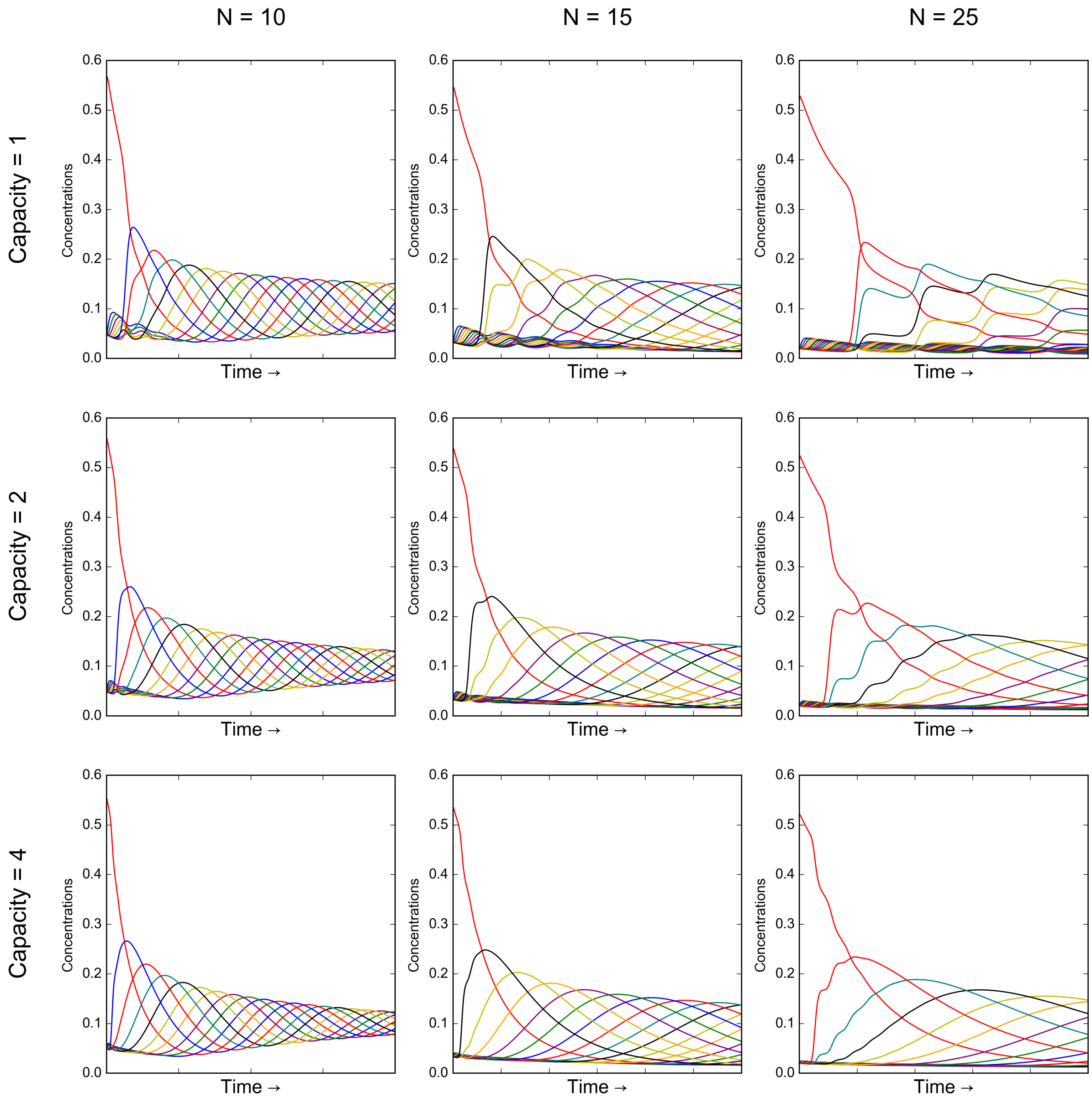

Figure 2.3. Niche Constructing Solution Curves. The columns correspond to N=10, 15 and 25, left to right, and the rows correspond to capacity factors C = 1, 2, and 4, from top to bottom. The initial conditions for each simulation allowed the first rule type to dominate; r_1 was equal to .55, .533, and .52 for N=10, 15, and 25, respectively. The remaining types had equal concentrations. The graphs make clear that the niche constructing hypercycle has stable equilibrium points for high values of N and that increasing the capacity speeds the rate at which the system converges to the equilibrium.

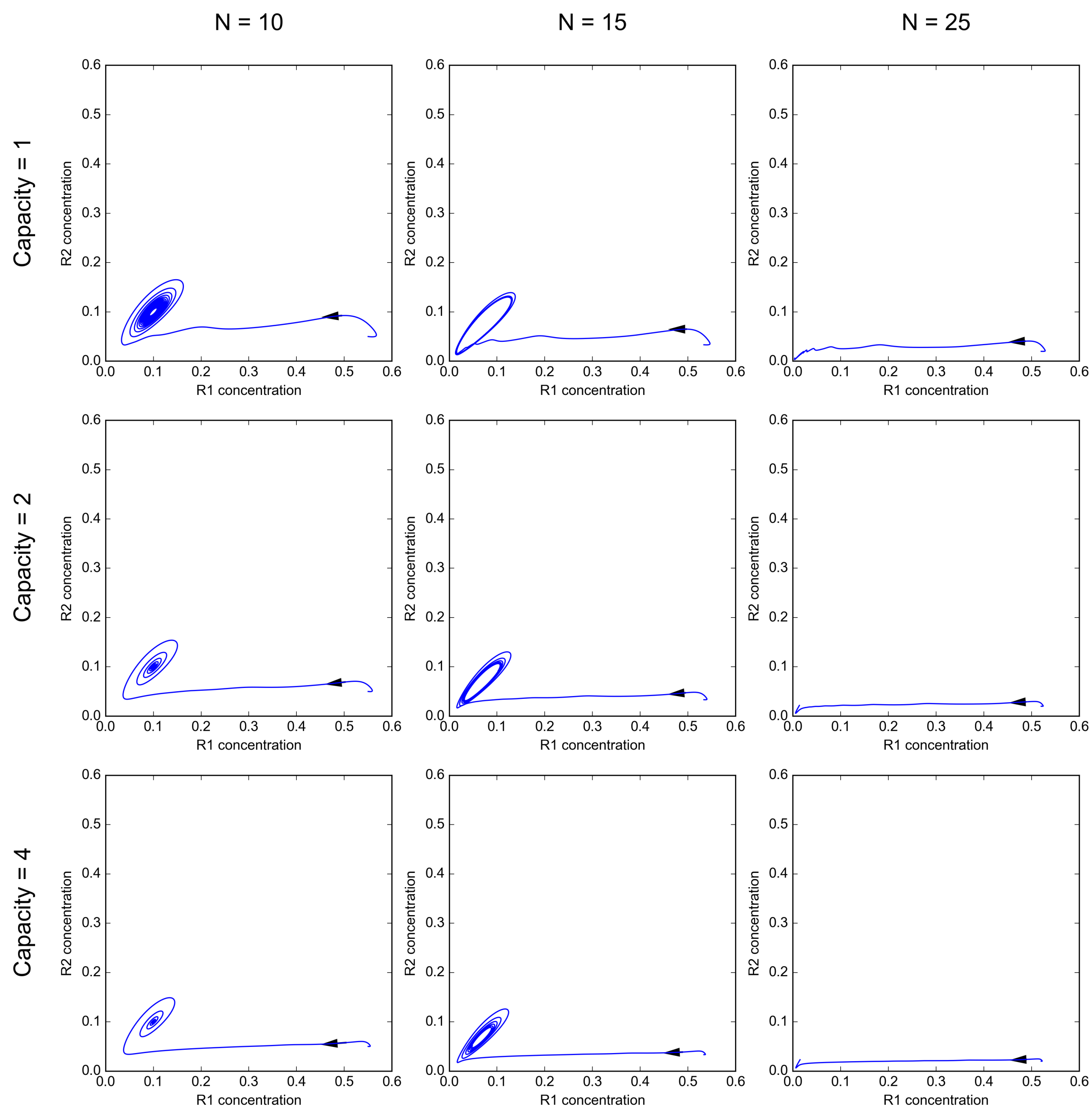

Figure 2.4. Trajectory Projections for Niche Constructing Hypercycle. The columns correspond to N=10, 15 and 25, left to right, and the rows correspond to capacity factors C = 1, 2, and 4, from top to bottom. The initial conditions for each simulation allowed the first rule type to dominate; r_1 was equal to .55, .533, and .52 for N=10, 15, and 25, respectively. The remaining types had equal concentrations. Each plot is the projection of the trajectory through the N-dimension space onto the r_1 and r_2-plane. This view makes clear the concentrations are converging to parity. Each trajectory spirals in the equilibrium point. Nota Bene: The trajectories in column two (N=15) are truncated and have not reached a stationary orbit. Were the trajectories to be calculated for a sufficiently large number of time steps, the orbits would become filled in.

This is the same argument made against the relevance of Hofbauer and Sigmund's finding that the original hypercycle is in fact permanent for all N, meaning no concentration reaches zero.

The small distances from zero make the system too vulnerable to consider it alive. The same might be said of niche constructing hypercycle, but this problem is attenuated as the capacity factor is increased. The greater the ability of the rules to alter the environment, the less time it takes for the corrective feedback to kick in. This helps ensure the system maintains a safe distance from the boundary as it begins to converge toward the equilibrium point. Thus, while the capacity factor does not influence the dynamics in the deterministic system, it is more likely to play an important role in any stochastic version of it.

The above analysis is for the version of the system in which a rule is replicated when its own transformation of a product leads to a successful interaction with another rule. In the original model, it is the receiving rule, not the sending rule that is replicated after a successful interaction. This choice is supported by a straightforward interpretation of autocatalytic chemistry, but is less plausible in social settings. This is fortunate because the niche-constructing hypercycle is fundamentally unstable when it is the receiving rule that is replicated. It does not support a cycle of even length 2. The reason for this is straightforward, although not necessarily obvious. Because the vast majority of transformations are not followed by pass to a compatible rule type, products are often being returned to the environment in a transformed state without any replication occurring. This quickly leads to a flattening of the distribution of product types, but little change in the distribution of rules. Replications only start to occur when rules of the *n*-th type start finding products of the *n*-th type. Those rules transform the product and succeed in passing it to the very abundant type-1 rules. This leads to the replication of type-1 rules, which maintains that type's advantage and increases the selection pressure on the other rule types. One rule type inevitably dies off and the hypercycle fails. This does not happen when it is the sending rule that is replicated because the replication of the *n*-th rule type creates selection pressure on the type-1 rule population. This reduction in selection pressure apparently leaves enough of a window for other rule types to grow in number and begin to stabilize.

Our stability analysis only looks at rule types. As the preceding paragraph suggests, the dynamics of the product concentrations can be interesting, but the form of equation 3b precludes the need to consider the property of stability. The concentration of a product type can reach zero will no ill effects. Furthermore, the concentration can never be less than zero. The former is true because products originate as another type and the new type need not currently exist for the transformation to take place. The latter is true because the only way the concentration of a product type is reduced is if one is transformed into the next type. Such transformations necessarily cease to happen when the population is zero. So while the dynamics of the product concentrations are integral to the stability of the hypercycle, there is no need to directly analyze the stability of this population.

Discussion

The stability of the niche constructing hypercycle is based in the feedback induced by having a malleable environment. The need to find suitable products to transform naturally limits the replication of recently successful rule types, as their success has ensured fewer of those products are available. And as the concentrations of products shift to types further along the cycle, the related rule types become more likely to replicate. Said another way, the peaks in the product concentrations are always one step ahead of the peaks in rule types. This is because unsuccessful passes result in the transformed product being returned to the environment, allowing that product concentration to build up before the related rule concentration does. The overall effect is a dampening of the selective pressures on vulnerable rule types (i.e. those with low concentrations).

While exploratory in nature, these results suggest that human's capacity to alter our environments could be an important factor in explaining the complexity of our species' social organization relative to other species. This is not an uncommon perspective (Atwell and Savit 2016; Boyd et al. 2011; Odling-Smee et al. 2003; Pinker 2010; Savit, Riolo, and Riolo 2013; Taylor 2004), but by wedding the niche construction mechanism to the hypercycle framework, we have explicated a framework that excels at accounting for the stability of novel networks of interdependencies. Furthermore, it offers a new explanation for why innovative industries tend to take hold in geographically bounded regions. Instead of benefiting from "network spillovers" between skilled individuals, the construction of a niche of alters the selection pressures in ways that maintains and even supports the growth of a diverse set of interdependent skills. Thus, it is less that social distances are lessened by geographical propinquity, but that important information about the relative value of skills is conveyed through a common and dynamic pool of resources. This informational pathway appears to play an important role in processes of self-organization independent of the physical space in which it is necessarily embedded. Indeed, in conjunction with previous research, our study of the niche construction mechanism in isolation suggests that the spatial extension of it only weakens its effects. This interaction and others that may arise with it merit more analysis and our ongoing work explores such interactions.

Conclusion

The hypercycle model has been lauded as an "information integrator" that allows for the emergence of wholes with complex interdependences in settings otherwise too noisy for self-organization. This capacity, however, is limited to a relatively small number of interdependences. This number can be increased somewhat by spatializing the model, but this paper instead models the endogenous formation of the product environment, a process referred to as niche construction in the literature on evolution. By coupling the population dynamics of the rule types to the dynamics of the product types, a powerful feedback mechanism emerges. The addition of this feedback supports the emergence of significantly more complex interdependencies (up to at least 25 rules types), including when the process begins with the products all of the same type and a single rule type dominates the population. Even with such unfavorable conditions, the rule types converge to the stable equilibrium point. The addition of a capacity factor, a measure of the rules' ability to alter the common product environment, can speed the convergence and protect the system against random disturbances. Taken together, these results show the potential of the niche construction process to be a powerful aid to the self-organization of interdependent elements. We analyzed a simple model for analytical purchase, but in practice this mechanism would operate alongside others and this paper is meant only as an exercise to highlight its potential.

Should a niche construction mechanism prove operant in social life, it would provide an account of the importance of geography in economic life different than the prevailing "knowledge spillover" explanation (Funk 2014; Gertler 2003; Whittington, Owen-Smith, and Powell 2009). The structuring of the local environment itself would be instrumental to the process of creating complex networks of interaction by constraining any pathological growth of any single type of interaction. As suggested by the hypercycle equation's deep relationship to replicator dynamics, the niche construction mechanism links the fitness of species to a common resource environment. This creates more powerful feedback and is more sensible than just directly linking the fitness of the species because the productive capacity of skilled individuals is limited both by the other skills present and the resources necessary to apply the skills.

Appendix 2A: Extensive form of the Niche Constructing Hypercycle

A direct translation of the agent-based models that appear in the work of Padgett and collaborators would include chains of transformations. This is because when an agent successfully transforms a product, that agent attempts to pass it to another agent who can transform it again. If such an agent is found, the new agent receives the product, transforms it and then looks to pass it to another agent. This will continue until an agent fails to find an agent with a compatible rule type, at which point the product is returned to the environment.

The probability of chains of significant length occurring is very low. Indeed, in a system with 5 rule and product types, if the concentrations of both rules and products are balanced, the probability of a chain of only two transformations occurring is $r_i p_i r_{i+1} r_{i+2} = .2 * .2 * .2 * .2 = .0016$. The probability of a product making it around the cycle (i.e. from product type 1 to product type 5) is a little more than $1/16000$. Nonetheless, given there are enough agents in the system that even low probability events do occur, it is worth exploring the effect of accounting for chains contra the results from equations 2 and 3.

A binomial expansion makes it possible to reduce what would be an infinite number of possible chain lengths to a single term. Consider the probability that a rule of type r_i is replicated in a given time step after a series of transformations starting with a product of type p_{i-1}. For a system with 5 types, that is equal to sum of all the successful single step transformations, all the 5-step cycles ending that time step, all the 10-step cycles ending that time step and so on. For rule type r_1, this can be written as the following:

$$p_5 r_5 r_1 + p_5 r_5 r_1 r_2 r_3 r_4 r_5 r_1 + p_5 r_5 r_1 r_2 r_3 r_4 r_5 r_1 r_2 r_3 r_4 r_5 r_1 + \cdots$$

Thus:

$$\Pr(r_i \to 2r_i \mid p_{i-1}) = p_{i-1} r_{i-1} (r_i + \ r_i r_{i+1} r_{i+2} r_{i+1} r_{i+4} r_i + r_i r_{i+1}^2 r_{i+2}^2 r_{i+3}^2 r_{i+4}^2 r_i^2 + \cdots)$$

Factoring out the r_i, it becomes clear that all chains can be included by writing the expression as follows:

$$\Pr(r_i \to 2r_i \mid p_{i-1}) = p_{i-1}r_{i-1}r_i \left\{\sum_{i=0}^{\infty}[r_i r_{i+1} r_{i+2} r_{i+3} r_{i+4}]^i\right\}$$

By the binomial theorem, the infinite sum is equal to $1/[1 - r_i r_{i+1} r_{i+2} r_{i+3} r_{i+4}]$. Thus

$$\Pr(r_i \to 2r_i \mid p_{i-1}) = \frac{p_{i-1}r_{i-1}r_i}{1 - r_i r_{i+1} r_{i+2} r_{i+3} r_{i+4}}$$

This expression only accounts for chains starting with a product of p_{i-1}being removed from the environment and the full growth term for r_i needs to include chains originating with other product types. These terms are the same as above except for the addition of the partial cycles of transactions before it. Thus,

$$\Pr(r_i \to 2r_i \mid p_{i-2}) = \frac{p_{i-2}r_{i-2}r_{i-1}r_i}{1 - r_i r_{i+1} r_{i+2} r_{i+3} r_{i+4}}$$

The overall growth of rule type r_i is the sum of all these terms. Factoring out the common terms and adding the dilution flux term, the final growth rate of rule type r_i can be written as:

$$\dot{R}_i = \frac{R_i R_{i+1}}{1 - \prod_{j=1}^{N} R_j}\left(P_i + \sum_{k=1}^{N-1}\left[P_{i+k}\prod_{h=i+k}^{N-1+i} R_h\right]\right) - R_i\bar{f}$$

where,

$$\bar{f} = \sum_{i}^{N} \dot{R}_i$$

By similar logic, one can model the growth rate of product type p_i as the following:

$$\dot{P}_i = \frac{R_{i-1}(1-R_i)}{1 - \prod_{j=1}^{N} R_j}\left(P_{i-1} + \sum_{k=i}^{N-2+i}\left[P_k \prod_{h=k}^{N-2+i} R_h\right]\right) - \frac{R_i(1-R_{i+1})}{1 - \prod_{j=1}^{N} R_j}\left(P_i + \sum_{k=i+1}^{N-1+i}\left[P_k \prod_{h=k}^{N-1+i} R_h\right]\right)$$

Naturally the behavior of this system is dominated by the terms with the fewest number of interactions, that is, those terms that appear in equations 2 and 3. A side-by-side numerical analysis of the systems showed them to be nearly indistinguishable so for the sake of parsimony, we present the results of the analysis the simplified system.

Appendix 2B: Alternative Niche Constructing Hypercycles

In a testament to the detail with which Eigen and Schuster analyzed the hypercycle, they proposed a version that has important similarities with the niche constructing version presented in this paper (Eigen and Schuster 1978). Referred to as the hypercycle with translation model, it explicitly represents the translation of the RNA sequence of a given molecule into a catalytic protein. This protein can bind with a molecule of a different type and can then replicate that molecule. Importantly, however, that catalytic protein is not converted into something else in the process. It persists in the complex with RNA species it originally bonded with, possibly separating only later. Thus the translation process can create concentrations of catalytic molecules, but lacks the input-output dynamic we believe is important to the application of the hypercycle framework to social setting. Nonetheless, their analysis of the equations showed that hypercycles with translation allowed for slightly more complex hypercycles.

Another way of conceiving of an input-output hypercycle would be to ignore the requirement of finding another rule to transform a product for replication. Replication would simply occur after a successful transformation of the product and the newly transformed product would be immediately returned to the environment. The associated equations are S1 and S2. The solution curves and trajectories appear in figures S1 and S2. The results are qualitatively very similar to those presented in the body of the text.

$$\dot{r_i} = p_i r_i - p_i \sum_{j=0}^{n} p_j r_j \tag{S1}$$

$$\dot{p_i} = p_{i-1} r_{i-1} - p_i r_i \tag{S2}$$

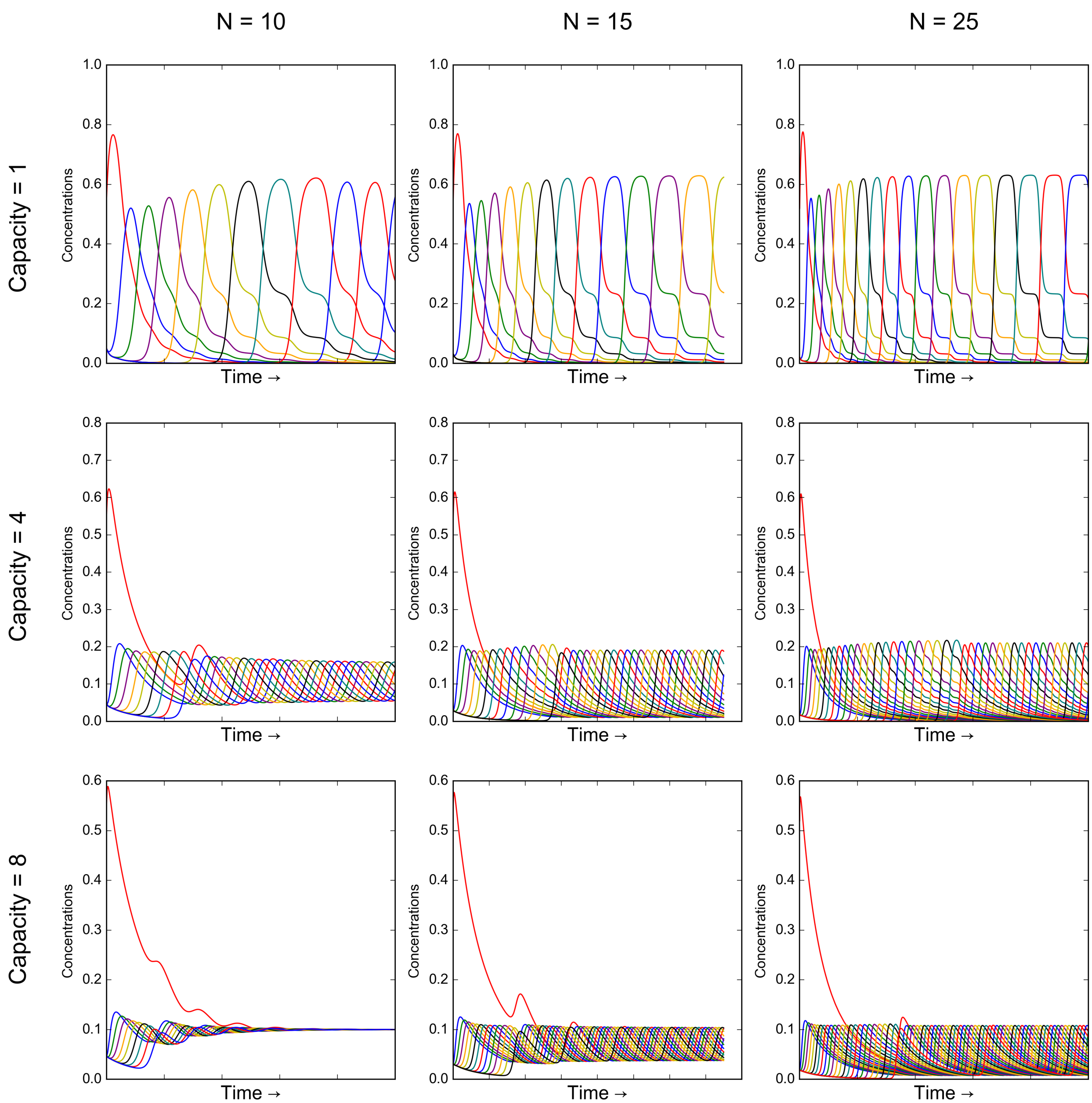

Figure 2.5: Solution Curves for the system defined by equations S1 and S2.

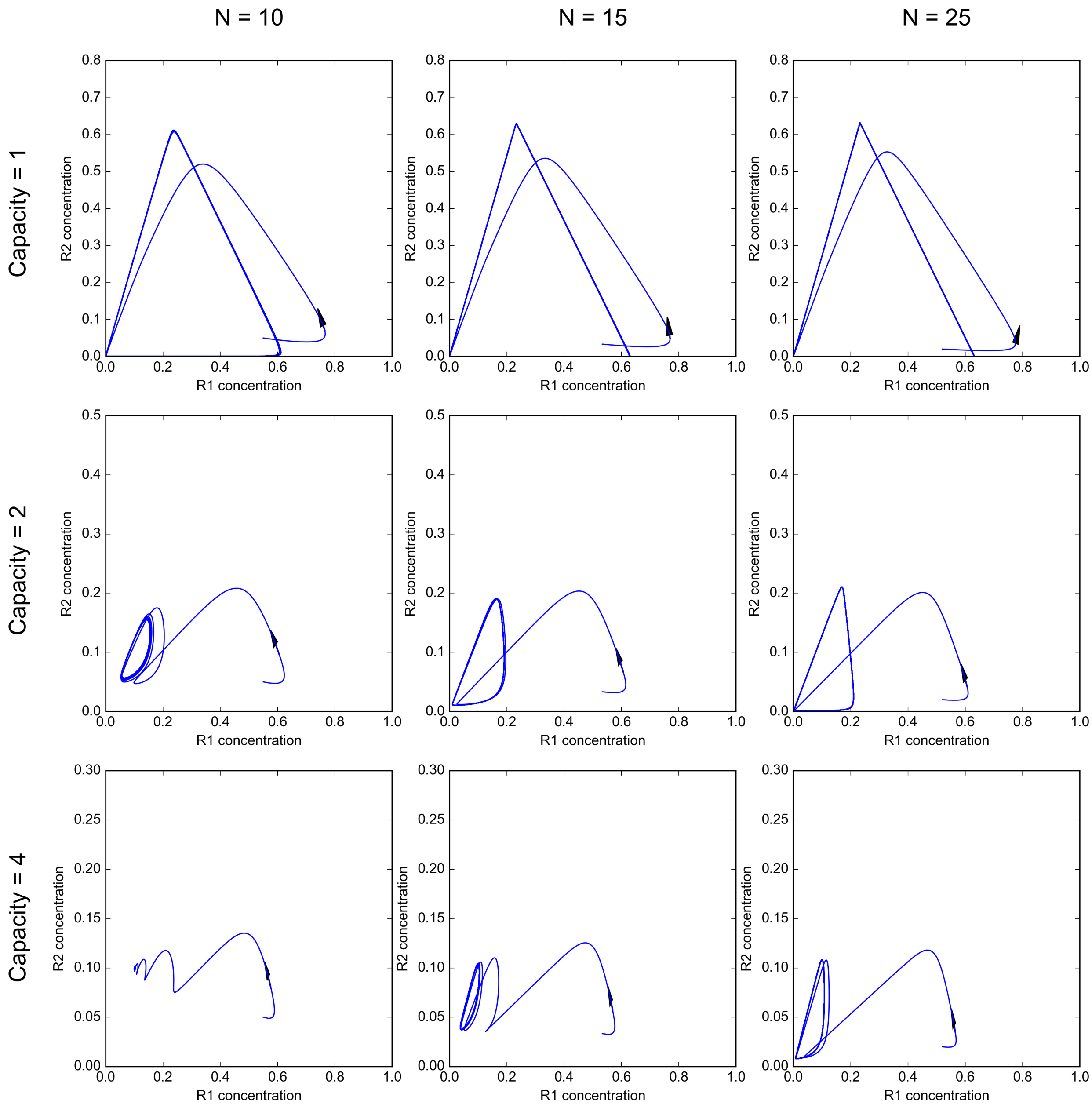

Figure 2.6: Trajectories for the system defined by equations S1 and S2.

Chapter 3: The Value of Niche Signals in Social Dynamics: An Experimental Study of Extra-Network Social Signals

Abstract

In addition to being embedded in social networks, individuals are embedded in physical space and, now, digital publics. These spaces are teeming with socially relevant signals actors can use to learn about broader patterns within the population. What is the informational value of such signals as they occur alongside those traversing social networks, a comparatively well-understood domain? This paper reports the results of a large group experimental design in which participants attempt to coordinate to create an arbitrary convention. Participants embedded in a variety of common network topologies are unable to reach a consensus convention when information can only flow through network ties. The addition of small number of signals across the public space, however, often leads to successful group-wide coordination. The number of such signals necessary for successful coordination depends crucially on the average path length of the network. This result corroborates views that material objects can be important to social and particularly cultural life and suggests such signals merit consideration alongside other sources of information in the study of group dynamics.

Introduction

Research on group dynamics and networks has transformed our understanding of social life, from how actors gain social advantages (Burt 1992; Gargiulo and Benassi 2000; Granovetter 1973; Mizruchi and Potts 1998; Nahapiet and Ghoshal 1998) and how groups perform in organizations (Cummings and Cross 2003; Lazer, Friedman, and Friedman 2007; Mason and Watts 2011; Reagans et al. 2001; Rulke et al. 2000; Sparrowe et al. 2001) to why behaviors are similar (Burt 1987; Friedkin 1984; Mizruchi 1993) , how behavior and information diffuses (Bakshy et al. 2011; Centola 2010; Watts and Dodds 2007) and how culture (Centola et al. 2017; Derex and Boyd 2016; Shaw 2015) and organizations (Padgett and Powell 2012) emerge. The cumulative results show that social networks condition what is possible for both individual members of a group and the emergent properties of the group as a whole. As is often explicit in this field of research, network structure is rarely itself a variable of interest. Rather, it is a useful way of tracking interactions that include exposures to something, most often signals that yield information. Information gained from interacting with network neighbors can drive individual behavior, and the heterogeneous patterns of interactions and exposures can determine the emergent group outcomes. Social network analysis excels at operationalizing this insight, but this network view of exposures and information does not track socially relevant signals from other sources.

The fields of media studies and mass communication analyze the ways visual and audio media influence the beliefs and behaviors of individuals and groups. From the perspective of social behavior, exposure to mass media is qualitatively different than within-network exposures; significantly more people are reached by the same signal, receivers can form expectations that others have received the signal as well, and the information can describe the state of the social system itself. The broad reach of broadcast mechanisms and its implications for behavior makes it appealing for media and marketing outlets. Expecting that others have received the same information can have important effects on more strategic behavior (Gintis 2009). Finally, when broadcasted information describes the aggregate state of the system, it can be a powerful determinant of behavior, as when economic data are used in making investment decisions or bandwagon effects (Nadeau, Cloutier, and Guay 1993). Recognizing the important qualitative differences between local, network signals and global, broadcast signals, researchers have studied the effects of combining them (Bass 1969; Goel et al. 2016).

The distinction between local and global information is important and well known but it is not a comprehensive typology of information sources in social life. This paper focuses on another type of information that can emanate from the traces found in a shared social environment of the activities or choices of others. These traces can be used to infer, consciously or not, the beliefs, knowledge, preferences and characteristics of other actors, whether the observer can positively identify the actors or not. Consider visiting an urban neighborhood to evaluate it as place to live; the counts and types of bicycles, for instance, one observes can yield relevant information about the values, income, or habits of the residents. Other objects such as motor vehicles, strollers, clothing, or landscaping might provide similar insights. These traces can be visual (including text), but are often auditory—overheard conversation or music—or olfactory—smells of tobacco or coffee. They might even include chance, unrepeated interactions. The potential informational value of these traces is not readily apparent[6]. In fact, unlike in the example of exploring new neighborhoods, we are most often navigating social environments in which we have extensive social networks that provide more direct information. When this is the case, such traces might appear to be just a weaker source of the same basic type of local information. However, this is often not the case because different social networks, or distant parts of the same network, can occupy the same public space, ensuring that many of the traces are produced by socially distant actors. Propinquity has long been known to be an important factor in social and industrial organization (Fujita, Krugman, and Venables 2001; Logan 2012; Voss 2007) and there is some research on the interplay between physical and network-social space (Browning et al. 2017; Whittington et al. 2009), but the importance of signals in public spaces for group dynamics has gone largely unstudied. I refer to these signals as niche signals*,* in reference to the idea of a constructed niche. However, public life is no longer exclusively physical because of the robust digital communities that exist today and this new social proximity outside of social networks needs to be acknowledged. Thus niche encompasses both physical and

[6] Several research programs highlight the importance of human and other objects in human affairs but do not explicitly pursue this as a matter of information. Material-semiotic approaches (Callon 1998; Latour 2005; Law and Mol 1995) seek to understand the importance of objects to the realm of ideas and concepts. Likewise, distributed cognition (Hutchins 1995) seeks to understand how cognition can be distributed across many individuals through the externalized products (objects) of cognition. The material culture tradition focuses on the rich cultural meanings and messages that can be embedded in objects (Tilly et al. 2006).

digitals spaces as necessary.

Niche signals are distinguishable from within-network signals by at least two features. First, they are relatively abundant and can be consumed with little engagement. This allows an observer to collect these signals and create semi-aggregate information about the state of some system with relative ease; one can learn a great deal about the incomes of a neighborhood by going down only a few streets and observing the models of the vehicles. Second, because these signals can come from socially distant actors, they can yield information about the broader state of the social setting otherwise difficult to ascertain; noting the food ordered by patrons—typically socially distant—can be a good way to learn about the strong points of a restaurant's menu. These features of niche signals do not make them generally relevant to understanding group processes, however. Relevance requires that human actors are in fact observing these stimuli, that observation can influence behavior, and finally that the behavior undertaken in light of observation affects the outcomes of group processes. While there is significant evidence that these stimuli are a regular part of human cognition and behavior (Call and Carpenter 2002; Heft et al. 2014; Hoppitt and Laland 2013; Rietveld and Kiverstein 2014; Withagen and van Wermeskerken 2010)—indeed, ecological psychology argues the *affordances* we attribute to stimuli in behavior settings are instrumental to cognition and action (Barker 1968; Gibson 1977)—its role in determining the emergent outcomes of group processes has not been studied.

To begin to understand the role, if any, such niche signals play in social life, this paper uses an experimental design to show they can alter at least one important class of group dynamics, the emergence of conventions. Conventions are the solutions to group coordination problems with the important feature that the solutions are arbitrary in the sense that an alternative could have worked as well (Lewis 1969; Marmor 2009; Young 1993). The particular solution matters much less than the fact that the vast majority of relevant actors is aware of and behave in accordance with the convention. Social life is rife with conventions, from core cognitive machinery like the words of a language to unimportant practices like "proper" use of silverware. As used here, arbitrariness does not mean that all potential solutions are equally as good and this fact might suggest groups should converge to superior alternatives, but any Nash equilibrium would do and even that likely requires unrealistic assumptions (Gintis 2009). In practice, groups select and lock into inferior conventions even when better alternatives are known, such as continued use of the imperial and US customary systems of measurement. An established convention creates shared expectations for behavior that disincentivizes deviation. This self-reinforcing feature of conventions makes them particularly durable and an important part of social and cultural life instead of just momentary states of an exploration of a problem space (Gintis 2009). It also suggests problems with conflicts of interest can in practice exhibit elements of conventionality in their solutions, as Bicchieri (Bicchieri 2006) argues is the case with social norms that curtail self-interested behavior at the expense of others. Thus the study of conventions is very much the study of how groups come to have shared expectations and mental representations, a core undergirding of culture and sociality more generally.

In spite of the importance of conventions and their relative analytical simplicity, the group dynamics, and more specifically the patterns of information exposures, leading to their spontaneous emergence are only very recently starting to be studied. Conventions can of course be established by top-down mechanisms such as the coordinated dissemination of aggregated information, authoritative fiat, or the implementation of rewards for coordination, but a significant number of conventions emerge without such support. Rather they emerge spontaneously from a bottom-up process of self-organization (Centola and Baronchelli 2015; Helbing et al. 2014; Steels 1995; Young 1993). Individuals observe the behavior of others and use this information to inform their future behavior, which others then observe. Whether or not this iterative process leads to all individuals exhibiting the same behavior depends on what individuals are able to observe and how they act on what they observe. This makes the process ripe for social network analysis and careful observation of behaviors, but, while online data sources can afford the opportunity to study networks and realistic behavior, it is immensely challenging to fully identify information exposures and therefore impute cognitive processes. A behavioral experiment, while sacrificing some realism, allows for full control over information exposures, and this paper builds on a model and design first proposed by Centola and Baronchelli (Centola and Baronchelli 2015).

The "Name Game" and Prior Results

Centola and Baronchelli (C&B) propose the "name game" as a large group behavioral experiment for studying the effect of network topology on the emergence of conventions. Participants embedded in a network interact as pairs of neighbors over many rounds and attempt to submit the same name for a pictured individual. The sheer number of possible names ensures the arbitrariness of solution to the coordination problem. Matching within the pair is rewarded and not matching is penalized. There is no direct incentive for global coordination, but, as is the case with real conventions, global coordination ensures beneficial local interactions. Group sizes varied from 24 to 96 participants[7] and three networks—a one-dimensional lattice of degree 4, a random graph with constant degree 4, and a fully-connected graph (i.e. homogeneous mixing)—were used as the primary treatments. Remarkably, the results showed a global convention emerged only in the homogeneous mixing treatment. In trials with the random and lattice networks, sub-global conventions emerged but a single alternative never won out.

This result confirms the importance of interaction topologies for group dynamics but begs the question of whether conventions can in fact be the result of self-organization. Homogeneous mixing is a mathematically pithy and sometimes-useful first order approximation of interactional processes, but it also undermines the very idea of social networks as providing meaningful structures for interaction. By itself the emergence of global conventions with homogeneous mixing might be an encouraging sign that it is possible on heterogeneously structured networks, but given the negative results for such networks, the homogeneous mixing case becomes an abstract case with little empirical value. Instead we are left wondering if conventions can in fact self-organize or if they necessarily require institutions or authorities to come into existence. Yet the success with homogeneous mixing does confirm that, given the suitable exposures to information about what others are doing, conventions can self-organize. The question I focus on in this article is: what types of exposures along side those resulting from being embedded in social networks can lead to successful self-organization? The following experiment shows niche signals in even small amounts can be sufficient.

Setup

To introduce niche signals into the "name game," the whole group is treated as if it occupies the same social (or even physical) space in spite of the social distances inherent to the social networks. Conceptualizing socially distant actors as being in the same space makes it

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[7] The boundary between small and large groups is not firm and depends on the setting (Levine and Moreland 1990). There is, however, considerable evidence that the outcomes of small group processes do not scale as the size of the group increases (Lowry et al. 2006; Wheelan 2009). While it seems wholly possible that there are more than two scales, the window between dozens and hundreds appears to be distinct from small groups (N<10).

plausible that participants would periodically be exposed to information about the behavior of others within the group at large. These exposures take the form of each participant being shown a name or two, depending on the treatment condition, played by any other group member that round. It is shown on the round's result page along with the name played by their partner. There is no information given regarding who played the name or whether it matched the name played by the respective playing partner. For each participant names are drawn at random without replacement and can include null values if the corresponding player failed to submit a valid name (See *Software and Subject Management Details* in the Supplemental Information for details on game play). Importantly, there is no direct benefit for matching any or all of these additional names and, furthermore, without the knowledge of the corresponding partner's behavior, the value of that name for coordination's sake is not knowable. It is merely a trace of socially relevant activity observers can process as they see fit.

Based on the finding in C&B that the size of the group did not have an effect on the outcome, all trials in this design were conducted using 24 participants. The design includes the three networks topologies in the original—a random network with constant degree 4, a circular lattice of degree 4, and the fully-connected network—but also includes as an additional factor a small world network created using the Watts-Strogatz algorithm (Watts and Strogatz 1998) initialized with the circular lattice of degree 4. Small world networks share important characteristics—local clustering and short characteristic path lengths—with real world social networks (Watts 1999), but as an interpolation between the lattice and random networks, a small world network would not have added anything to the analysis in the original experiment. However, the niche signals treatment factor in the present experiment interacts with network topology and makes the results for small world networks relevant.

The second factor of niche signaling has three conditions: participants may be exposed to no niche names, one such name, or two such names. The inclusion of the no-name condition replicates the original experiment and trials in this condition were done before the others to confirm the commensurability of the game interface in spite of minor design differences (see Model Details in the Supplement Information). Because the fully connected network produces global conventions without the addition of niche signals, no trials were conducted for the other conditions.

Results

The results of 32 trials of the full experiment appear in Table 3.1 below and show that exposures to niche signals can indeed make it possible for global conventions to emerge in spatial networks. The effect is partly dependent on the network topology. The fact that trials in the same treatment cell exhibit different outcomes indicates the presence of one or more additional factors, the details of which are discussed below. The larger pattern, however, shows a clear trend in the efficacy of niche signals as the network's average shortest path length, otherwise known as the characteristic path length, is decreasing.

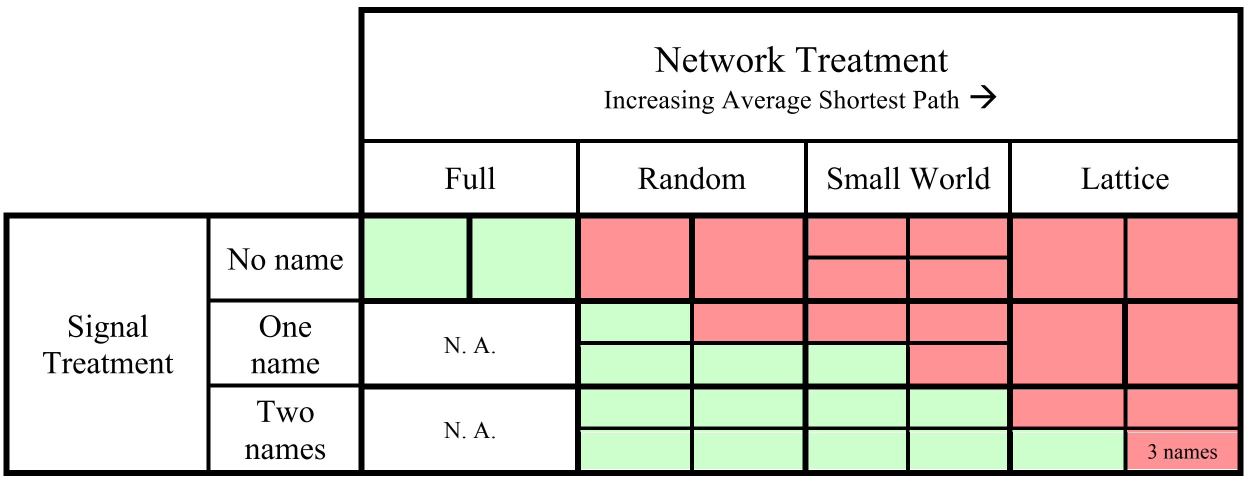

Table 3.1: Experiment Results: Each box in the cells of the table represents one trial of the experiment for the given treatment combination. If the box is green, a global convention emerged. If it is red, one did not. The size of the box does not indicate anything other than the fact that some conditions had fewer trials, because they were replicating the results in C&B or, in the case of the one-name lattice treatment, very unlikely to lead to a global convention. One of the trials for the lattice network exposed participants to three names. It is identified within the cell for the two-name treatment.

The average shortest path length (ASPL) is a measure that operationalizes the idea of social distance and is calculated by averaging all the shortest paths between all pairs of nodes. Fully connected networks have an ASPL of 1 and the circular lattice with degree 4 has an ASPL of 3.39. For comparison, the ASPL of the entire Facebook network was 3.57 as of 2016 (Bhagat et al. 2016). Because random and small world networks are ensembles of networks, there is not a precise ASPL for the topology. The average for the networks used in the trials had ASPLs of

2.34 and 2.51, respectively. The relationship between ASPL and niche signals is sensible in light of both research on the diffusion of information and the results in C&B. Because lower ASPLs correspond to ease of diffusion (Lazer et al. 2007; Watts 1999; Yamaguchi 1994), we would expect the fully-connected network (i.e. homogeneous mixing) to have a higher success rate for the emergence of global conventions. The addition of niche signals can help overcome the deficiencies of topologies with longer ASPLs in regards to the circulation of information, but the amount necessary is proportional to the lengths of the average shortest paths.

Average shortest path length cannot be the only factor mediating the effect of niche signals, however, because one of the crucial features of small world networks is that the ASPL is comparable to that of random networks of the same size and average degree, yet it appears that more niche signals are required for a global convention to reliably emerge for small world networks. This is because of the high local clustering characteristic of small worlds. In virtue of the higher rate of closure among triads, local clustering is associated with successful local coordination. However, local coordination often comes at the expense of global coordination because the tacit benefits of global coordination are not enough to overcome the immediate benefits of maintaining local coordination.

In addition to ASPL and clustering, there at least two more factors influencing outcomes. Separable from the overall network topology is the exact sequence of partner pairings (e.g. exposures). Pairings are randomized throughout the 25 rounds of play but the same for each distinct network within the broader topology (see Networks in the Supplemental Information). The sequence of pairings engendered by the exact network is a likely explanation for the presence of both potential outcomes within the same treatment cell. The other potential explanation is participant skill or naiveté. While not formally tracked, the suitability of participants' responses to available information varied, as would be the case in real social dynamics. Such suitability can be the result of mental faculty but also conscious strategies undertaken with the knowledge they are playing in a highly complex environment. Indeed, some participants appeared to intuit the value of anchoring behavior (i.e. being unresponsive to the choices of others), which can foster local coordination, but extreme commitment to this strategy by multiple participants would necessarily prevent the emergence of global conventions.

Group Dynamics of Emergence

The temporal dynamics underlying the above outcomes bifurcates within the first several rounds, as can be seen in Figure 3.1. The successful emergence of a global convention features the rapid winnowing of the number of alternatives in circulation in the first third of the rounds and then the more gradual elimination of all but one. However, the second stage does not necessary follow from the first. Failure to quickly reduce the number of alternatives in circulation ensures no global convention will emerge, but success in the first stage does not guarantee success in the second stage. This importance of the number of names still in circulation is somewhat at odds—but not inconsistent—with the analysis of the dynamics presented in C&B. That analysis found that failure in early rounds to coordinate locally (i.e. low rate of partner matches) was the basis for future global coordination, as a single alternative won out more gradually. Conversely, success in the early rounds lead to protracted competition among robust alternatives. This remains the case in the no-name treatments and can be seen in the first row of Fig 3.1. But in the one- and two-name treatments, early failure is not a prerequisite for eventual global coordination. Rather, there is a unique combination of a low coordination success rate and, yet, a rapid reduction of the number of alternatives in circulation in the homogeneous mixing treatment. The trials for the lattice treatment exhibited high levels of local success early on, but not a suitable diminution of the number of alternatives to overcome the propensity toward entrenched competition. Trials with the random network treatment had low success rates, but a large number of names remained in circulation deep into the rounds.

The addition of niche names, however, allowed for quick reduction in the number of alternatives to be paired with a robust level of local success. In the homogeneous mixing treatment, the rate of local success is low in the beginning because of the low probability of repeat interactions, but a handful of names are nonetheless becoming popular within the population. In the spatial networks, a higher probability of repeat interactions often facilitates local success, but it is in only the niche signal treatments that the number of names in circulation can also be quickly dropping. This reduction is necessary but not sufficient for a global convention to emerge. Once only a few names are in circulation, the chance of convergence to a single name depends on the rate of local success.

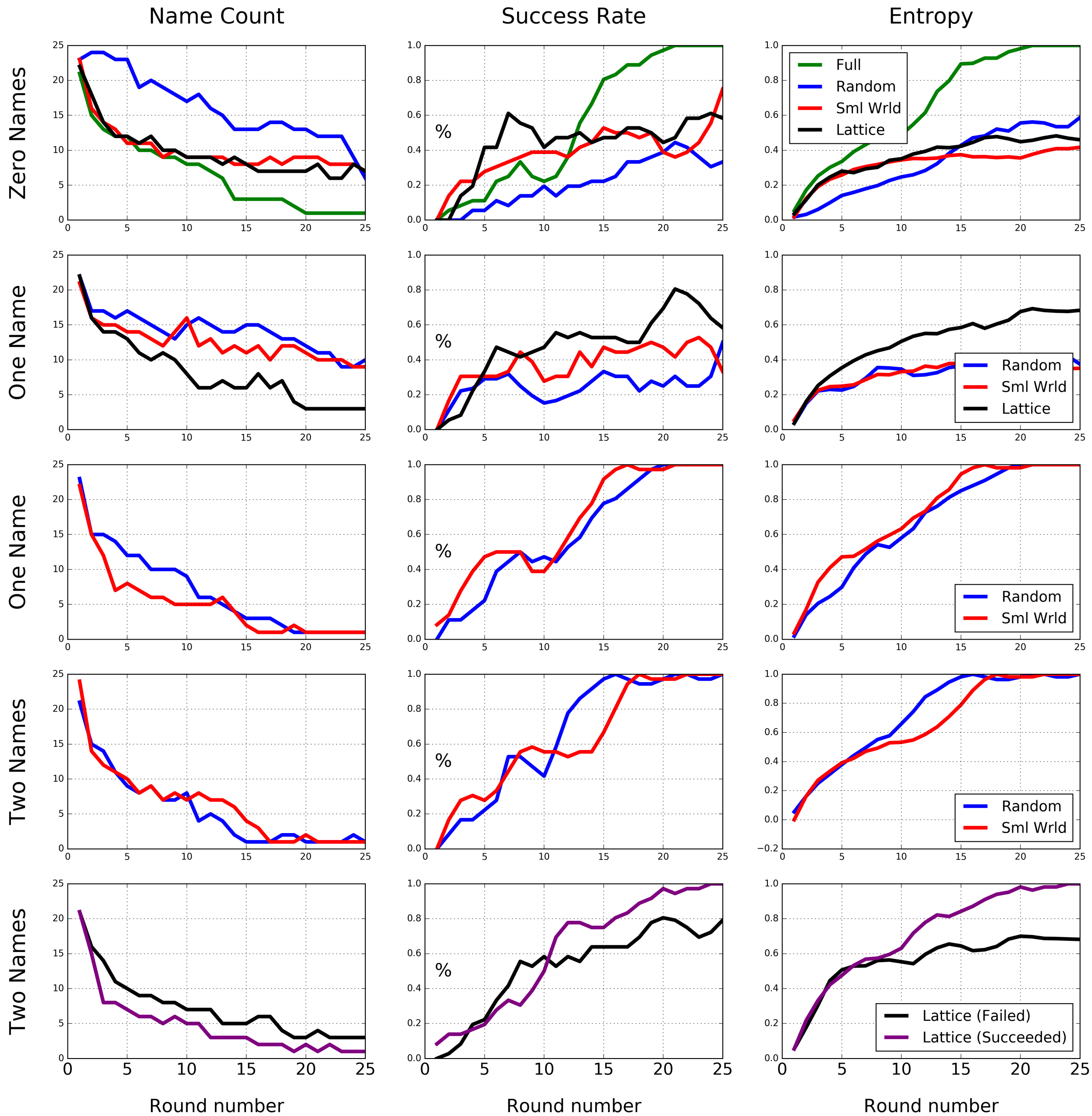

Figure 3.1. Example Dynamics: Examples of dynamics leading to global conventions and not. Column one shows the number of names in circulation in a given round. Being in circulation is defined as having already been played (participants occasionally submit new names after the first round) and will be played in the present or a future round. This definition accommodates the fact that participants alternate names between rounds and names can reappear in spite of not occurring in the present round. Column two shows the success rate, the fraction of partners who successfully coordinated, as a 3-value moving mean. The third column shows the normalized entropy of the distribution of names to highlight trials in which very few names are in circulation, but they are relatively balanced in their number of occurrences. Each row displays the time series for the name count, success rate and entropy for a

number of trials. The network treatments for the row are identified in the legend in the third column. The respective trial is the same for each panel in the row. The niche signals treatment is identified to the left of the row.

High rates of success in the middle rounds means clusters within the network are converging toward different alternatives, which can compete indefinitely. A lower rate of success, however, suggests participants are still exploring and will ultimately push the group toward a global convention. This reflects the logic described in C&B, but it appears in the second stage of the process instead of the beginning. The higher the clustering in the network, the fewer names in circulation and the more experimenting in the middle rounds are needed for the group to converge on a single name. The exposure to niche names can both rapidly drive down the number of names in circulation, presumably by making participants more aware of and amplifying nascent patterns in the names, and by maintaining the exposures necessary to give participants the ability to continue to explore. The latter is dependent on the former because fewer names make exploration more effective.

Discussion

The above results demonstrate that the addition of niche signals can help engender the behavior required for conventions to emerge in groups embedded in spatial networks that otherwise inhibit such emergence. This suggests that when conventions are the result of bottom-up self-organization, the diffusion of information via niche signals is a necessary, albeit not sufficient, condition. The clustering natural to social networks defines the dynamics and outcomes of group processes (Browning, Feinberg, and Dietz 2004; Fang et al. 2010; Lazer et al. 2007; Mason and Watts 2011; Mizruchi and Potts 1998; Shaw 2015; Uzzi and Spiro 2005) but the availability of niche signals can alter these processes. Furthermore, surprisingly few niche signals are required; knowing what a small fraction of the whole population is doing can be sufficient to tip the group dynamics toward successful coordination.

As a problem of coordination, the creation of conventions is particularly challenging because of the size of the groups and the number of possible solution. These features however are distinct from challenges present in competitive and other non-cooperative large group settings, so it is far from clear what impact niche signals might have in those situations. Processes in which sub-group differentiation is desirable are likely to be affected, but when benefits are more localized and there are little in the way of network externalities—as in the case in a variety of types of strategic interaction—the chances of an effect seem lower. Nonetheless, a great deal of social life requires coordination across large groups and the effects exhibited in this experiment merit exploring the effects of niche signals in empirical settings.

The ability of niche signals to effectively shorten social distances raises the question of whether more network ties could have the same effect. One reason this might not be the case is that niche signals have a distinctive structure to them; as currently operationalized, it is a remarkable tool for understanding the state of the whole system because the probability of seeing a name in any given round is directly proportional to its frequency in the population. If more structure is introduced such that individuals are repeatedly sampled from the same regions of the system, the informational value of niche signals would likely decline. In the world, of course, there is more structure to niche signals than what was implemented in this experiment; the addition of such structure would likely resemble ecological networks, which map standard social network and their spatial loci into a bipartite network of social and physical space (Browning et al. 2017; Browning and Soller 2014). Whether more realistic patterns in propinquity would alter the observed results is a valid and open question.

Conclusion

In addition to being embedded in social network space, we are embedded in physical and digital space. Those spaces often contain the traces of the socially relevant behavior of others. Those niche signals are a potential source of information that has largely been neglected, but the experimental evidence presented here shows it can alter group dynamics in important ways. Particularly in settings involving the coordination of behavior, the high degree of clustering common in social networks inhibits the self-organization of coordinated behavior, but the addition of a small number of niche signals can be enough to tip the group toward coordinated behavior. This suggests these signals might play important roles in social dynamics more broadly in virtue of their ability to disseminate information widely without the costs of broadcast mechanisms.

Appendix 3A: Supporting Information

Subject Recruitment

All subjects were recruited through Amazon's Mechanical Turk marketplace. This platform enables the recruitment of workers to complete online tasks and has been validated as source of subjects for a wide range of behavioral experiments (Casler, Bickel, and Hackett 2013; Crump, McDonnell, and Gureckis 2013; Hauser and Schwarz 2016; Mason and Suri 2012; Paolacci and Chandler 2014; Rand 2012; Shank 2016). To build the subject pool, any worker with a reasonably healthy history of work on Mturk was offered compensation to complete a short training module and take a comprehension test. The task paid well for the amount of time it took so it was easy to recruit workers into the subject pool. This initial interaction familiarized subjects with the interface and game structure, but also satisfied Mturk's requirements for uniquely identifying and communicating with the worker in the future. This allowed the creation of a well-defined subject pool and the gaining of control over which workers were permitted to join live sessions of the experiment. The day before a scheduled trial, a number of subject pool members were invited to play. Following the recommendation of Mason and Suri (Mason and Suri 2012), roughly four times as many pool members were invited than was necessary to run the experiment. Those invitees were contacted shortly before the scheduled game as a reminder and again at the start of each session in order to provide a link to the interface.

The subject pool included slightly more than 300 members at any given time, as members were removed periodically for being unresponsive to invites and then replaced. Pool members were allowed to complete up to five sessions; the average number of completed sessions was 2.95, with an average of 20 days between sessions. For each game a list of invitees was created from this pool using the following criteria: No participants from the last session can be included; those who were recently invited but did not complete a session receive the highest priority; those who have yet to be invited get the next highest priority; those who have been invited but have not played get the next highest priority; for the remaining pool members, priority is less than the previous categories and inversely related to how recently they completed a session. If ever a set of members of equal priority was larger than what is necessary to create the list of invitees, the correct number of members was added by sampling uniform at random from that set. The above procedure was repeated until no more than four participants who completed the same previous session were included.

Game Play Details

The game interface was created using the oTree, an open source python platform for experiments (Chen, Schonger, and Wickens 2016). As participants arrive for a session, they are shown a brief description of the task and the IRB statement of risk (Exempt-status). If they accept the task, they are shown the game instructions, which include a small comprehension test. Next, they must agree to not use means outside of the interface to attempt to coordinate. This is largely an attempt to induce guilt if necessary because the real controls against such attempts are built into the software (see Software and Subject Management Details). Once they agree, they are taken to a waiting page until enough participants arrive. Subjects are paid one cent for every five seconds of waiting and are shown how long they have been waiting and their bonus for that time. This greatly increases the retention of subjects and their satisfaction with the task and compensation, which is crucial for maintaining a responsive pool.

Once enough subjects have arrived, the game begins. Participants are shown a picture of a headshot of a younger woman and are asked to submit a name for the pictured woman. Participants have 15 seconds to submit a name and failure to do so in that time results their submission as being recorded a null. Fig S1 is an example of this submission page. After everyone has submitted, the results are displayed. This differs from the design in C&B, which allowed for an asynchronous progression through rounds. While it seems unlikely to make a difference, synchronizing the rounds was necessary in this design because two treatment factors required sampling from all names played in a round. To maintain commensurability between all treatment factors, rounds were synchronized for all treatments, a choice that ultimately did not have an effect.

Partners who successfully coordinated earn $0.10. Partners who did not coordinate are penalized $0.05, unless their current cumulative total is already $0.00. The results page always shows the name both partners played, whether they matched, the amount of the reward or penalty, their current cumulative rewards and their history of successes or failures through the previous rounds (but that the names associated with those successes or failures). In the treatments where it was applicable, additional names where displayed. Fig S2 is an example of the results page. This page times out after 10 seconds. The submission and results page constitute of round of play. There are 25 such rounds in each session. After the 25 rounds, if applicable, participants were ask if they thought the appearance of the random names influenced their choice of names to use with partners. The final page reported the participant's final earnings, broken down into base pay, waiting bonus and game bonuses, and offered the opportunity to leave feedback.

Software and Subject Management Details

In order to ensure the subjects' experience corresponded to the ideal experiment and that the experiment is internally valid, there are a number of important details to the design of the software and management of subjects. Most of these features described below were added after reviewing data from trial runs of the experiments and research on the experience from the perspective of the workers done through direct (and compensated) correspondence and reviewing forums that host robust communities related to working on Mturk (e.g. MturkNation, TurkerHub, Reddit).

In general, workers on Mturk are interested in participating in academic research but not at rates lower than they typically earn. In fact, because a new academic researcher lacks a good reputation (see Turkopticon) and presents a risk to workers, a premium on the typical rate can be necessary to ensure data quality, especially if the task takes more than a couple minutes. The modal worker is not doing tasks for entertainment, but rather to supplement income (Ipeirotis 2010; Paolacci, Chandler, and Ipeirotis 2010).This makes them sensitive to the effective hourly wage, and, although there is variability in their reservation wages, most workers seem to have the federal minimum wage in mind. Because most choose to accept a task based on a rough calculation of the effective hourly wage, any misrepresentations of estimated earnings or time to completion are likely to provoke ire.

Importantly, because workers think in terms of an effective hourly wage, the compensation structure of the experiment needs to correspond to the workers' *overall* incentive structure in the Mturk marketplace. In particular, a significant portion of the overall payment must be guaranteed for the completion of the task. Workers always have the opportunity to quit the current task and start a different one and therefore are often aware of a changing opportunity costs. If the task progresses slowly or bonus earnings appear lower than expected or advertised, a small guaranteed payment might lead them to exit the task in spite of already having sunk costs. It is important then that the opportunity costs at any given stage of the game are less than the subjects' reservation wage. In practice this means the guaranteed payment should be large relative to potential bonus earnings and idle time should be additionally compensated. The former incentive structure generally corresponds to rational behavior in regards to opportunity costs, but furthermore does not appear to undermine the ability of within game incentives to "induce preferences" in the sense of Smith (Smith 1976); once the guaranteed payment meets the reservation wage, in-game bonuses become an exciting opportunity to exceed the worker's earnings goal and workers try in earnest to maximize bonus earnings.

The compensation of idle time should in principle not be necessary if that time is included in the estimate of the time necessary to complete the whole task, but workers generally view idle time as distinct from time spent on the task, likely because the experience of waiting makes them more aware of opportunity costs. Casual experimentation led to an idle-time compensation structure that delivered an effective hourly wage close to the prevailing reservation wage and was broken into small increments. Paying one cent for every five seconds of waiting ensured a wage of $7.20/hour and that any amount of what could be perceived as "unpaid" time was very small. Additionally, live tracking of the elapsed time and accrued bonus on the wait page created a gratifying experience for workers of being able to watch earnings grow.

A complication of this overall compensation structure is that it is more challenging to implement a "show-up" payment often used with traditional subject pools. Ensuring that the required 24 subjects are available requires over-recruiting and even carefully monitoring arrivals and immediately removing the task from the Mturk listings once enough accept still often results in subjects in excess of 24. The Mturk platform does not allow people to be turned away once the task has been accepted, but one can ask workers to "return" the task. Unfortunately this precludes being able to compensate them through the normal means, requires them to trust you to follow up, and generally risks upsetting them. Furthermore, given that workers have been personally invited and have been watching for an email to start the task, sending them off with a smaller show up fee might harm their responsiveness to future invitations. While it increased costs, the best long-term solution was for subjects in excess of 24 to play a version of the game against a network of bots designed to make moderately intelligent choices. None of those subjects ever gave any indication they knew they were not doing the real task (although interestingly, some playing live participants commented that they thought they were playing bots). Subjects who played against bots were paid what they earned and were later dropped from the analysis.

Once subjects joined a session (after having read a brief description of the task and the IRB statement), they were shown the game instructions. This page had a comprehension task built in; rather than clicking a standard button to advance to the next page, subjects were directed at the end of the instructions to click a button hidden as the text "match names with playing partners" where it first appeared in the instructions. Knowing to click these words and scanning for them reinforced the basic task of the game and ensured active engagement. Roughly 10% of would-be subjects never made it passed this stage, although it was not possible to tell if they left the game for other reasons. Any subject who did not pass this comprehension test was unable to join the game and was forced to return the task.

Those subjects who passed the instructions and comprehension page were then asking to agree to not attempt use means outside of the game's interface to coordinate. This is a real concern for a population that has a robust set of forums and chat rooms dedicated to its community. I describe the primary software and management mechanisms used to defeat such attempts below. By asking subjects to agree to not use external means of coordination, a very weak form of control, I hoped to make subjects think twice about engaging in such behavior, but more importantly, create grounds for removal from the subject pool if there was evidence of attempts to coordinate.

If subjects agreed to not use external means of coordination (all did), they were taken to a page to wait until enough subjects arrived. This page showed them the number of minutes and seconds they have been waiting and their compensation for that wait. Once 24 subjects made it to the wait page, the game began. The first page of each round displayed a headshot of a younger woman and a field to enter a name. An example of this page appears in Fig 3.2. (With only two exceptions, the picture was always a younger woman because pretesting showed that other demographics had some focal points; photographs of middle age and older men without distinctive characteristics often quickly elicited a handful of competing alternatives (e.g. Bob, Mike, and Bill). The same was true of older women (e.g. Janet, Susan, Patty). Pictures of younger women (roughly 25-45) elicited a broad range of first submissions.) Participants had 15 seconds to submit a name and were taken to a wait page until all participants submitted names. On the results page, participants were shown the name they submitted, the name their current partner played, and, where applicable, the other randomly submitted names. They were also explicitly told whether the names matched, their payoff for the round, their cumulative earnings and their history of matches and failures (but not the related names). This page timed out after 10 seconds, although participants could advance past it to a wait page. An example of this page appears in Fig 3.3.

After 25 rounds of game play, where applicable participants were asked if they thought the presence of the random names influenced their choice of names (True/False). The final page showed their total earnings and broken them down into the various parts. It also offered the opportunity to leave open-ended feedback. Payments were issued through the game interface after the data were reviewed.

As mentioned above, I took several measures to ensure there was no external collusion among the subjects. Together these measures address multiple potential means of collusion and work together to all-but-ensure it does not happen. First, as subjects arrived the related IP addresses are screened to make sure there is only one subject per address. The first subject to arrive from any address is allowed to remain, but all others are blocked from continuing, informed why, and asked to return the HIT. It is not uncommon for Mturk workers to work in the same household or workspace and while they might honestly avoid collusion, I aired on the side of caution and permitted only one. The more problematic case is a worker with multiple Mturk accounts. This is a violation of the Mturk Terms of Service agreement, but by their own admission on forums, some workers use multiple accounts. Those willing to ignore such rules might also try to use virtual private networks to use different IP addresses for each account, but they would have had to do that before arriving. Furthermore, in virtue of how invitation groups are chosen, the probability of two or more of their worker IDs being present in the same group is very low. This is because the experimenter controls which worker accounts receive an invitation to a game and have the necessary "qualification" for it. (A qualification is a virtual token within Amazon Mechanical Turk platform that can be used to control which workers can do which tasks.) Without an invitation and the requisite qualification, workers are unable to join a session.

I used qualifications to ensure that no more than 4 workers ever played the same session together. The final precaution I took to protect against *in vivo*–collusion was to make sure there was no relationship between arrival time and the location in the network; while small-scale efforts at collusion could be successful if those colluding are network neighbors, the nature of the game renders such efforts ineffective or possibility counterproductive if would-be colluders are not network neighbors.

Within the game itself, there are several features that undermine efforts at collusion. The first is actually just a basic design of the game; participants have only 15 seconds to submit a name. Failure to submit costs a participant rewards and can lead to expulsion from the game, a fact participants are reminded of every time they fail to submit. Given this time constraint participants typically submit immediately (~5 seconds). Even those who do not submit immediately have very little time to attempt to communicate with other participants about emerging patterns in the names. Timed submissions do nothing to protect against premeditated attempts at collusion, however. Given workers know the date and time of the game in advance, they might seek each other out on forums in advance and agree to use the same name. I have found no evidence of this on the forums I was able to gain access to (some have very high bars for admission), but I nonetheless added more comprehensive features to defeat such efforts. The primary means is a screening and blocking of names that exhibit surges in frequency. A name that appears for the first time with more than two instances is "blacklisted" for that round. It is not farfetched for the name "Sarah" to be the first submission for multiple participants, but, airing on the side of caution, my software barred any name that first appeared with three or more instances. When a name was barred, those submitting the name were told the name is blacklisted, but not why. Partners of those submitting the barred name were informed that their partner had not submitted a name, not that it had been barred. Multiple names could be barred in any given round, but the barred status is confined to that round only. If one or two instances of a previously barred name are submitted in a subsequent round, it is accepted without comment. This is because participants frequently exhibit the suboptimal behavior of introducing new names well into the game and there is no reason for barred these submissions (this behavior was also observed in C&B). This barring mechanism was triggered a total of 20 times in the 825 total rounds of play. All instances occurred in the first round of play. 12 of instances were three participants submitting the same name. Five instances included multiple names being barred. The largest incident was the submission of the same name by 9 participants. The barring mechanism effectively removed the name from circulation, as participants immediately abandoned it. Crucially, this means that a barred name never became a global convention. Interestingly, only 5 of the trials for which the barring mechanism was trigger ultimately resulted in a global convention, suggesting something about the barring mechanism or the behavior it targets harmed the prospects for future success. It is clear that, whether premeditated or coincidence, these instances did not contribute the emergence of conventions, although they might have inhibited it in some instances, leading to the underestimated of the effect of niche signals.

The screening of names for the purpose of barring is only applied to names that have not yet appeared in the session. Once a name has been successfully introduced, it might still be implicated in collusion efforts happening outside of the game interface. If the name "Sarah" is submitted by a single participant in the first round, but then by 10 participants in the second round, collusion could be the reason. That is not guaranteed to be the case, however. After a participant submits the name, their partner sees it and is very likely to play it. In treatments where random names are also shown, any number of other players may have seen the name on their results page and accordingly played it. (For each participant, names are sampled without replacement from all names played that round. This sampling is repeated for each participant, meaning any given participant's names are independent of the names other participants are shown and, in spite of it being unlikely, in principle all participants see the name played by one individual.) Given this structure, preventing collusion requires judging whether a name is spreading around the network *too quickly*. To do this, I track each participant's exposure to names, meaning simply any name they have seen or successfully played. Once a participant has been exposed to a name, I assume it is completely reasonable for them to play it and therefore the spread of that name to this participant did not happen outside the confines of the game interface. One could have a more demanding definition of exposure that considers the likelihood that participants will forget names seen many rounds ago, but implementing a suitable rule for the game would require making specific assumptions about how participants process the information that may not be justified. Furthermore, the real goal of tracking participants' exposure to names is to identify when a participant has played a name they have not been properly exposed to, yet participants often exhibit the unfortunate behavior introducing new names well into the game.

To reconcile the idea of proper exposure with the fact the participants contribute names they have not been exposed to, only one player per round is permitted to play a name they were not properly exposed to. If two or more participants submit a name they were not properly exposed to, the name is barred for all such participants and their submission is recorded as a null. Others playing the same name but who have been properly exposed do not have their submission barred. While not a foolproof system for guarding against impermissible coordination, it would take an impressive amount of organizing by the participants to defeat and still grants participants significant latitude in name choice. This type of screening happened only 6 times in the 792 applicable rounds of play and none of the affected names went on to become a global convention.

The two mechanisms of barring name described above offer significant protection against any organized effort on the part of participants to game the system. Another possible way to game the system would be to submit natural focal point words, such as “woman” or “name”. Such efforts would have the virtue of being of not needing to be centralized. This potential problem is addressed simply by creating a list of invalid inputs, that is, words the input field will not accept thereby preventing the participant from submitting and advancing to the next page. Whereas barring surges in names requires the names to have been submitted and tallied, focal point words can be screened out before submission and participants can still submit a valid name. Roughly twenty focal point words were screened-out, including a number of obscenities. Furthermore, any names that appeared in the trainings module were added for the obvious reason that participants could be primed to focus on them.

A few additional design features work to ensure the integrity of the experiments. The pictures of the individuals to be named by participants were changed every two games. No worker in the subject pool can play two games in a row, so the changing the picture every two games ensured no worker ever saw the same picture. The usual means of downloading images was also disabled for the game just in case workers considered attempting to use the image as a means of coordination.

As the above description of the software suggests, using Amazon Mechanical Turk as a subject pool presents some challenges and still has some of issues any subject pool can have, but most of these issues can be addressed through proper subject pool management and software design. The attempts to game the system were successfully defeated and if anything led to the underestimation of the effect of niche signals. In principle a very sophisticated effort built around knowledge of my defeat devices could go undetected by my software, but even in the highly improbable event such an effort succeeded regularly, one would still need to account for the consistent pattern in the results; the information dynamics play a crucial role in determining group-level outcomes. Finally, related to the consistency of the results, the fact that subject pool members often participated in several games allowed them to learn from their experience and possibility improve their play overtime, but this fact only bolsters the central pattern in the results; when a group is able to find a global convention does not depend on the skill of the participants but rather the information dynamics.

Network Design Details

All networks were generated using the python package NetworkX (Hagberg, Schult, and Swart 2008). The small world networks had a rewiring probability of .2 and where guaranteed to be connected. These graphs were used to create pairs of neighbors for the 25 rounds of each trial. Participants need a partner for each round, so the set of pairings for each round was chosen random from among complete pairings. Because the sequence of pairings could have its own effect, the sequences were reused for the different treatments of niche signals. For example, the 12 trials with small world networks used only four network-pairing sequence combinations, reusing each of the four once in each information treatment. There was no obvious effect of pairing sequences so no further analysis was pursued.

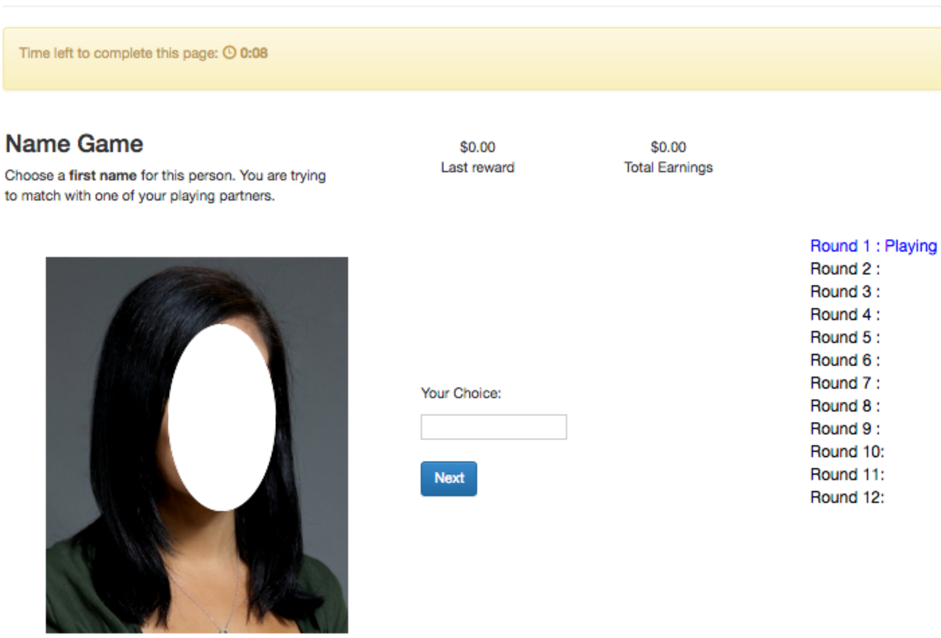

Fig 3.2. Name Game Submission Page. It displays the time remaining to submit, the total earnings, the last reward (or penalty), the current round and round histories.

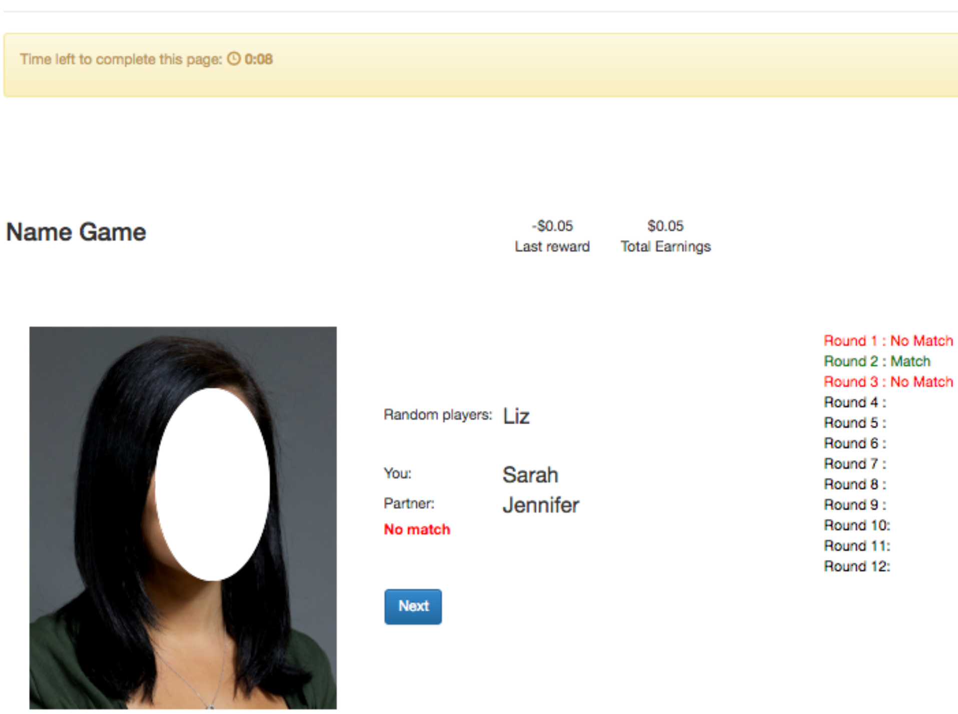

Fig 3.3. Name Game Results Page. Note the display of the participant's, the partner's and a random player's name.

Chapter 4: Meaning Production for Cultural Objects in a Networked Public

Introduction

Humans' evolutionary success can in many ways be traced back to our willingness and ability to cooperate despite the temptations of narrow self-interest (Axelrod 1984; Fehr et al. 2002; Gintis and Bowles 2011; Henrich et al. 2001; Henrich and Henrich 2007; Ostrom 1990; Roughgarden 2009). Cooperation is part of phenomena as diverse as group hunts, economic exchange, the production of knowledge, and, importantly, the building of consensus around the meanings associated with public symbols, behaviors, and objects. This cooperative tendency has allowed humans to self-organize into societies of great size and complexity. But do these advancements afforded by cooperation diminish our very capacity to cooperate? Many have argued that modern societies have new patterns of social interaction that reduce social cohesion and therefore cooperation (Arendt 1948; Bishop 2008; Etzioni 1994; Fukuyama 2000; Putnam 2000; Simmel 1903). A lack of cohesion suggests fewer social ties spanning across social groupings, and we know those ties are vital for acquiring the knowledge and perspective about the larger world so necessary for cooperation and consensus building (Burt 1992; Centola and Baronchelli 2015; Granovetter 1973; Lazer et al. 2007; Sparrowe et al. 2001; Watts 1999; Watts and Dodds 2007).

A robust literature has emerged around the role of the internet in political life (Adamic and Glance 2005; Bakshy, Messing, and Adamic 2015; Brundidge 2010; Colleoni, Rozza, and Arvidsson 2014; Dahlgren 2005; Kahler 2015; Oates, Owen, and Gibson 2006; Sunstein 2001) and foregrounds the question of whether we can continue to be a cooperative species if the internet is transforming how we interact in fundamental ways. This research, however, focuses on the particular problem of democracy in the public sphere, a domain rife with tensions. The internet may well exacerbate these tensions, but this need not be the case for all domains of social life. Much of the information consumed via the internet is less about politics and more about basic knowledge, economics, and culture. The production of consensus in these domains is also important for the smooth functioning of society. Are the changes in how we interact endangering our capacity as a society to produce consensus in these domains as well? To begin to answer this question, I study the production of meaning in a "networked public" (Boyd 2010; Ito 2008), a public sphere created by modern communication technologies like mobile phones or the internet. In particular, I focus on the production of meaning in the domain of literary fiction. As a genre, literary fiction is rich with potential themes and meanings, but the reading public often focuses on particular themes, thereby producing the public meaning of the book (Griswold 1987). Today much of this complex process happens online. This shift has likely altered the dynamics of the process itself but also offers the possibility of a more detailed analysis of it with extensive and public data. I use data from the website Goodreads, the home of a robust and public literary community, to explore the production of meaning in the realm of literary fiction.

To do this I use the Latent Dirichlet Allocation (LDA) approach to topic modeling (Blei, Ng, and Jordan 2003) in a novel way. With human supervision, the LDA model is a powerful tool for identifying the themes present in a corpus of documents. It is a generative probabilistic model, which attempts to impute the hidden set of topics that "generated" the observed documents. This is an unsupervised algorithm in the sense that there is no measure to judge the fit of a particular outcome; furthermore, exploring the full set of possible distribution is computationally intractable. Instead, human intelligence is generally required to judge the validity of the results. However, the machinery of the LDA can be used to explore the general structure of the topic space without trying to interpret the semantic content of the topics. Here I compare sets of documents from different time periods using many possible topic distributions derived from the LDA model. Statistically analyzing these sampled comparisons reveals basic features about the topic space including whether the posts of users are converging on a set of salient themes over time.

The evidence is mixed. Close to half of the analyzed books have statistically significant shifts toward fewer topics being discussed by the community, but there are reasons to belief the effect size is quite moderate. This suggests that as a networked-public, Goodreads is not conducive to the production of public meanings. One reason for this might be that the audience of readers for each book, while very open, is not socially close as measured by the site's friendship network. The experimental work in Chapter 3 showed the longer those distances are, the more public information is necessary in order to facilitate group coordination. This suggests a networked-public like Goodreads is not a good venue for the production of public meanings.

The Public Sphere Online

Habermas proposed the *public sphere* as virtual space in which individuals engage in discussion about items of mutual interest (Habermas 1991), often for the purpose reaching a consensus position. His interest in these discussions is related to the functioning of democratic societies and therefore the public sphere is generally equated with politics. The advent of the internet created a whole new type of public sphere and a field of study around the political public spheres online (Adamic and Glance 2005; Bakshy et al. 2015; Brundidge 2010; Colleoni et al. 2014; Dahlgren 2005; Kahler 2015; Oates et al. 2006; Sunstein 2001). Because this sense of public sphere is restrictive in a way that Habermas found important to the concept, he relegated other social discourse to the *private sphere.* Critics have argued this insistence on the public sphere containing only political discourse misses how intrinsic to politics identity is and how identity is constructed in and for the public (Boyd 2010; Calhoun 1992; Fraser 1990). This critique suggests the core facet of the public sphere—a community, imagined or otherwise, meeting to discuss items of mutual interest—can be fruitfully used in nonpolitical domains. The usefulness has only grown as the internet has created a whole new dimension of social life in which individuals freely congregate to discuss topics of interest in a very public fashion. While not all new technology-enabled platforms for social interaction are public in the Habermasian sense, there are enough such spaces that researchers have labeled them "networked publics" (Boyd 2010; Ito 2008; Varnelis and Friedberg 2008).

The distinction between the public sphere and networked publics is important because the latter has its own unique features. Content shared in a networked public can persist over long periods of time, be easily replicated or modified, reach larger audiences and be indexed for search (Boyd 2010). If these features alone are not enough to change the dynamics of public discourse, in networked publics the boundaries of social contexts are much more porous and audiences are often truly imagined, as there need not be the dyadic interactions through which one gets to know one's audience (Boyd 2010). These differences are grounds for believing networked publics are a unique social form worthy study in the own right. This is made all the more important by the fact that these networked publics are supplanting the public spheres once present in physical space.

While commenters often worry about the effects of networked publics on political discourse, there are good reasons to believe that network publics can be very effective forums for groups to reach consensus in other domains. The low cost of engagement and the exposure to a wide range of content, often by accident (Brundidge 2010), afford the opportunity for more robust public discussions. As the work in Chapter 3 showed, exposure to signals and information in public spaces can help push group dynamics toward a coordinated outcome instead of sustained competition. Thus, instead of new communication technologies inhibiting our species' ability to cooperate, they could in fact improve the prospects for success. This paper explores that claim by focusing on the emergence of public meanings for cultural objects, in this case novels of within the genre of literary fiction. The website Goodreads is a networked public that is home to a robust community of readers who engage with others as a part of their reading practices. Before detailing the site, the data and the analysis, I turn to describing why literary fiction is a domain ripe for group coordination.

The "Fabrication" of Meaning in Literary Fiction

Fiction is often rich with meaning, but most commenters and authors agree that no one person controls the meanings ascribed to a text by its reading public (Livingstone 2005). The text itself constrains the possible meanings in obvious ways, but within those constraints, the readership has great power to find meanings. This happens against the protestations of the authors who believe readers are obliged to do their best to understand the author's intentions. Even an author as revered as Flannery O'Connor, who argued strongly for the primacy of authorial intentions, had to acknowledge that a text takes on a life of its own.[8]

Cultural sociology is very sympathetic to this view and often sees cultural objects as capable of

[8] "The writer can choose what he writes about but he cannot choose what he is able to make live."-Flannery O'Connor.

supporting a multitude of meanings. This raises an important question of how those meanings come into existence, a process Griswold has referred to as the “fabrication of meaning” (Griswold 1987). In her study of the reception the works of Barbadian author George Lamming in the United States, Great Britain and the West Indies, Griswold showed the three national readerships focused on race, language, and national identity, respectively, in the interpretation of Lamming’s work. This finding shows that the meanings present in a literary text are many and interpretation is a rich social process that can allow any of the available themes become more salient than others.

The fact that meaning is socially “fabricated” cuts against the commonplace assumption that there is a straightforward relationship between texts and readers. This unproblematic model of “intentionalist interpretation” (Carroll 2000) is depicted in Figure 4.1 below. In this model, the author has semantic content in mind (intentions) as they craft the text. Miraculously, the author is able to put that semantic content into a textual form that allows any reader to interpret the work as having the exact semantic content of the author’s intention. No serious scholar of literature would fully endorse this view, but articulating it thusly helps to reveal that meaning must be fabricated to some degree.

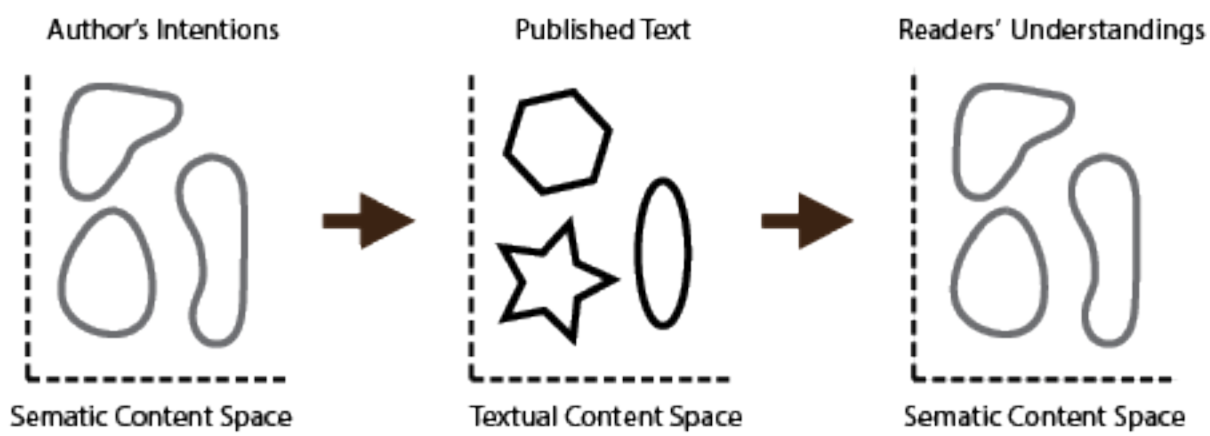

Figure 4.1: Intentionalist Model of Interpretation: This graphic depicts a model of the production of literature that is unproblematic. The author has a set of themes in mind while writing the book, depicted in the left hand “semantic content space.” The written work cannot not correspond directly to the semantic themes the work is engaged with, but there is a rough correspondence in the “textual content space.” Nonetheless, readers are able to successful interpret the textual content to gain the semantic content intended by the author.

Griswold argues that the fabrication of meaning is a function of social contexts; “The meanings attributed to any cultural object are fabrications, woven from the symbolic capacities of the object itself and from the perceptual apparatus of those who experience the object” (p. 1079). Individuals from different social contexts will inevitably have different apparatuses, “expectations and concerns” (p. 1077), and those guide the process of interpreting the work. This argument is presented graphically in Figure 4.2.

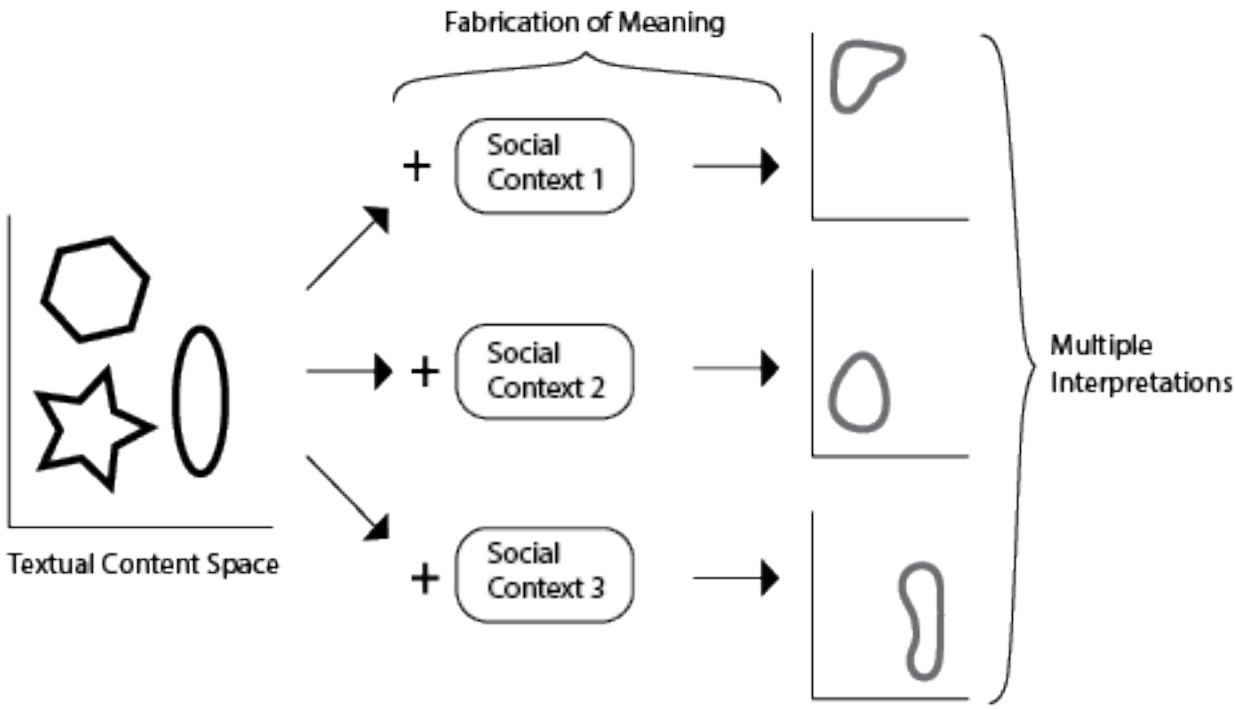

Figure 4.2: The Fabrication of Meaning: As shown by Griswold (1987), meaning is fabricated; because an author’s intentions cannot be directly extracted from the text, readers situated in different social contexts are likely to have different semantic associations with the text. This can give rise to multiple interpretations of the same text.

The assertion that different social contexts will produce different cultural meanings does not by itself describe how that happens. Griswold argues the reviews written by the literary elites of the respective nations tended to focus on (or avoid, in the case of Great Britain’s colonial past) issues salient to their nation’s history because their perceptual apparatuses were primed to find these things. Some diversity existed across the individual reviews, but the literati tended to independently focus on the same handful of themes. Thus, the meaning of the text was the summation of many individualistic acts of interpretation. This argument is presented visually in

Figure 4.3. From the text, individual readers craft interpretations, and the joint distribution of the themes from these interpretations creates a more general sense of the cultural object for the broader public. There is no need or opportunity for the individuals to coordinate their individual interpretations.

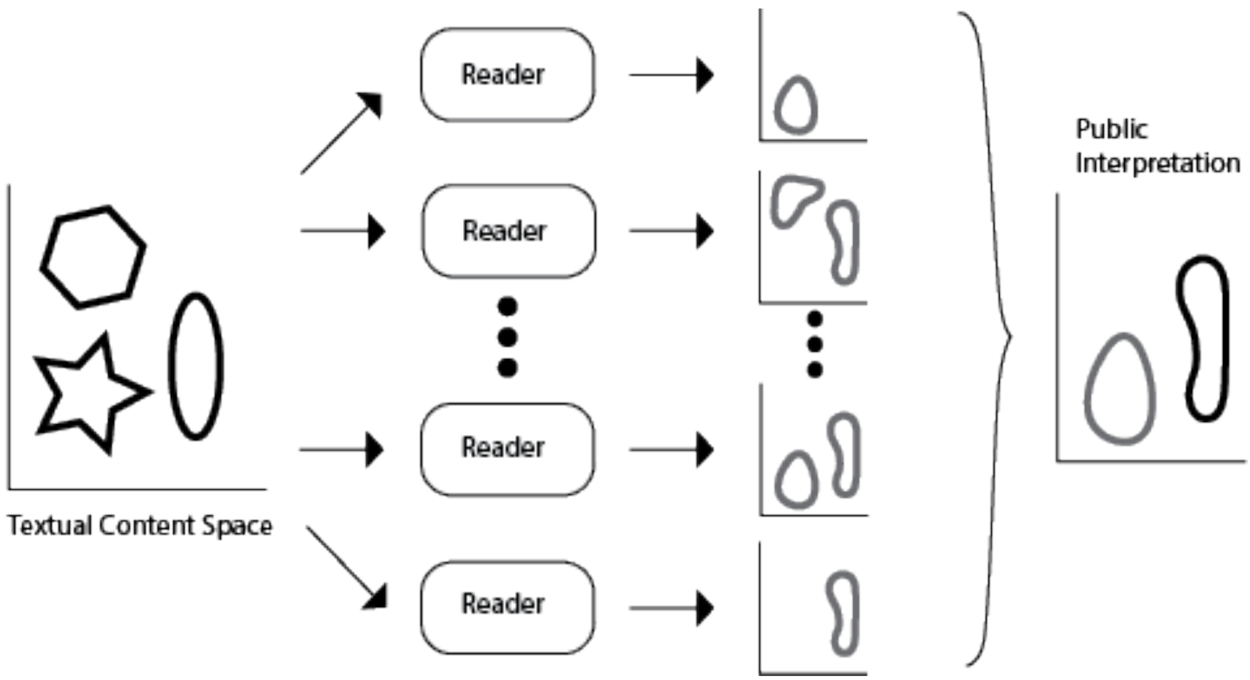

Figure 4.3: Public Meaning as Joint Distribution: Within a social context, the fabricated meaning could be produced in several ways. One way, depicted here, is to look at the joint distribution of individuals' semantic interpretations of the textual content of the book. The "theme" on the right of graphic representation of the public interpretation is darkened because of its prevalence in the individual interpretations. The readers are not interacting in a meaningful way, but the group has created a dominant meaning for that social context.

A same outcome might be possible without assuming that the readers start with very similar perceptual apparatuses. Instead, as public interpretations are shared, they create the perceptual apparatus, or anchoring frames, for future readers. If these frames resonate enough with later readers, those readers' interpretations would look similar to the early interpretations. If this process is repeated for long enough, eventually some interpretations become entrenched. This process is depicted in Figure 4.4.

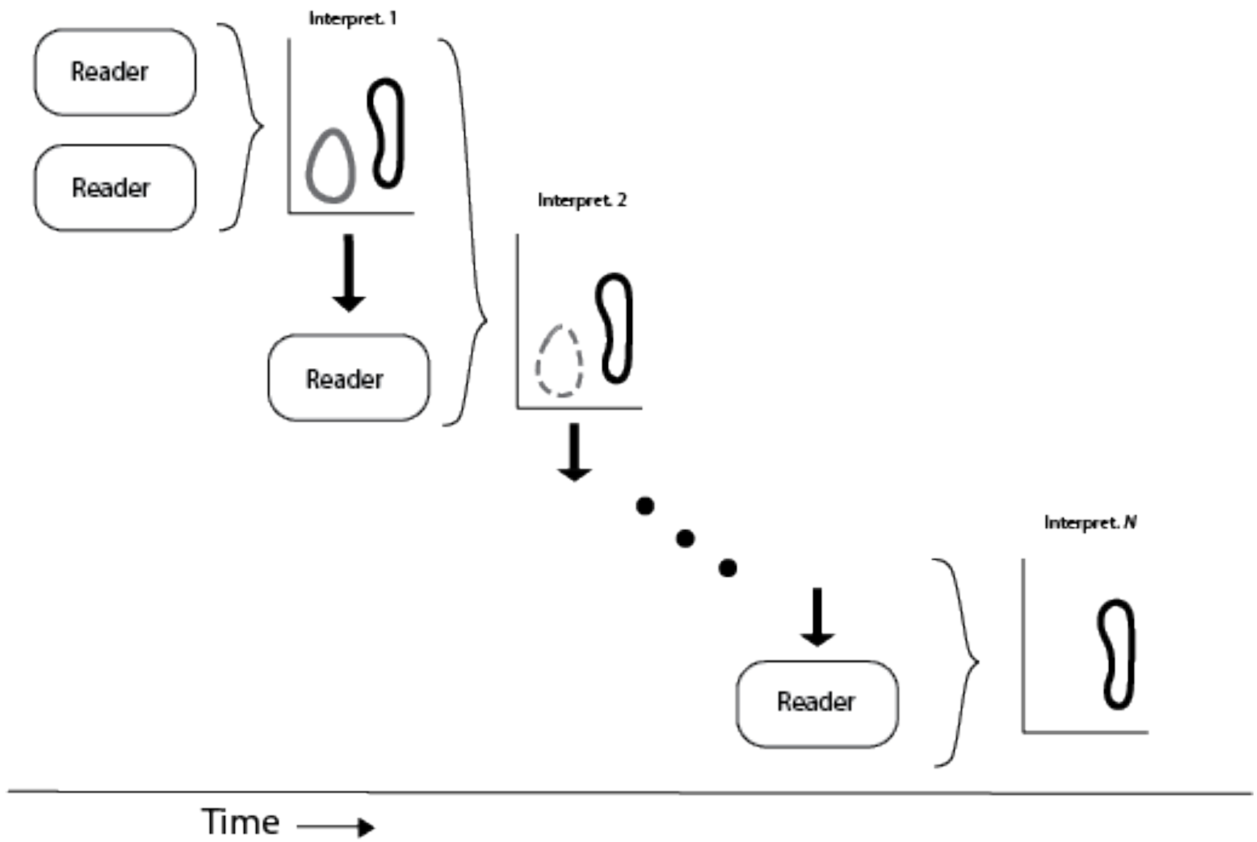

Figure 4.4: Public Meanings as Consensus Meaning. Early readers create frames and perceptual apparatuses for others by making their interpretations public. This influences later readers' interpretations, which can carry forward through readers and time.

This alternative mechanism of the fabrication of meaning is a form of coordination. While Figure 4.4 depicts a single chain of influence, there can be many more sources of influence within a networked public like Goodreads and the production of a consensus interpretation depends crucially on the pattern of exposures to these influences (see Chapter 3). That a shared interpretation could emerge through such a mechanism is not obvious, and the question of its tenability reflects the basic problem of coordination in networked publics. Following the work of Griswold, I now analyze the production of meaning by an audience of fiction readers.

Data and Methods

The *act* of reading fiction is, with few exceptions, a private activity, but for a significant portion of the reading public, the *practice* of reading is not wholly private. Before, during and after reading a text, they might read or write reviews, seek out and share recommendations, describe and discuss texts with others, use texts for making points or drawing comparisons, and deploy texts as symbolic capital (Bourdieu 1984). Recently, these activities have moved online where readers can more readily do all of these activities. For the English speaking world, two sites in particular dominate this space: Amazon.com and Goodreads.com[9]. While Amazon.com has automated book recommendations and asks purchasers of books to rate and review them, it is not a social networking site in the sense that one can formally establish relationships with other users. Goodreads, however, is a social site that allows users to create profiles, write public or private posts, add friends, join and contribute to discussion groups and forums, create public lists of books, and see the activities of friends and others. The site's mission "is to help people find and share the books they love" (Goodreads.com 2007). At the time of data collection, the site claimed some 40 million registered users, 1 billion books in its database, and 45 million reviews of books. This heavy traffic leads the site to often be in the top 100 most visited sites in the United States. According to traffic-tracking service Quantcast, in the period covering the submission of the data analyzed herein, the site had roughly 10 million unique visitors based in the United States and 20 million unique global visitors each month (Quantcast.com 2017). Of the global visits, about 25% came from the combination of the United Kingdom, Canada, Australia and India. The site hosts pages for books published in languages other than English and links translations of the same text such that the content on a book's page is not always in the same language. The user base is heavily female (74%) and, compared to the composition of all internet users in the US, is young; 17% are 17 years old and younger, 36% are 18 to 34, 20% are 35 to 44, 27% is age 45 and above. The users have more college degrees and significantly more graduate degrees than average.

This site is exactly what researchers have in mind when they refer to *networked publics*. Users come to the site on a regular basis seeking to engage with others, cultivate an identity and

[9] Goodreads.com was established as an independent site in early 2007, but purchased by Amazon.com in early 2013 (Amazon.com 2013). Goodreads.com appears to remain largely independent with the exception of prominently placed links to Amazon's marketplace for the purpose of buying books.

community, and consume information related to culture and society. While there are low engagement users who passively use the site, a great deal of the networking, reviewing, posting, and discussing is done by a group of avid readers who engage with the site extensively in a public fashion. All reviews, ratings, comments and membership in groups are public and, in principle, visible to all. Roughly 80% of users maintain a public profile page, meaning their friendship connections, posts, and bookshelves—user-constructed collections of books already read or to be read—are visible to any registered user. By the standards of leisure related social networking sites, it is a very open community; in 2012, only 20% of users of social networking sites reported having a wholly public profile (Madden 2012).

Unlike social networking sites built around a network of friends, Goodreads is built around the webpages for books. Publishers will submit titles, imagery, cover descriptions and blurb, and author information for the creation of the page, except for small and independent presses where the author will often submit the information. While the publisher/author and users with a special "librarian" status can update this information, the reviews and ratings are contributed by the site's users and can only be modified by the original poster or Goodreads' staff when necessary. Thus, a book's page quickly becomes the creation of the user-public. Users rate the book, submit reviews, comment on reviews, like reviews, ask questions, categorize into genres and post trivia. The reviews are the most public aspect of the page, as each features the name, profile picture, rating, timestamp, and comments and likes in response to the review. When a user visits the page, reviews written by "friends" are displayed on a section beneath the basic information on the page, and reviews from the broader community are beneath that. The community reviews are presented in an order calculated by a proprietary algorithm that factors in the number of likes, how well-liked the reviewer's other reviews are, how recent the review is and the length of the review (Goodreads.com 2017), although message boards suggest the exact ordering depends on the user actually visiting the page. If more than 30 reviews exist, the user must page through to find more or adjust the sorting criteria.[10] This matters because it is common for books published by established presses to have hundreds and thousands of reviews. (Highly successful books will have hundreds of thousands of reviews and millions of ratings.) This list evolves as reviews are added over time.

[10] The maximum number of reviews a user can retrieve is 10,000, a limit that matters for the research purposes.

The content of the reviews varies significantly. Some are just a verbal expression of the evaluation of the book (in addition to the 1 to 5 star rating system). Others include extensive plot summaries. A significant fraction includes visual components like pictures, GIFs, or other art. The modal review, however, highlights one or more aspects of the book the reviewer found salient. Together these reviews could constitute a public discourse on the title, or a cacophony of users speaking past each other. The social nature of the site and prevalence of commenting and liking reviews suggests it is might be the former. Instead of surveying users about behavior, some forms of which they might not be consciously aware, I analyze the text of the reviews using the techniques of natural language processing. The volume of texts and the focus on dynamics over the meanings within the text makes the analysis ripe for a computational approach. The details of the analysis follow the description of the sample.

Sample

Of the million of books on Goodreads, a small percentage have the ambiguities necessary for the type of analysis I am proposing; in addition to documenting the process of the fabrication of meaning, Griswold (Griswold 1987) shows the process requires the text itself to have enough ambiguities to be interpretable in a variety of ways. Because such ambiguities are the hallmark of literary fiction, the sample is restricted to that genre. However, because works of literary fiction can fit in multiple genres, identifying literary fiction is not straightforward. While regular readers of literary fiction might recognize the title and cover imagery conventions of the genre, or the publishing houses known for it, to construct a sample of titles of literary fiction, I rely on site users' categorization of individual books. Users can place books on "shelves", self-defined collections of books. The site supplies some names, but allows user to make their own. The site tabulates the names of all the shelves the book appears on and displays the top ranked names and the number of users using that name on the book's homepage as the "genre" of the book. I classify a book as literary fiction if the number of users putting the book on shelves with the names "literary fiction" or "literature", an alterative name of the same genre, would be a top 10 genre, a threshold that takes into account that some categories are very broad (e.g. fiction, contemporary, 2015).

Another criterion for inclusion in the sample is that the book is a debut novel. This restriction prevents reviews from incorporating themes from or comparisons to an author's previous work. Such information would generally be an element of the fabrication of meaning, but inclusion here could introduce hard to account-for historical factors. Furthermore, the audience for debut novels is more likely to be comprised of readers for whom the practice is an important part of their identity. While not testable, I assume the importance of identity leads to more engagement with the community and the review writing process. Within literary fiction debuts, I focus on titles published between 2011 and 2014. This period begins well after the site became the main online literary community and ends at a point that allowed for the collection of at least two years of review data for all titles. The bulk of reviews are submitted in the first half-year after a book's publication, but there is often a longer tail over the next 18 months. Two years then covers most reviews, except in some cases where a movie adaptation or highly successful second book spurs new interest. Finally, the book needed a minimum of 500 and a maximum of 10,000 reviews at the time of collection. The lower bound was necessary for analytic purposes and the upper is the maximum number of reviews a user can access on the site. To avoid any issues regarding how the site's proprietary algorithm determines which reviews are visible, I simply restrict the sample to books for which I could retrieve all reviews. A random sampling from the population of all books on the site was not practical[11] so I used several different lists of titles identified as literary fiction by other sites[12] to construct a population. From that, I sampled until I had 51 books meeting the above criteria. These books are treated as individual cases to be considered, not the observations from a population of reviews constituting a larger discourse around literary fiction. While that larger discourse is ripe for analysis, here I focus on the many simultaneous meaning-making projects that have some degree of autonomy from each other. Finally, only 30 of these cases are included in the final analysis because the others were used for exploratory analyses.

Data

I collected all the reviews posted for each of the 51 books. After identifying the user posting the review, I collected, if possible, the user's list of friends and list of titles in the

[11] Truly random sampling is possible, as each book has a unique integer identifier on the site. However, there is no easily discerned numbering system and because the population is so large and diverse, the rate at which suitable titles would be found is extremely low. Even if a thousand suitable titles were published each year (there are not), in expectation, a random draw from the population of over a billion books would find a suitable book only one in a quarter million times.
[12] For example, the Morning News Tournament of Books and The Million's "Most Anticipated" lists.

bookshelf identified as "read." This resulted in 122,562 reviews and 85,825 unique reviewers. 81 percent of those reviewers maintained a public profile, allowing for the construction of a friendship network with 2,037,000 nodes and 3,790,000 ties. 2,019,000 of these nodes are in the giant component, but only 68% of reviewers are in it, in virtue of their privacy settings (19%) or because they are members of a small component (13%). This highlights some of the different ways users engage with the community on the site. The "read" bookshelves identified a total of 1,754,000 unique titles users identified as read[13], 947,000 of which appeared on multiple lists. The most commonly identified title, "To Kill a Mockingbird", appeared on 31,000 lists.

The reviews themselves are of primary importance for the present research question and were collected with basic metadata including date and time posted, the associated rating, and how many likes it received. To be included in the data for analysis, the review needed to have 25 or more words. This both screened out reviews will little content and ensured the documents were suitable for the topic modeling method. Reviews were also excluded if they appeared after the publication of another fiction title by the same author in order to prevent readers interpreting the first book based on their reading of the second. Finally, the foreign language reviews, as identified by the Google language detection library, were removed. The analyses were conducted on a book's collection of reviews, which were stemmed and stop-listed to remove high frequency words.

Natural Language Processing and Topic Modeling

Natural language processing is a set of computer-aided techniques for processing text. It ranges from identifying root words and parts of speech to translation of texts and the identification of meaning. The contexts in which these techniques are used are diverse, and therefore their successful application very often requires the expertise of a native speaker to guide the automated aspects. The techniques vary greatly in their statistical bases, but together create of powerful suite of tools for approaching large corpuses of text.

The basic question this paper seeks to answer is: Do the number of themes readers address in their reviews tend to decrease over time? The goal then is to be able to locate each

[13] Some users appeared to interpret "read" in the future tense, as in "to read", and added thousands of books to the list. I collected only 1400 titles from these lists and did not exclude them because the aspirational identity implicit in them could be just as important as the virtue cultural capital of previously read books.

review within a space of themes or topics that are emerging from the reviews themselves.[14] The field of topic modeling arose to do just that and matured with the invention of the *Latent Dirichlet Allocation* (LDA) model (Blei et al. 2003). An LDA is a generative probabilistic model that treats a topic as a distribution over the words present in a collection of documents. The individual documents of within the collection are treated as a finite mixture of those topics. As a mixture model, it allows individual texts to reference multiple topics instead of simply the most prominent one. Figure 4.5 depicts the intuition behind the model visually.

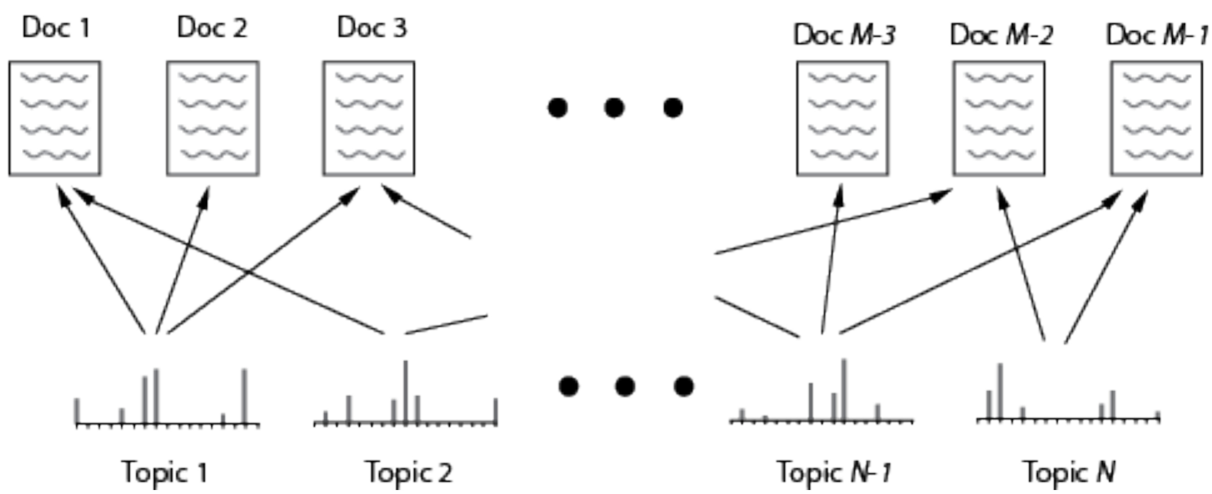

Figure 4.5: LDA Depiction: The model assumes writers create documents with a number of topics in mind. These topics can be identified by the co-occurrence of comparatively unique words and so each topic is modeled as a discrete distribution over all the words occurring in more than one document. Each document can be identified as a distribution over the topics, as indicated by the arrows identifying the generation process. For example, Document 1 references Topics 1 and 2 and Topic 1 is referenced by Documents 1, 2 and 3.

In many settings, understanding what topics individual documents refer to is the ultimate goal, but first the underlying set of topics needs to be identified. The assumption is that a number of topics exist in the background of a corpus and individual documents reference some of them. The basic research question then is what set of topics generated the observed documents, or in

[14] It would be desirable to use the text itself to understand the themes, but literary fiction is very much about "showing" instead of "telling" and therefore the words we most often associate with themes or topics are not common in the text itself. For example, the word revenge appears only nine times in all of Moby Dick. This disconnect between the literal text and its potential meanings would hamper any analysis of the text itself. But even if that analysis were possible, the position this project takes is that meaning is something created by the text's interpreters. (However, the potential meanings are presumably constrained by the text itself.)

probabilistic terms, what set of topics is most likely to have generated the documents. If we could observe topics, the problem would be straightforward, but because the topics are hidden variables, an LDA calculates a conditional distribution of the topics given the observed documents. If it were possible to do this for all possible topic structures, it would be easy to determine what topic structure was most likely to have generated the documents, but this is computationally intractable for all but the smallest collection of documents. Instead, as is the case with all probabilistic models, we are left to approximate that posterior distribution of topics within the word space.

Both stochastic and deterministic techniques can be used to perform the estimation, but because of free parameters and the noisy nature of the observations, either class of techniques can yield a wide range of results. Thus, a great deal of the process is left up to the human overseeing the process and interpreting the results, making topic modeling a very subjective endeavor (Chang et al. 2009; Grimmer and Stewart 2013). Having confidence about the positive identification of the topics in a discussion around a book, let alone dozens of them, is an intractable task. Thankfully, the content of the topics is not relevant to the present research question. Instead, we are interested in changes in how documents are distributed over topics through time.[15] This is fundamentally a question about the structure of the population of documents and not their content; thus, while LDA is primarily the re-estimation of nuisance parameters until the results are interpretable by humans, I assume those parameters are bounded and normally distributed and then seek to identify patterns present in all individual estimations. This is very similar in principle to what agent-based modelers do when they run multiple trials of the same stochastic process with identical initial conditions. Conducting multiple trials is not equivalent to running more iterations of the estimation process because these techniques are either stochastic themselves (Gibb's sampling) or deterministic but reliant on the initial prior distributions (variational methods) and yield different results independent of the number of iterations. Each trial then is a new sampling of the true posterior distribution and yields more information about its structure. Multiple runs of the LDA process are not uncommon on trial data

[15] This should not be confused with what a dynamic topic model does (Blei and Lafferty 2006). That model captures the change of the distribution of *words* to *topics* over time in order to address the problem of the same idea being expressed through different words as knowledge changes. This type of change happens over long periods of time and is not relevant in this application.

as the analyst attempts to improve the human intelligibility of the results, but these runs are not considered a part of their analysis. Here, however, such trials are the core of the analysis.

The validation of topic models requires domain experts, and in this setting there are none[16], so I approach the problem statistically. I treat results of an LDA as one data point about the "true" posterior distribution of topics and collect 30 such data points for each set of parameters for the LDA. There are several parameters for the LDA algorithm, the main one being the number of topics. This quantity must be fixed because it is equivalent to the dimensionality of the posterior distribution, and attempting to infer the likelihood of the dimensionality is not possible. The other parameters are hyperparameters controlling the sparsity of the posterior; these I hold fixed at widely used values. The number of topics ranges from three to ten. Thus, for each book there are a total of 240 trials of the LDA estimation process. However, because the number of topics is a key assumption about the structure of the problem about which we have no prior probabilities, I treat the 30 trials for each number of topics as a unique case and only look at the average measures for book-topic count cases. Using a subset of 30 books then yields a total of 240 book-topic count cases.

Before describing the measures I use to track the change in the discussion, it is important to clarify that comparisons are made only within a single LDA. Each LDA defines a set of topics, and it is sensible to compare the prevalence of those topics in the reviews at different points in time. One such comparison constitutes an observation. While it might be fruitful to consider individual documents in light of a topic space constructed by the sum of the trials, this is not the approach taken here because of the challenges around understanding the uncertainty present in such an approach.

Measures

The first goal of this analysis is to understand whether the range of themes in public discourse around a book winnows over time. Another way of asking the question is whether those reviewers joining the discourse later focus on a narrower range of themes than earlier reviews did. Topic modeling can answer the second form of the question. To do this, I run a trial

[16] This research posits that the act of reading a review creates anchors that influence the reading of future related text, so in principle a human cannot do an unbiased reading of the entirety of the reviews. I do believe, however, a careful coder can get pretty close.

of LDA to approximate the topics present in the whole corpus of reviews. I order the individual reviews chronologically and divide the corpus into three sequential slices of roughly equal sizes. No attention is given to posting dates, just chronology, meaning the last third of reviews likely cover a wider range of posting dates, as the rate of new postings declines over time. I then sum the topic distributions of all the documents in the first slice to calculate the prevalence of topics in that time period. This is repeated for the last time slice. The resulting distributions are approximations of what topics were discussed in the respective time periods.

To compare the prevalence of topics in these two time periods, I calculate the Shannon entropy for each distribution and compare them. Entropy is a useful measure of how ordered a categorical distribution is because it is agnostic about how the frequencies are distributed to categories and only considers the how the frequencies relate to each other. Thus, if the reviewers merely stop discussing a particular topic and replace it with a new one, the entropy is unchanged. It will only decrease if some topic weightings grow at the expense of others. The entropy for *N* topics at time *t* is defined as

$$H_t = -\sum_{i=1}^{N} p_{i,t} \log p_{i,t}$$

Entropy is equal to one when the distribution is uniform and equal to zero when all observations fall in single category. Thus, the lower the entropy, the more peaked the distribution is. Comparing entropies between the first and last time periods then reveals whether the discussion is focusing on a narrower range of topics over time. This would be the case when $H_1 - H_3 > 0$.

As suggested above, it is possible that the public discourse is changing significantly without any appreciable change in entropy. This type of change, while not immediately relevant to the question at hand, could be a useful diagnostic of whether there is any movement in the discussion over time in the event that prevalence of topics is not narrowing. A static distribution of topics would imply the site is not host to dynamic discussions in any meaningful sense and is just a repository of individual thoughts. To track this sort of change, I use the Jensen-Shannon divergence (Goldberg et al. 2016; Lin 1991; Pechenick, Danforth, and Dodds 2015) measure. This divergence is derived from the more common Kullback-Leibler divergence, but is symmetric. The Kullback-Leibler divergence between distributions *P and Q* is defined as

$$KL(P \mid\mid Q) = \sum_{i=1}^{N} p_i \log \frac{p_i}{q_i}$$

The Kullback-Leibler divergence from P to Q is not the same as from Q to P, so the Jensen-Shannon divergence solves by defining a third distribution of the average frequencies and comparing the originals to that average. The average distribution *V* is defined as

$$V = \frac{1}{2}\,(P + Q)$$

and the Jensen-Shannon of P and Q is then

$$JS(P \mid\mid Q) = \frac{1}{2} KL(P \mid\mid V) + \frac{1}{2}\, KL(Q \mid\mid V)$$

A divergence of zero means nothing has changed, but a positive divergence means one of three things. Like the entropy measure, if the prevalence of some topics is increasing over time, the divergence will be positive. This would also be the case if the prevalence of particular topics were decreasing over time. However, these changes will be captured by the entropy measure, and we only want to know if there are any kinds of changes in the case that the entropy is unchanged. Thus, we use the measure to determine if there are nonetheless shifts in structure of prevalence of topics when there is no change in entropy.

The basic hypothesis for each book-topic count case is that some topics come to dominate the discussion over time. The entropy measure tests that, and the divergence measure either corroborates it or checks to make sure the discussion is dynamic. If the discussions are in fact narrowing, an important follow up question is whether reviews are starting to look more similar or if there is any sort of polarization. This is where the Jensen-Shannon measure is more useful. It can compare individual documents to the distribution of topics for the whole group for the document's respective time slice. In cases where the discussion is narrowing, the reviews could begin to look more like each other or they could become more polarized. The divergence of individual reviews to the group averages can provide some insight into how polarized the discussion is at any given time, but more important is whether the discussion is becoming more or less polarized over time. In a secondary analysis, I compare the average individual divergences for the first and last time slices.

I first test the hypothesis that the change in entropy is greater than zero for each book-topic count case. If statistically significant for the measures from the LDA trials, this decrease in entropy would indicate that the same comparisons would hold for the true posterior distribution of the topics. The effect size however is not readily interpretable. While a full analysis of the behavior of the measures is not possible here, a few examples can give an intuition. Consider a model with 4 topics and distribution A, B and C, as depicted in Figure 4.6. The difference in entropy between A and B, and A and C, is approximately .067. The difference between B and A, and C and A is then -.067. The divergence from A to B, A to C, B to A, and C to A are all .0164. The difference in entropy between B and C is zero, but the divergence is .0617. Both these measures are comparable for different numbers of topics (e.g. when A = [.125,.125,.125,.125,.125,.125,.125,.125] and B = [.2,.2,.125,.125,.1,.1,.075,.075], the difference in entropy and the divergence remain the same as in the first example).

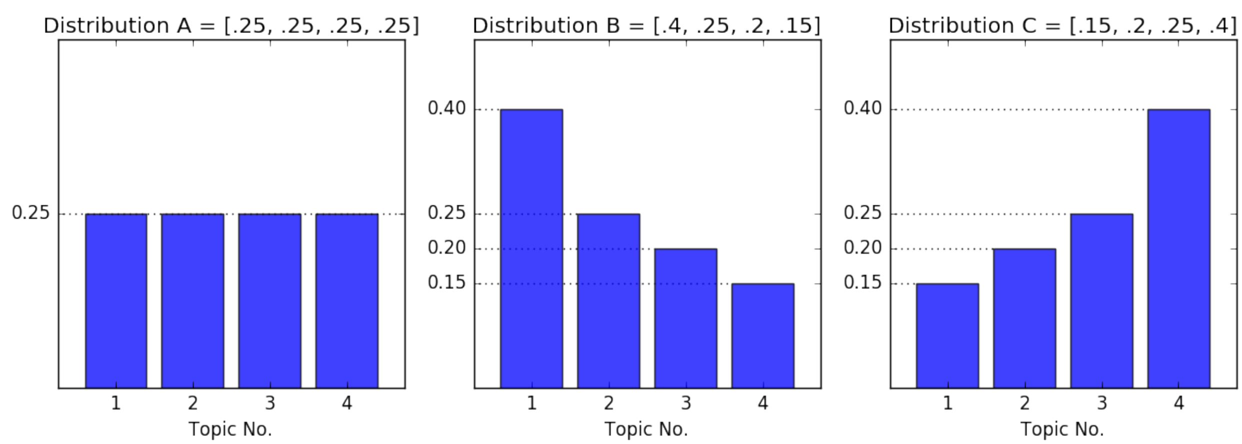

Figure 4.6: Several Example Distributions: B and C are identical with respect to entropy but not with respect to divergence.

Results

Table 4.1 reports basic data about the books and the reviews of them, as well as the average shortest path length between all pairs of reviewers of that title. Some of

Book	Author Gender	Number of Reviewers	Review Period (Days)	Avg. Review Length	Min. Review Length	Max. Review Length	Average Path Length	Fraction In Gnt. Cmp.
18498569	Female	4334	728	55.619	2	595	4.827	0.712
17225311	Female	1565	1107	77.806	2	995	4.233	0.845
10996342	Male	6097	1861	65.642	5	93	5.003	0.828
16045140	Female	1227	1093	81.938	6	1171	4.691	0.863
13366259	Male	1904	1406	71.999	6	680	4.937	0.793
12401556	Female	6823	1568	73.702	2	1318	4.833	0.807
18428067	Male	2534	611	68.703	3	834	4.956	0.837
17333230	Female	4209	1077	84.618	2	1246	5.002	0.741
10364994	Female	1199	1883	70.608	7	510	4.881	0.809
8366402	Female	6031	2044	61.353	6	1189	5.107	0.771
17934521	Male	1094	945	68.084	6	859	4.711	0.813
12408149	Male	922	651	61.038	8	718	4.719	0.83
15852479	Female	1193	1157	86.984	8	696	4.719	0.808
17830123	Male	2131	694	71.48	6	889	4.976	0.788
10846336	Female	1140	742	67.889	7	537	4.704	0.853
13330761	Male	2426	637	54.183	3	1017	4.907	0.819
18652002	Female	2110	799	70.85	6	525	4.693	0.791
18507827	Female	750	743	62.297	6	543	4.953	0.837
10306358	Male	1035	1778	59.59	7	411	4.511	0.826
11250317	Female	3961	1848	85.414	2	1267	4.482	0.703
15781725	Female	2489	1337	60.151	5	499	5.209	0.75
17333319	Female	4212	1037	56.57	5	647	4.782	0.778
9902278	Female	818	1286	50.502	5	347	4.499	0.814
13320466	Female	2937	1315	55.771	7	566	5.158	0.786
16158508	Female	1465	1078	66.952	7	791	4.913	0.811
13593526	Male	1127	1526	68.929	7	558	4.888	0.765
10149142	Male	1701	1532	63.735	7	691	4.747	0.847
12888599	Female	2060	1463	64.607	4	570	4.949	0.774
16099196	Female	781	1128	70.083	7	700	4.608	0.835
13540215	Female	2994	1422	57.92	7	775	5.249	0.756
Avg. 1-15	9f/6m	2826.87	1171.13	71.164	5.07	822	4.82	0.807
Avg. 22-30	7f/2m	2010.56	1309.67	61.674	6.22	627.22	4.866	0.796

Table 4.1: Basic book data. The *Average Path Length* is the average distance between all pairs of reviewers in the giant component of the friend network. The *Fraction in Gnt. Cmp*. (giant component) is the number of pairs in the giant component over the total number of pairs. The review lengths are of the stemmed and stop-listed reviews, so while the full text of the reviews had at least 25 words to begin, the stemmed version can have as few as 1 token. Last two rows are, respectively, the averages for the books that clearly exhibit some convergence and those that do not.

Book ID	3 topics	4 topics	5 topics	6 topics	7 topics	8 topics	9 topics	10 topics
18498569	0.077	0.068	0.056	0.051	0.034	0.034	0.032	0.021
17225311	0.036	0.036	0.031	0.035	0.032	0.027	0.019	0.015
10996342	0.058	0.059	0.064	0.066	0.061	0.067	0.063	0.058
16045140	0.041	0.036	0.030	0.025	0.021	0.023	0.015	0.019
13366259	0.011	0.024	0.021	0.022	0.025	0.025	0.025	0.016
12401556	0.062	0.061	0.061	0.058	0.056	0.053	0.054	0.049
18428067	0.072	0.066	0.060	0.055	0.041	0.029	0.019	0.025
17333230	0.039	0.037	0.043	0.027	0.035	0.033	0.028	0.027
10364994	0.013	0.015	0.015	0.014	0.026	0.019	0.020	0.020
8366402	0.056	0.065	0.065	0.061	0.053	0.063	0.055	0.056
17934521	0.046	0.046	0.035	0.037	0.034	0.033	0.027	0.018
12408149	0.048	0.032	0.033	0.032	0.020	0.025	0.012	0.019
15852479	0.010	0.014	0.017	0.013	0.019	0.015	0.012	0.010
17830123	0.055	0.047	0.033	0.023	0.016	0.017	0.011	0.001
10846336	0.045	0.037	0.029	0.026	0.015	0.008	0.007	-0.001
13330761	0.049	0.044	0.041	0.028	0.020	0.014	0.005	-0.004
18652002	0.063	0.051	0.031	0.035	0.021	0.013	0.006	-0.001
18507827	0.066	0.052	0.032	0.023	0.020	0.007	0.008	0.003
10306358	0.031	0.021	0.017	0.017	0.017	0.011	0.001	-0.003
11250317	-0.006	-0.026	0.009	0.006	0.032	0.027	0.039	0.036
15781725	0.063	0.047	0.023	0.022	0.000	-0.000	-0.009	-0.013
17333319	0.024	0.014	0.005	0.005	-0.011	-0.008	-0.008	-0.018
9902278	0.034	0.019	0.002	-0.001	0.006	-0.008	-0.003	-0.014
13320466	0.004	0.006	0.011	0.002	-0.001	-0.005	-0.014	-0.010
16158508	0.030	0.006	0.003	0.002	-0.003	-0.007	-0.010	-0.014
13593526	0.013	0.001	0.005	-0.005	-0.014	-0.013	-0.021	-0.024
10149142	0.022	-0.002	-0.011	-0.009	-0.007	-0.011	-0.010	-0.018
12888599	0.013	0.002	-0.006	-0.011	-0.011	-0.015	-0.019	-0.015
16099196	-0.032	-0.025	-0.009	-0.006	0.006	0.006	0.003	-0.006
13540215	-0.031	-0.027	-0.026	-0.023	-0.023	-0.016	-0.019	-0.017

P < .001 P < .01 P < .05

Table 4.2: Differences in Entropy: Results of 30-sample T-test for 240 book-topic-count cases. Each cell is colored according to its test statistic and contains the average decrease in the topic entropy over time. The books are ordered by weighting the cases according to the number of occurrences of the various significance levels.

these variables will be discussed below. Before testing whether the measures differ significantly from zero, I use the Jarque-Bera test (Jarque and Bera 1980) to explore whether there is a significant probability that the data points are not distributed normally. Of the 240 book-topic count cases, not a single population of measures was significantly different from normal. Therefore I conducted a one-tail one-sample T-test with the null last time slice is equal to zero. The results are reported in Table 4.2.

For 13 of the 30 books, the difference in entropies is statistically different from zero for *all* topic-counts. The effect sizes vary both between books and across the number of topics but nonetheless indicate a shift toward fewer topics being discussed. The practical implications of a shift associated with those effect sizes are not immediately clear, and additional analysis will be necessary to give a meaningful assessment. What does seem clear is such effect sizes are not associated with the emergence of a consensus reading of the book, a point I return to shortly. Then there is a second group of books for which the difference is significant for most topics, except the cases with a large number of topics. Finally there is a sizable group of books that exhibit significance for only a few or no number of topics. Interpreting this table as a whole then, one can conclude that the community's discussion of a book can often begin to coalesce around a subset of the earlier topics, but in other cases it does not happen at all. The probability of it happening is at least close to 50%, but ultimately depends on how many topics truly are present in the discussion. While it might seem reasonable to conclude that a small number of topics is likely, an assumption that would mean convergence is more probable, Goodreads is a unique, engagement driven community and it is not clear what number of topics would be likely. Furthermore, given the vastly different themes works in literary fiction, the breadth of the discussion is likely to vary between books.

The ambiguous nature of these results suggests other factors might drive the outcome. The most obvious factor is the text itself. While this project assumes the public reading of a text has some measure of independence from the words on the page, that reading is certainly constrained by the text itself. However, gauging the interpretive challenges these individual works present is not possible on the very grounds this study is predicated; meaning is a cultural phenomenon and therefore must be analyzed at the level of the group, and an individual analyst's reading of the text would be insufficient for identifying the inherent ambiguity of the texts. There are, however, other features that might help explain why some books do exhibit a shift toward few topics. The gendered marketing and interpretation of fiction is often noted (Ellis-Petersen 2015; Flood 2013; Matthews and Moody 2007) and Goodreads itself reports the audience for books by female authors is 80% female while it is 50% for male authors (Goodreads.com 2014). As the averages Table 4.1 show, however, the gender of the author would be a weak predictor of a shift toward fewer topics. Perhaps then a feature of the population of the reviewers predicts the shift? The averages for the group of books clearly exhibiting convergence (the first 15) and the group clearly not exhibiting convergence (the last 9), presented at the bottom of Table 4.1 indicate that neither the number of reviewers nor the length of the reviews is of importance. A shorter period for the collection of reviews, an artifact of the logic by which the sample was constructed, might miss the important winnowing phase of the dynamics, but, in fact, also does not appear to play any role in predicting the shift. Finally, the connectivity of the reviewer network, as measured by the fraction of reviewer pairs in the network's giant component, and the network distances between reviewers are essentially equal for both groups of book.

There may be much to be learned by a more detailed analysis of the audience. The data on the books the reviewers have read may reveal important information about the pre-existing tastes of the reviewers. A narrower range of tastes among the readers and reviewers would likely make easier the process of winnowing topics. Alternatively, high-centrality reviewers or popular reviews might be key to the process; I have the data to explore both factors in future work on this project. However, the value of such work is not yet known because first I need to better understand the size of the effect for the case when it is present. There are reasons to be pessimistic that the effect size is related to an appreciable reduction in the number of topics being discussed; the results of the experiment and the data in Table 4.1 suggest Goodreads is in fact may not be a good platform for encouraging the emergence of consensus views. The average path lengths between reviewers is long, and the experiment in Chapter 3 showed it would take a significant amount of niche signals to overcome path lengths as long as those between Goodreads reviewers.

Another reason to think there is a low chance of the convergence being meaningful to human interpreters is that there is evidence that the conversation maybe polarizing. I compared the individual reviews to the group level topic distribution for that time period using the Jensen-

Shannon divergence. That divergence is a measure of how similar an individual review is to the general frequency of topics. While we would certainly not expect all reviews to look the same as the prevailing frequencies, we might expect them to start to look more like the general discussion over time. If the average Jensen-Shannon divergence is decreasing from the first to the last time period, that would be a strong indicator of an emerging consensus regarding themes. Conversely, an increase in average divergence would indicate the conversation is becoming more splintered, with different groups contributing specific themes to the conversations. Table 4.3 shows there is evidence of increases and decreases in average divergences, as well as evidence of neither. An increase in average divergence is compatible with a general reduction in the number of relevant topics, but also indicate the existence of tensions that make a more significant winnowing of topics unlikely; different segments of the audience are focusing on different themes, a type of sorting that forestalled global coordination in the experiment in Chapter 3. This again suggests a real shift toward a few topics dominating is unlikely.

Discussion and Conclusion

Taken as a whole, the results above paint an inconclusive picture about the group dynamics of reviewing books on Goodreads. The fact that close to half of the books exhibit a decrease in topic-prevalence entropy over time suggests that later reviews are indeed focusing on fewer aspects of the work. This is valuable support for the hypothesis that, as a networked public, Goodreads can facilitate discussions leading toward consensus. The size of the shift toward fewer topics is not clear, however. As a first order problem, while there is a shift toward fewer topics for 13 books for all studied topic counts (3 through 10) and for all but one for two more books, the size of effect is variable across the number of topics. Thus, as a matter of model selection, we do not know which best captures the true magnitude of the shift in spite of having a high degree of certainty that one exists. Beyond this issue, a loss of entropy is hard to interpret as a measure of change in discourse. I provided a toy example to give the slightest of intuitions behind the measure, but, frankly, a great deal more can be done to study the behavior of the measure more generally. Furthermore, that would only be one step in understanding how to interpret effect sizes. The next step would be to assess what meaningful consensus looks like in terms of entropy. It seems clear that, functionally speaking, a consensus meaning is established before the topic-prevalence entropy reaches zero. Consensus meanings do not invite further commentary, so actors cease to engage each other around that item of mutual interest, and the discourse halts. Thus, as a matter of measurement, consensus would be achieved at non-zero entropy, but it is not at all clear what would be a suitable value in any given case.

Book ID	3 topics	4 topics	5 topics	6 topics	7 topics	8 topics	9 topics	10 topics
18498569	0.017	0.014	0.011	0.009	0.005	0.003	0.003	-0.000
17225311	0.002	0.003	-0.000	0.001	0.000	-0.000	-0.002	-0.003
10996342	0.008	0.006	0.006	0.005	0.005	0.005	0.004	0.002
16045140	0.006	0.002	0.002	0.000	-0.003	-0.002	-0.004	-0.003
13366259	0.000	0.004	0.001	0.002	0.003	0.003	0.003	0.002
12401556	0.014	0.015	0.013	0.011	0.011	0.009	0.009	0.008
18428067	0.007	0.004	0.000	-0.002	-0.006	-0.010	-0.014	-0.014
17333230	0.004	0.005	0.005	0.002	0.002	0.000	-0.000	-0.000
10364994	-0.004	-0.003	-0.002	-0.003	0.002	0.001	0.003	0.003
8366402	0.009	0.009	0.009	0.006	0.005	0.006	0.005	0.003
17934521	-0.001	-0.002	-0.007	-0.007	-0.005	-0.006	-0.007	-0.008
12408149	0.019	0.011	0.011	0.009	0.008	0.007	0.004	0.007
15852479	-0.003	-0.002	0.000	-0.003	-0.000	-0.001	-0.002	-0.002
17830123	0.009	0.006	-0.001	-0.006	-0.009	-0.010	-0.014	-0.015
10846336	0.007	0.002	0.000	-0.001	-0.003	-0.004	-0.006	-0.008
13330761	0.004	0.001	-0.003	-0.007	-0.010	-0.013	-0.018	-0.019
18652002	0.018	0.013	0.005	0.005	-0.001	-0.004	-0.006	-0.010
18507827	0.017	0.011	0.007	0.003	0.002	-0.001	-0.003	-0.003
10306358	0.007	0.004	0.002	0.003	0.004	0.003	0.000	-0.000
11250317	-0.013	-0.017	-0.008	-0.008	-0.001	-0.001	0.004	0.002
15781725	0.012	0.007	0.002	0.000	-0.004	-0.006	-0.008	-0.008
17333319	0.010	0.008	0.006	0.006	0.003	0.003	0.002	-0.000
9902278	0.003	-0.001	-0.004	-0.006	-0.004	-0.005	-0.003	-0.006
13320466	-0.003	-0.005	-0.005	-0.008	-0.008	-0.010	-0.011	-0.011
16158508	0.001	-0.004	-0.004	-0.004	-0.003	-0.004	-0.006	-0.008
13593526	0.004	-0.001	-0.001	-0.007	-0.007	-0.008	-0.008	-0.009
10149142	0.015	0.007	0.004	0.004	0.006	0.002	0.002	0.001
12888599	-0.001	-0.007	-0.010	-0.012	-0.014	-0.017	-0.019	-0.018
16099196	-0.016	-0.011	-0.006	-0.004	-0.002	-0.001	-0.002	-0.001
13540215	-0.006	-0.005	-0.005	-0.004	-0.005	-0.003	-0.006	-0.004

P < .01 P < .05 P < .01 P <.05

Table 4.3: The Difference in Average Divergences. Each cell is colored according to the results of a two-tailed T-test for a significant difference from zero for the difference in the average divergence between time periods. The number reported in the cell is the average difference.

Related to the interpretation of entropy as a measure of convergence is the result that the prevalence of some topics can be increasing while the discourse is becoming more splintered. By measuring the divergence of an individual document from the general pattern of topics in circulation in the time period it was contributed, I showed that over time individual documents could become less like the group level distribution of topics. This means the group distribution is a summation of distinct threads of conversations instead of reflective of the modal reviewer. If this pattern continues, the group is not headed toward consensus but rather a protracted state of discord. But this can also be a transient state of local coarsening that is a natural part of the production of consensus. This pattern was often observed in the experiments of Chapter 3. Nonetheless, entropy can be decreasing while such a splintering process is happening and therefore cannot be immediately equated with what we typically mean by consensus. Adequately measuring the convergence process accordingly will require multiple or a composite measure. Finally, there is also the thorny issue of the behavior of the LDA model for low entropy corpuses. The LDA process is somewhat biased against identifying heavily skewed distributions as the posterior (Blei 2017; Grimmer and Stewart 2013) and therefore might not perform well if the documents are truly converging on a small number of topics. Nonetheless, the encouraging signs of the nascent consensus producing-dynamic above warrant further work here to better understand the issues.

Beyond the problems of the interpretability of the entropy measure, there is also a great deal of variation across books to be explained. A substantial number of books exhibited very different patterns in the significance of their entropy loss. For some, the significance of the effect depends on the number of topics in the model, and for others the measure was never significant. In fact, post testing shows several of the books to experience a statistically significant *increase* in entropy over time. This reveals the presence of one or more currently unobserved explanatory variables. I have shown basic features like the gender of the author or the size or number of reviews do not appear to be factors. There is much more to be explored, however, in terms of the composition of the readers and the dynamics of influence. I have data for exploring both these sources of influence.

As noted in the data description, I collected the reviewers' "bookshelves", their self-identified collection of books they have read. These lists can be used to compare the tastes of users in order to assess whether having a readership with similar tastes is important for driving convergence. Assuming readers tend to prefer books of certain types, the bookshelves can be thought of as vectors in a multidimensional space of genres. For a variety of reasons the best methodology for extracting the latent genres from the collection of lists is again the Latent Dirichlet Allocation model. (The LDA model is in fact more suitable for data like these because book titles do not exhibit properties of words like polysemy and homonymy or need to be cleaned of high frequency words. I have already run the data through the model and obtained very sensible results.) There are several reasons why the LDA is a great, if not the best, way to approach comparing readers' tastes. For one, readers will read books from multiple genres, perhaps in different proportions, and as a mixed membership model the LDA is designed with exactly that property in mind. Secondly, readers likely read different amounts, and that makes it challenging to directly compare the bookshelves. Finally, readers can be reading in the same genre but not have listed the same books. It is easy to be a fan of mystery novels, even steampunk-urban-fantasy-mystery novels, and not have read the same titles as follow fans. By approaching taste as a location in a genre space, readers can be located near each other in spite of having very different bookshelves. By measuring the divergence of tastes between readers, it becomes possible to measure the diversity of the reviewers' taste and test whether it can help explain why some cases show signs of convergence and others do not.

Another data set that could yield any number of insights into the causes of the different outcomes is the site's friendship network. Drawing on this sample, I have already shown the average shortest path lengths between pairs of reviewers to be high. The experiment results in Chapter 3 showed the higher that average, the more niche signals are necessary for the process to lead to convergence. The very open nature of the community and the layout of the site allows for exposure to a great deal of niche signals, but determining if those play a role in the outcome—the original motive for this whole project—will require better understanding the influence of particular documents. As is often the case, social influence can be equated with being central in the network of friendships, and I will calculate and compare the standard centrality measures. However insightful, centrality measures would exclude the content of the reviews from consideration alongside the reviewer's independent influence. Other techniques, like document influence models (Nallapati, Mcfarland, and Manning 2011) and collaborative topic modeling (Blei 2017) can be used to explore the interplay between text and non-textual factors.

While significant work remains on this project, I am encouraged by its general direction. The results were initially disappointing, as I expected more books to exhibit a winnowing of the related discussion, but I now believe the variation observed offers the opportunity to learn more about what can make a digital platform host to an effective "networked" public sphere in which groups strive for consensus instead of a medium through which individuals speak past each other.

Chapter 5: Conclusion

The aim of the work that constitutes this dissertation is to understand more about the sources of information that can facilitate self-organization in social systems. This is a challenging problem analytically because information is not an external resource, but rather is something produced through the process of self-organization itself. This endogeneity allows for independent mechanisms of information production to amount to something more than the sum of their parts when operating concurrently. A major motive in the design of this dissertation was a concern that today's focus on network mechanisms might sometimes be excluding signals that carry information relevant to self-organization. The signals I have in mind are those present in the broader social environments, be they physical or digital, that are not attached to known alters but nonetheless can be used to infer the practices, knowledge, preferences, or values of the broader population. I refer to signals of this type as niche signals. Physical propinquency can help explain the knowledge spillovers that allow economic clusters to thrive (Fujita et al. 2001; Funk 2014; Gertler 2003; Whittington et al. 2009) and can similarly be a source of the signals I study. However, a significant proportion of social life has moved online and the digital public spheres created by communication technologies, *networked publics* (Boyd 2010; Dahlgren 2005; Ito 2008), constitute a whole new social space in which individuals can encounter each other. To reflect the importance of these digital realms for the type of signals I study, I use the term niche to mean both physical and digital spaces.

To assess the potential importance of these signals, I conducted three very different studies. In the first, I used a modified form of the hypercycle equation (Eigen and Schuster 1977; Padgett 1997; Padgett and Powell 2012) to explore the effect of the signals provided by the endogenous structuring of a common resource environment. Coupling the hypercycle dynamics to a dynamic environment significantly increased the complexity (i.e. length) of the resulting hypercycles. While the model is minimal, the results suggest that the information embedded in these products is a powerful aid for self-organizing systems. To assess if the same is true in human interactions, the second study made use of a behavioral experiment. Participants embedded in various network topologies attempted to coordinate with partners to name a pictured individual. The surest way to coordinate is if everyone plays the same name, that is, a global convention. A previous experiment showed global conventions do not emerge in heterogeneous networks (Centola and Baronchelli 2015), but my work showed that the addition of a small number of niche signals facilitated the emergence of a global convention, although the number of signals necessary depended on topology of the network. I believe this is an unintuitive, but important result; if a small number of these signals can alter the outcome of one dynamic process, we ought to be exploring its role in a wide range of dynamic processes. The final project originally sought to assess whether an effect of these signals could be identified empirically within a unique dataset on discussions around literary novels. That might happen eventually, but the project is currently focused on first understanding whether there is any sort of convergence in the discussion. This is a challenging problem methodologically and while I have made significant progress there is still much more to be done.

I will continue addressing the same basic question as I move forward with my work. The theoretical framings and terminologies may change, but I believe there are several trends that make this work valuable. The first is the fact that dual-process models of cognition are being integrated into sociological theories (Lizardo et al. 2016; Vaisey et al. 2009). Social science research involving information processing focuses on the signals recipients consciously process, but the types of signals I'm studying might not be processed consciously, but nonetheless create the background against which we make conscious decisions. The recent growth in the appreciation of the cognition happening unconsciously gives me the space necessary to pursue my agenda.

A second trend is the rise of algorithms. Networked publics like the one I studied in Chapter 4 are structured in part by human-designed algorithms. These programs determine users' exposures to various signals in these public spheres and might well introduce biases into dynamic processes. There is already plenty of work on online "echo-chambers" (Barberá et al. 2015; Bessi et al. 2016; Colleoni et al. 2014; Dahlgren 2005; Prior 2013), but others have pointed out these spaces also expose us to a wide range of signals, often inadvertently

(Brundidge 2010). Thus, understanding the role of these algorithms requires a framework for assessing the importance of these small, currently analytically neglected signals.

The final trend is a blurring of the boundaries between computational methodologies in the social sciences. In particular, I am excited about the prospect of the integration of behavioral experiments with natural language processing (Fong and Grimmer 2016). While there are still details to be worked out in the statistical models, experimental designs could help control some of the issues that make assessing the roles of various mechanisms in social dynamics so challenging to study. My work with the Goodreads data made these challenges clear, and while I have no intention to stop doing research on observational data, I believe that work would be made stronger by complementary work creating bridges between the world of rich text and well-specified mechanisms. Furthermore, I believe I am well positioned to carry out that work as I move forward.

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