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Using big data to map the network organization of the brain

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Abstract

The past few years have shown a major rise in network analysis of “big data” sets in the social sciences, revealing non-obvious patterns of organization and dynamic principles. We speculate that the dependency dimension – individuality versus sociality – might offer important insights into the dynamics of neurons and neuronal ensembles. Connectomic neural analyses, informed by social network theory, may be helpful in understanding underlying fundamental principles of brain organization.

Neuroscientists are increasingly analyzing distributed patterns of connectivity between spatially dispersed brain regions, placing the topic of network interconnections at the center of the field (Behrens & Sporns 2012; Bullmore & Sporns 2012; Sporns 2012; Supekar & Menon 2012). What lessons might Bentley et al.'s quadrant analysis of social networks have for understanding brain networks? We propose that the role of dependency – the west–east dimension of individuality versus sociality – might be particularly important for understanding the dynamics of neurons and neuronal ensembles.

Dependency is ubiquitous in graphs characterizing real-world phenomena, and it is useful to consider how it might arise. Analyses of random networks (also called random graphs) may begin with a collection of nodes joined by edges at random. A large body of results have been obtained: The subject goes back to the Erdős–Rényi model of 1959–1960 (see Erdős & Rényi 1960), but the corresponding results bear little relation to graphs that arise in real-life situations, where edges are characteristically added with some dependence on edges that are already present.

A more interesting class of networks, which has received much recent interest, are so-called “small networks” in which most nodes are not directly connected to each other, but can be reached from every other by a small number of hops. This sort of network is often explained

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in the popular literature via the “Kevin Bacon Game” in which the nodes are actors and the edges connecting them represent their having appeared in the same movie. The question is then posed of how many edges one must follow (how many nodes one must hop between) to get from Kevin Bacon to any given actor. Each actor then gets a “Bacon number” which represents how many hops away from Kevin Bacon they are. Remarkably, most successful actors have a Bacon number less than or equal to 5. Such networks, in the context of the four-quadrant human decision-making map (Behrens & Sporns 2012), would represent a trend toward the east – more sociality, and more chances to connect lead naturally to such networks. Such networks have many interesting properties including a tendency to have a small number of nodes with very high degrees of connectivity – something that can be looked for in (big) data. Similar patterns appear in anatomical connections in the brain (Sporns et al. 2002) and in synchronization networks of cortical neurons (Yu et al. 2008).

Various mechanisms can give rise to such networks, the most popular being the Watts-Strogatz (W-S) mechanism (Watts & Strogatz 1998), which is constructed by iteratively rewiring a pre-existing graph (something which might be expected to model evolution on a pre-existing network), and the Barabási–Albert (BA) model (Barabási & Albert 1999), which is based on the notion of preferential attachment, where new nodes are added with connections made preferably to those which already are more connected. The BA model, for example, has been used to model the World Wide Web (www) where one might well expect that more people would add new links to a more popular (more linked to) site than to one less used. A general review can be found in Albert and Barabási (2002).

The BA model also gives rise to an interesting distinction from the W-S mechanism in that it gives rise to power-law or “scale-free” networks where the number of nodes with some number of connections depends as a power of that number. This gives rise to long-tailed distributions (Behrens & Sporns 2012). Indeed, this behavior is found by Bentley et al. in their Figure 1 (target article, sect. 2). Again, this sort of behavior can be sought in big datasets and can give valuable information about the possible origin of a given network configuration. So far we have assumed a deviation from randomness (an appearance of structure) due to fairly deterministic processes where, even if edges appear randomly, their probabilities depend deterministically on other factors. Relatively little is known if one weakens this dependence by the addition of random noise.

As an aside, we note that the north–south axis is described as “the extent to which there is a transparent correspondence between an individual's decision and the consequence of that decision” (target article, sect. 2, para. 4). If we interpret this as a weakening of a direct cause-effect relationship, we suggest that this might indeed be modeled as noise – something that has been much less studied in the physics community, yet which could surely be added to models which have been considered, in some cases perhaps analytically, but also certainly via computer simulations. Spin-glasses are often used to model network dynamics (Binder & Young 1986) where a temperature-like parameter represents noise, but this work tends to be done to represent correlations between activities at nodes rather than on the dynamics which drives the formation of edges – that is, the structure of the network itself.

Big-data approaches from the social sciences are already motivating significant new developments in characterizing brain networks. Over recent years, connectomic analyses of brain activity in large datasets have elucidated the network architecture of the brain (Behrens & Sporns 2012; Sporns 2012; Supekar & Menon 2012) and identified fundamental principles of the brain's graphical organization (Bullmore & Sporns 2012). New approaches promise to shed light on brain networks implicated during specific cognitive tasks, such as altered network interrelationships during volition regulation of emotion (Sripada et al. 2013). Such brain mechanisms involved in specific cognitive tasks might ultimately be helpful in understanding brain-behavior responses to real and increasingly social stimuli – for example, parents responding to baby-cries (Swain & Lorberbaum 2008; Swain et al. 2004; 2011), the complex array of social responses involved in parenting (Swain 2011) – and to broader societally directed behaviors such as altruism (Swain et al. 2012). Such approaches may be helpful in understanding underlying mechanisms of psychiatric disorders such as obsessive-compulsive disorder (Leckman et al. 2004; Mayes et al. 2005), generalized social anxiety, and autism that involve pervasively abnormal functioning in social domains.

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