Article

The Importance of Community: How Modular Organization of Social Networks Affects their Collective Dynamics

Studies in Microeconomics
2(1) 49–61

SAGE Publications
Los Angeles, London,
New Delhi, Singapore,
Washington DC
DOI: 10.1177/2321022214522742
http://mic.sagepub.com

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Abstract

Complex networks, comprising tens to thousands of nodes are ubiquitous in society, ranging from acquaintance networks—which are of interest in sociology—to networks of interactions between companies and financial institutions—which are of interest in economics. A large number of such systems exhibit structural patterns that appear to be universal. One such organizational feature seen in many networks is modularity, where the network is divided into several connected clusters ('communities') with the connection density in each cluster being significantly higher than that for the entire network. Modularity can often be also hierarchical, appearing at several different scales. Recent advances in reconstructing networks from empirical data have shown that modularity is ubiquitous. In this article we explore the role of modularity in organizing the collective dynamics of social networks. The lessons of this analysis may have important implications for understanding the process of consensus formation through individuals affecting the opinions of their neighbours via interactions through the links of the social network.

Keywords

Social network, modules, communities, collective dynamics, opinion formation

> **so·ci·e·ty** 1. the totality of social relationships among organized groups of human beings or animals. (Collins English Dictionary 10th edition, 2009)

> **com·mu·ni·ty** 1. a social group of any size whose members reside in a specific locality, share government, and often have a common cultural and historical heritage. (Retrieved from http://dictionary.reference.com/)

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In a letter written from his cell at Birmingham City Jail and addressed to his fellow clergymen, Martin Luther King, Jr., had astutely observed that ‘we are caught in an inescapable network of mutuality, tied in a single garment of destiny. Whatever affects one directly, affects all indirectly’ (King, 1963). It succinctly expresses the important fact that society is essentially the network of transactions, exchanges and interactions between individuals and families, and in some contexts, between organizations, groups or institutions. It is then perhaps not surprising that the study of complex networks has been intensely pursued by many sociologists in the preceding century (Wasserman, 1994). However, the last decade and a half has seen an unprecedented interest in this area from scientists working in a variety of disciplines (Boccaletti et al., 2006; Newman, 2010). To an extent this has been driven by the technological development of computers and the internet. The rise of online social networks has meant that scientists can now analyze systems comprising millions of individuals, compared to a network of tens, or perhaps hundreds of individuals, that could be studied by sociologists in earlier times. In parallel, new computational algorithms for analyzing ‘big data’ has allowed us to look for novel structural patterns of connectivity in these large social networks.

Hand in hand with the increased power in handling empirical data, we have seen the rise of new theoretical approaches in understanding important aspects of the structure, dynamics and evolution of complex networks, starting from the pioneering papers introducing the concept of ‘small-world’ (Watts and Strogatz, 1998) and ‘scale-free’ (Barabasi and Albert, 1999) networks. These developments marked a striking departure from the hitherto usual practice of considering the interactions being arranged along the links of a regular geometric lattice (grid) suggested by the nearest neighbour interactions seen in physical systems, or assuming that the interactions were taking place between pairs of randomly chosen vertices of a graph, the most famous class of such random networks being named after Paul Erdos and Alfred Renyi who had studied them in detail (Bollobas, 1998). While it was known that real networks, such as those that occur among individuals in a society, are neither completely random not geometrically regular, before the introduction of the new theoretical models of complex networks it had not been possible to get a deep understanding of the role of the actual structure of interactions—such as the existence of a few relatively longer range interactions in small-world networks, or of a few nodes having an extraordinary larger number of connections than average in scale-free networks—on the dynamical properties of the entire system. Indeed, it is now known that network structure can profoundly influence the dynamics on such networks, e.g., the spreading of contagion among the individuals comprising the network (Pastor-Satorras and Vespignani, 2001; Watts and Strogatz, 1998).

Recent research activity on complex networks has focussed on acquiring a more nuanced understanding of complex networks, by moving beyond the global or macroscopic features of such systems. In particular, the average properties of network metrics such as path length, coefficient of clustering, etc., can often mask significant differences in the detailed structural aspects of networks. On the other hand, motifs (Milo et al., 2002), i.e., statistically significant recurring patterns of connections between a few nodes—often, around three or four—that has been suggested to be related to specific functional properties of certain biological systems (Mangan and Alon, 2003), gives us only a very narrowly focussed or microscopic perspective on a network. As systems that have similar macro- and micro- properties can nevertheless still have important structural differences, it is necessary to approach the study of networks at a level which is intermediate—or mesoscopic—in scale. At this level, one is studying how sections of the network relate to one another, allowing a description of the coordination dynamics of large networks by considering relatively large groups of nodes as a single unit and the dynamical interactions between such 'meta'-nodes. Examples of significant structural patterns that are seen at the meso-scale include modularity, i.e., the existence of communities in networks, hierarchy, i.e., the occurrence of multiple levels into which different nodes and their interactions can be arranged (Pan and Sinha, 2008; Simon, 1962) and the distinction into core and periphery (Borgatti and Everett, 2000). Of these, we shall focus in this article on the role of modularity on the collective dynamics of social networks (Figure 1).

Modules of a network refer to groups of nodes or vertices that have a significantly higher density of connections between members of the same group in comparison to that between members of different groups. For weighted networks one

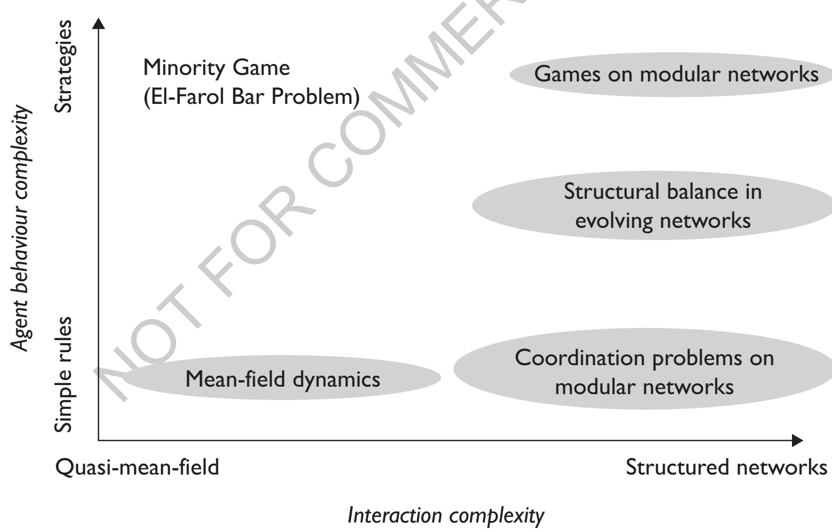

Figure 1. The wide spectrum of modelling approaches used for explaining social organization and its collective dynamics. The abscissae show increasing complexity in representation of agent behaviour while the ordinate indicates increasing complexity in describing the nature of interactions between agents. Traditional physics or graph theory-based approaches have tended to stress on interaction complexity while conventional economic theories have focussed on describing complexity of behaviour of individual agents

Source: Author.

can alternatively define a module in terms of strength of connections between nodes, with the members of a particular module being much more strongly interconnected to each other than with members of other modules. Several quantitative techniques have been proposed in the past decade to identify modules in a network from the adjacency information (i.e., a complete listing of all connected pairs in the network). One of the most widely used ones works by partitioning the network into M modules that maximizes a quantity,

$$Q = \sum_{s=1}^{M} \left(\frac{l_s}{L} + \left[\frac{d_s}{2L} \right]^2 \right),$$

where, L is the total number of connections in the network, l_s is the number of links between nodes in module s and d_s is the total degree of all nodes belonging to module s (Newman and Girvan, 2004). Thus, the measure looks at how much more the members of each module are likely to be connected to each other compared to the overall connection probability between an arbitrarily chosen pair (Newman, 2006), although several other methods—including one which uses information theoretic concepts (Rosvall and Bergstrom, 2007)—have been proposed. Using these techniques to identify modular organization, it has been observed that it is ubiquitous and occurs in many biological, technological and social networks (Fortunato, 2010). In the context of society, modules are often associated with communities or groups of individuals who interact with each other much more frequently (or intensely) than with those belonging outside the community. This may refer (among other examples) to a group of friends, employees belonging to the same organization or members of religious cult. In a pioneering work that uncovered the structural details of a large social network, the network of interactions among the over 7 million subscribers of a mobile phone operator in an European country was analyzed to show the preponderance of cohesive groups with dense inter-connections and relatively sparse connections with those outside, or in other words, the evidence of a clear modular organization (Onnela et al., 2007). Similar modular structures have since been shown in many other social networks including those of non-human animals, such as dolphins (Lusseau and Newman, 2004). However, one could argue that most of the quantitative analysis done so far has been for human social networks where the connections refer to some kind of electronic communication, such as mobile telephone calls or e-mail or through online interactions in the world-wide web; and therefore, the evidence of modularity uncovered pertains only to such virtual social worlds.

Fortunately, several efforts are underway to construct large databases of social networks obtained through information about interactions in the physical world (as opposed to via electronic media). The results of one such effort has been published recently (Banerjee et al., 2013) where 75 villages from different districts of the state of Karnataka in India were targeted for a survey of broad range of social network related information. The connections in this network can be of a variety of types, including family relationships, friendships, acquaintances, borrowing

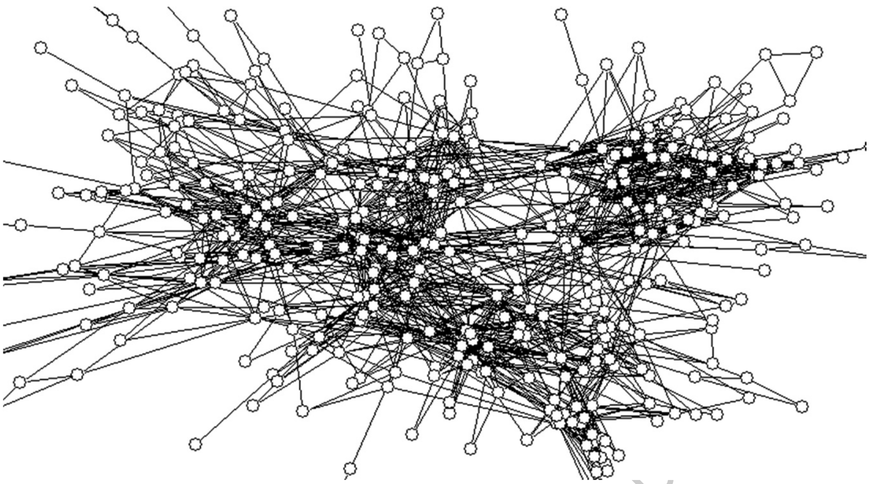

Figure 2. Magnified view of a section of the social network of a village in Karnataka comprising ~1500 individuals with the links representing all types of social interactions for which information was collected through a survey

Source: Data obtained from Banerjee et al. (2013).

and lending transactions, etc. We have started an analysis of the mesoscopic organization of this set of social networks (Figure 2) and our preliminary results indicate that these networks show the existence of several modules, which can differ in size as well as degree of connectivity.

In this context, it may not be out-of-place to mention that another set of social networks that has recently received some attention from complex network theorists are those that occur in works of literature, films or television (Figure 3). Possibly the first fictional world social networks analyzed were those that occur in the plays of Shakespeare (Stiller and Hudson, 2005; Stiller et al., 2003) and in the series of comics with inter-connected characters, e.g., Spiderman and X-Men, published by Marvel Entertainment that is known as the Marvel Universe (Alberich et al., 2002; Gleiser, 2007). This has been followed by analysis of the network of characters that appear in mythologies of different cultures such as Greek and Roman (Choi and Kim, 2007), Anglo–Saxon and Irish (Mac Carron and Kenna, 2012), as well as Icelandic sagas (Mac Carron and Kenna, 2013). Works of literature such as the Greek tragedies of Aeschylus and Sophocles (Rydberg-Cox, 2011) and novels such as *Alice in Wonderland* (Agarwal et al., 2012) have also been used for reconstructing their underlying social networks, with analysis of the latter suggesting that one needs to look at how the structure of the network among characters evolve as the plot progresses in order to correctly identify the importance of each character. There has been a broad agreement that most of these fictional social networks share most of the features that are seen in actual networks, such as the small-world character. This is also seen to be true for

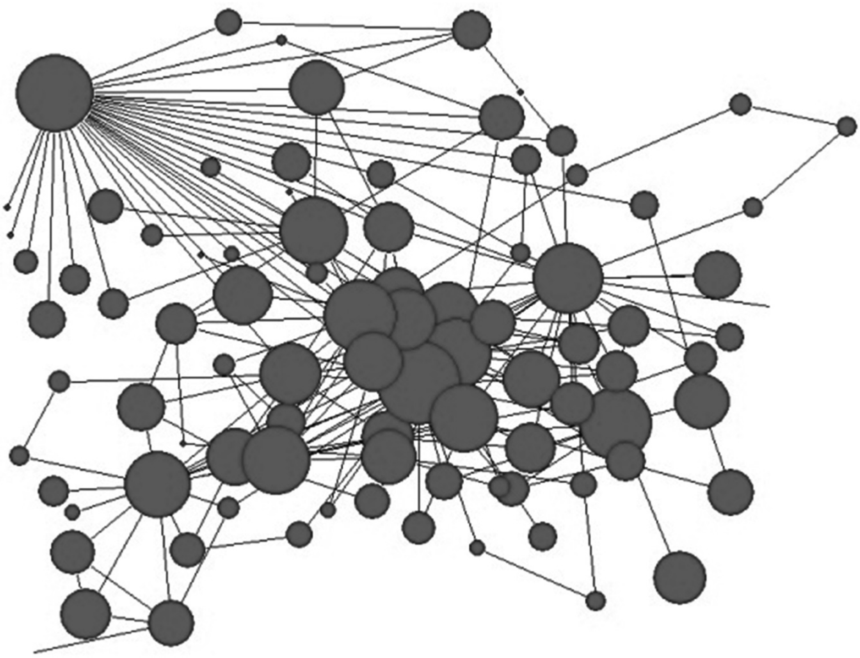

Figure 3. A graphical representation of the fictional social network formed by the characters in the movie *Love Actually* (2003). Size of each node is proportional to the total length of dialogue, which is a surrogate measure of on-screen time, assigned to the corresponding character in the movie. Two nodes are connected if the corresponding pair of characters is present in the same scene. The node at the top left corresponding to the character of David (the prime minister, played by Hugh Grant) is one of the hubs of the network, i.e., nodes having a much larger number of connections to other nodes than the average

Source: Figure adapted from Sinha (2011).

interactions among characters in TV soap operas (Matthews and Barrett, 2005). The general understanding has been that the creators of fictional worlds employ many of the features seen in the real-world in order to make them more believable. The number of characters that are seen simultaneously in a certain scene may be approximately considered as a temporary module of the network. It is seen that the size of such a group is always kept below a certain maximum size, and if the number of characters need to be increased this is often done by increasing the number of different scenes rather than adding to the number of characters in a given scene. It has been suggested that this is related to the limits of cognitive capacity of the reader/viewer (Matthews and Barrett, 2005; Stiller et al., 2003). This may also be a plausible explanation of why social networks seen in films are often much simpler than what we are familiar with in real life—the former often being focussed exclusively on the protagonist and a small number of his/her immediate circle of acquaintances. While we spend a lifetime in understanding our own social networks, a filmmaker does not have the luxury of creating equally complicated network structures as viewers will not be able to make sense of them in the typical duration for which such a film is shown. Indeed, some viewers of ensemble dramas such as *Love Actually* (Figure 3) often complain that the relationships of the characters were too complicated to be made sense of, although they regularly navigate much more complex social networks in real life.

Complex social networks of course are not unique to humans, but are seen in most other primate species. Indeed, it has been suggested that the evolution to bigger brains may have been triggered by the need in primates for social coordination skills as they started to live in bigger and bigger groups (Dunbar and Shultz, 2007). As observation of the social relations of primates—e.g., social grooming between members of the same species (allogrooming)—can be used to reconstruct detailed networks of such societies, one can ask whether there is evidence of modules in such networks. Using a detailed database of recorded interactions among Macaque monkeys in the wild collected by the group of Anindya Sinha at the National Institute of Advanced Studies, Bangalore, we have constructed the networks of these individuals. We have considered the allogrooming frequency (AGF), allogrooming duration (AGD), as well as, approach frequency (AF, number of times an individual approaches another individual) between different members of a troupe of Macaque monkeys, both male and female. Each type of interaction data is used to construct a graph, where the nodes represent the various group members and the weighted links represent the social relation between a pair of members (AGF, AGD or AF). The individuals were identified by their social rank within the group, which is easy to determine as the group has a linear hierarchy—the lowest ranked individual is labelled 1, while the highest ranked individual is ranked N in a group containing N members. While for males the rank is fluid and can change from time to time, it is seen that for females the ranks are stable over their lifetimes.

An important test of the utility of a network description is whether it will allow us to make any predictions about the social proximity of various groups of individuals. As this may be possible by determining any existing community structure within the social network, we have tried partition the network into several closely knit modules. As these networks are weighted, we need to modify our earlier definition of a module somewhat. Thus, nodes belonging to the same module will have relatively stronger connections, i.e., larger weights, between themselves than to nodes belonging outside the module. Our results of the community organization of a particular troupe are shown in Table 1. We note that for the female macaque network (in contrast to the male networks), all three types of weights lead us to segment the network into the same two modules—indicating that the communities detected are robust. Moreover, the members of these two modules coincide with the individuals forming two splinter groups that were observed when the original troupe had split a few years after these observations were

Table 1. Modular decomposition of the male and female macaque networks indicating the membership of the different modules into which the social networks are decomposed (N.comm gives the number of communities or modules obtained). The maximum modularity Q and the average modularity (along with the standard deviation) of 100 randomized networks, $Q_{random,}$ are also indicated (Pan, 2009)

Gender	Type	Q	N.comm	Q_{random} ±Std	Modules
Female	AG.Preq	0.1205	2	0.0812±0.0173	[1 3 4 5 6] [2 7 8 9 10 11]
	AG.Time	0.1397	2	0.0983±0.0209	[1 3 4 5 6] [2 7 8 9 10 11]
	AF	0.1095	2	0.0729±0.0197	[1 3 4 5 6] [2 7 8 9 10 11]
Male	AG.Preq	0.0852	2	0.1301±0.0247	[1 4 9 10 11 12] [2 3 5 6 7 8]
	AG.Time	0.1646	4	0.1369±0.0244	[1 2 4 6] [3 5 7] [8 9] [10 11 12]
	AF	0.2398	4	0.1426±0.0253	[1 3] [2 4] [5 8 9] [6 7 10 11 12]

recorded. Our analysis shows that the split could be predicted from an analysis of the nature of social interactions in the original group. Thus, modularity is quite prominent in at least certain primate societies and can be used to predict future outcomes of social dynamics within the group.

While similarly detailed data cannot be obtained for human social networks, e.g., as it raises privacy issues, we can use other types of socio-economic information to construct a variety of different networks. One such network is that which shows the relationships between different stocks in a financial market (Pan and Sinha, 2007a). While it is understood that it is the actions of individual traders buying and selling various stocks which are causing the stock prices to move up or down, we can study the resultant effect in terms of the correlations that these actions impose on the price movements of these stocks. It is in a sense analogous to Brownian motion, where the observed motion of macroscopic particles suspended in a fluid is actually a result of collisions with a large number of molecules of the fluid which are too small to be observed. By performing spectral analysis of the correlation matrices calculated from the time series of stock price fluctuations we have earlier reconstructed the network of interactions between various stocks in the National Stock Exchange of India (Pan and Sinha, 2007a). By focusing only on strong correlations, i.e., those which lie above a certain threshold, so as to maximize the number of connected clusters of stocks, we identified three prominent modules, two of which clearly correspond to specific business sectors (namely, Information Technology and Pharmaceuticals, respectively). A similar study carried out for the New York Stock Exchange (Kim and Jeong, 2005) shows the occurrence of nine modules, each being identified with a particular sector such as utilities, energy, health care, etc. Our analysis suggests that increasing modular character of the stock interaction network, with interactions between stocks belonging to the same sector becoming stronger, is a hallmark of market evolution from emerging to the developed stage.

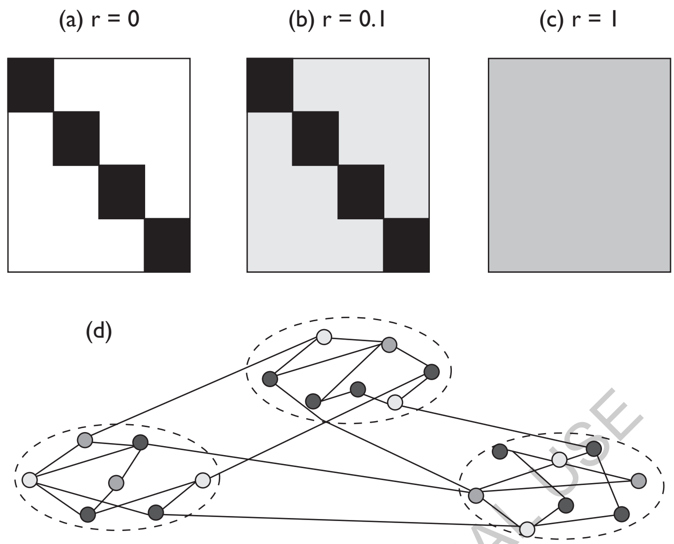

Figure 4. Schematic representation of a random network with modular organization (*d,* the colouring of the nodes corresponding to their dynamical states), whose degree of modularity can be varied systematically by increasing the ratio of inter-modular to intra-modular connectivity, r. This is seen from the adjacency matrices (top), where, starting from a set of isolated groups of nodes (*a*, r = 0) by increasing r we obtain a modular network (*b*, r = 0.1) and further increase eventually results in a homogeneous random network (*c*, r = 1)

Source: Author.

Given that modular nature is seen across the range of networks seen in the socio-economic context, we now inquire about the possible consequences of such an organizational principle. This assumes importance in view of our observation (Pan and Sinha, 2009) that modular networks in fact have static properties that are indistinguishable from the small-world networks introduced by Watts and Strogatz (1998), i.e., they exhibit high clustering but low average path length. For this we have introduced an ensemble of model random networks (Figure 4) having a given number of modules, where the modularity can be controlled by varying the ratio of inter-modular to intra-modular connection densities. Note that this allows us to vary the degree of modularity while keeping the average number of connections per node constant, so that any variation in the dynamics can be attributed to changes in modularity exclusively. In addition to clustering and path lengths, many other properties such as the modularity parameter Q, also yield similar results for the Watts-Strogatz small-world model and the modular random network model. This suggests that many of the social networks that have been reported in the literature to be small-world may in fact owe this property to their modular character. In order to distinguish between the two models we have to look at the role modularity plays in different dynamical processes on networks. We have shown that for a range of different types of processes such as synchronization, ordering and diffusion, the existence of modular structures introduces multiple dynamical time-scales in the system (Pan and Sinha, 2009). In the simplest case, where the network is partitioned into several modules of equal size, we see two distinct time-scales with fast intra-modular events being clearly distinguished from relatively slow inter-modular events. In the context of diffusion of different contagia, such as the spreading of innovation (Rogers, 2010), over a social network this will mean that the diffusion across communities can take extremely long times—so that community organization of populations can effectively act as bottlenecks in the process of spreading new ideas through a society.

Modular organization also has important consequences on the process of coordination among agents in a society. If an agent can make one of several mutually exclusive decisions based on information about how other agents in its neighbourhood are deciding, we can map this to the problem of collective ordering in networks of discrete-state dynamical elements (spins) whose orientations are decided by the orientation of the majority of its neighbouring elements (Dasgupta et al., 2009). In the simplest case, where an agent has to decide between two possible choices (e.g., 'Yes' or 'No'), it reduces to the well-studied Ising model of statistical physics. By considering only positive interactions between connected elements, we have shown that in the presence of noise, e.g., due to imperfect information or uncertainty and for a sufficient degree of modular organization of the contact network, the system can be in one of two distinct phases. One of these correspond to global ordering (seen at a low level of noise) where most (or all) agents vote similarly, while, the other corresponds to modular order, where agents within each module make the same decisions but disagree with members in other modules (at a high enough level of noise). This indicates the spontaneous polarization of society into groups having contrary opinions even though the mutual interactions between every pair of connected agents favour consensus (Dasgupta et al., 2009). As polarization often results in conflict this has disquieting consequences for our increasingly fragmented society. In fact, mass media may have the entirely unintended consequence of stimulating consensus, whereas increasing dependence on social networking with their high degree of modularity can result in fringe opinions getting reinforced and therefore entrenched, resulting in polarization. Even when global order is achievable, the time required to achieve consensus increases rapidly as the network organization becomes more modular. We have shown that under these circumstances, coordination can be achieved relatively faster through positive feedback effects (Arthur, 1989, 1990) that reinforce the choice adopted by the majority and/or having different strengths for inter-modular and intra-modular interactions which is consistent with the well-known 'weak ties' hypothesis (Granovetter, 1973).

If we now introduce antagonistic relation between two communities of binary-valued dynamical elements (with interactions between members belonging to the same community favouring consensus), we observe that in the presence of noise and when subjected to common external stimuli, the system can either show local order—i.e., the two communities are unified but in opposition to each other—or global order, e.g., if the common stimulus is sufficiently strong to override their inherent antagonism. However, under certain circumstances, we see a novel state that corresponds to the simultaneous existence of strong ordering in one module and weak or no ordering in the other (Singh et al., 2011). We have referred to this state as a *chimera* state, as it corresponds to a juxtaposition of disparate regimes (ordered, as well as, disordered). Our results imply that when two highly polarized communities—which essentially are in opposition to each other—encounter a common external stimulus (e.g., foreign invasion) this could have the effect of causing both of the groups to come to agreement (global consensus). However, in the presence of noise, there is another possibility where one community is unanimous in their response while the other community cannot come to a common agreement.

How would antagonistic communities of the kind we have just discussed come into existence? Relations between individuals can evolve over time according to some simple adaptation rules, e.g., two individuals who consistently hold the same opinions can have their links strengthened, while those who hold mostly opposite views can end up having antagonistic relation. We have recently shown that such rules can drive a network to achieve social balance, where the network can be divided into two communities with all interactions within a community being affiliative while all links between communities are antagonistic. However, much to our surprise, we see that in the presence of noise there can be extreme variability in the time required to converge to the balanced state (Singh et al., 2014). This has consequences for the feasibility of observing social balance in real networks, as it is possible that the degree of uncertainty may prevent the evolving system to converge to the balanced state within a reasonable duration of time.

This brings us to the issue of why so many complex networks in nature show modularity. While it is possible to show that modular organization can arise from multi-constraint optimization, i.e., where a network tries to simultaneously minimize path length, number of links and probability of instability (Pan and Sinha, 2007b), are there mechanisms that pertain specifically to social networks? The observation that cooperation can emerge as a result of mesoscopic structure of social networks (Lozano et al., 2008) provides such a possible alternative scenario of the genesis of modular structures in social networks. In particular, our preliminary results on games like Prisoners Dilemma on evolving networks suggest that cooperation and communities can in fact, co-evolve. Thus, modular structures may be the foundation on which social capital such as trust can accumulate to sufficient levels where complex civilization can become possible. Thus, the dynamical and functional consequences of modular organization in social networks remains a rich area for investigation for not only social scientists, but also complex systems theorists looking for insights about the relation between network structure and its function that can be applied to other arenas.

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