Parallels in Neural and Human Communication Networks

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Introduction

This chapter seeks to explore functional characteristics held in common by neurons in the brain and humans in society. A better understanding of the commonalities between brain network computation and human social network function may provide a framework for better understanding the potential for human computation as an emergent behavior. Establishing a mechanism by which differences and similarities in the computational potential of brain and human social networks can be evaluated could provide a basis by which human computation may be operationalized.

Natural systems are complex and dynamic, characteristics that make accurate prediction of their behaviors over time difficult if not impossible. This property is held in common by both physical systems such as the weather and the movement of the earth's crust and biological systems from genetics to ecosystems. Further, these are adaptive systems that have evolved over time to optimize their ability to survive in the face of changing environmental conditions at a range of time scales.

Complex systems are distinguished from complicated systems not on the basis of the number of constituent elements but on the potential to predict system output based upon an understanding of behavior of each element and its position in the system. The requisite characteristic of a complex system is the presence a large number of interacting non-linear elements, be they neurons or humans. The relevant property of complex systems for our purposes here is that they exhibit emergent properties; that is, macroscopic behaviors emerge from the interaction of constituent elements rather than being dictated by some controlling source (Chialvo 2010).

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A hallmark of complex dynamic systems is the presence of abrupt transitions from one physical or behavioral state to another that are termed phase transitions. Examples of such behavior include such everyday occurrences as the transition of water from a liquid to a solid state, or of liquid water to a gas when boiled. Such transitions also characterize biological systems with a common state transition seen, for example, in the alternations between wake and sleep.

A final property common to complex dynamic systems is their organization into interlinked networks. Systems are, by definition, composed of interconnected elements or components that act together to process a set of inputs and produce some behavioral output. Network theory provides a powerful tool by which to describe and analyze the interactions of complex and dynamic systems and has been used in the analysis of brain (Bassett and Bullmore 2006; He et al. 2007), human social (Brown et al. 2007; Gulati et al. 2012) and technical (Barabási et al. 2000; Wang and Chen 2003) systems. Further, network theory offers a common framework within which to understand both the similarities and differences in the computational potential of both neural and human communication systems that is the goal of this chapter.

This chapter will provide overviews of both neural and human social system composition and communication together with the network theory view of their global operations as complex, non-linear dynamic systems. Within that framework we will then move to commonalities in the processing mechanisms of both systems, followed by a short discussion of their differences. A more speculative section concerning the potential for human computation will finalize the chapter.

The Brain as a Complex Dynamic System

The brain is a complex adaptive system that controls organismal behavior to environmental stimuli. Accurate assessment of the context in which a behavioral response will be generated is essential to successful performance and, in many instances, to organismal survival. To achieve appropriate responses to environmental stimuli, the brain must be both sufficiently stable as to estimate the consequences of a response, and sufficiently flexible to respond to completely novel or unexpected stimuli.

The brain is composed of a large set of interacting complex cellular elements, the majority of which fall into the two categories of neurons and glia. Brain processing of both external and internal environmental stimuli involves a complex and incompletely characterized set of interactions between these cellular elements and their extracellular milieu. That said, as the neuronal elements generate the system output structure, the vast majority of studies have focused on the neuron as a central processing element of the brain and it will be on this element that we also will focus.

Neurons, and as is becoming increasingly clear, the glial elements with which they interact, communicate both individually and within circuits that enable dynamic aggregation of processing-specific populations. The system is hierarchical in the sense that circuits themselves interact to form increasingly complex circuits, leading to the identification of processing modules with distinctly different processing parameters (Felleman and Van Essen 1991; Meunier et al. 2010; Zhou et al. 2006).

An example of one such distinct hierarchical module is the retina of the eye, a complex and hierarchical network of interacting elements that receives light from the external environment, processes that input to provide information on both pattern and color in the external environment and transmits that highly processed information to multiple different circuits in the brain to not only enable the organism to "see" the external world, but also to inform other brain circuits as to the level of light in the external world as a separate input.

Human Social Organization Is a Complex Dynamic System

Human social systems are also adaptive, complex dynamic systems. Human social organization, like that of other social organisms, provides the system as a whole with an adaptive capacity that improves survival and viability. Social systems provide a stable organization in which each individual can operate with established rules by which flexible, adaptive responses may occur. Moreover, social systems undergo phase transitions at both local and global scales, from abrupt shifts in organizational leadership to political or social revolutions that dramatically reorder the social hierarchy (Garmestani et al. 2009; Holling 2001; Wilkinson 2002).

Individual humans are the basic processing element of human social systems. Each individual is unique and complex, and highly connected to other individuals in the society. Social organization begins with connections between individuals (Davidsen et al. 2002) which networks are then embedded in larger network(s). Communication in its multiple forms provides individual members of a society with information required to update experiential data used in decision-making and the guidance of appropriate responses to environmental stimuli.

Human social organization is hierarchical, and each individual is embedded in a complex network that includes family, friends, professional associates and acquaintances (for further discussion, see Analysis Section, this volume). This intricate extended network is clearly seen in the use of social networking sites such as Facebook, Twitter and LinkedIn, where individuals form communication links to others based on personal or professional affiliations. Such linkages extend beyond the individual through organizational behaviors and organizations, and at larger-scale to the behavior of the polity whether local, national, inter-national, or global.

Neural Communication Structures

Although neuronal morphology varies greatly, a characteristic structure can be defined that informs our understanding of the processing capabilities of single brain elements. Neurons are composed of a cell body, the soma, from which extend two different types of processes: the dendrites with are electrically conductive but historically considered passive, and the axon which actively transmits electrical signals. Classically, the dendrites are receptive cellular processes that act to pass information to the cell soma, which acts as the cellular processing element. While recent data points to dendritic processing capability (Spruston 2008) information flow to the soma remains fundamentally characteristic. The soma has a highly complex internal structure that provides substrates for information processing, plastic remodeling of cellular morphology and molecular biology, and health maintenance, which can be considered the complex internal structure of the basic brain processing element and not discussed further. From the soma, information is transmitted to other brain cellular elements via the axon. The receptive elements of the neuron are the receptors, which are proteins embedded in, and capable of movement within, the neuronal membrane. Receptors are found predominantly on dendritic membranes, but also exist on the soma.

The neuron is an electrically excitable element, with electrical current generated by the passage of ions across the cell membrane. As noted above, information is transferred between elements via specialized protein complexes known as receptors. The classical neuronal receptors are activated by chemicals synthesized in the neural soma and released based on the voltage potential of the somal membrane, providing the electro-chemical communication system of the brain. As these chemicals and their receptors are found in the brain they are termed neurotransmitters and neurotransmitter receptors. A large number of neurotransmitters exist, most of which bind to specific receptor proteins, acting to change the protein complex conformation and either open ionic channels through the cell membrane or initiate complex intracellular biochemical cascades to affect behavioral changes in the receiving cell. The process of electro-chemical neurotransmission occurs at a specialized region of contact between two cells known as the synaptic cleft. The synaptic cleft is an area of directed cell-to-cell communication, i.e., information is passed from one cell (the presynaptic cell) to another (the postsynaptic cell) unidirectionally. However, there may be more than one synaptic cleft present between two cells, providing for bidirectional information transfer. The presynaptic element is specialized for the release of neurotransmitter into the synaptic cleft. Once released into the synaptic cleft, neurotransmitters diffuse passively across this narrow gap between cell membranes (~ 20 nm). The postsynaptic cell membrane is rich in neurotransmitter receptors capable of binding the released neurochemical. Termination of signaling is accomplished by several mechanisms including reuptake into the presynaptic cell, diffusion out of the synaptic cleft, or enzymatic degradation, creating rapid, point-to-point communication.

While neurochemical communication is rapid, electrical synapses communicate between cells almost instantaneously. Signaling in this type of synaptic contact takes place through specialized transmembrane proteins called connexins that directly couple the presynaptic and postsynaptic membranes, allowing for rapid exchange of ions and metabolites between cells (Nagy et al. 2004; Scemes et al. 2007). This type of cellular communication mechanism has been found to link neuronal and glial elements (Nagy et al. 2004), to provide synchronized activity in glial elements (Theis and Giaume 2012), and to be important in state transitions in the brain (Haas and Landisman 2012).

In addition to rapid, point-to-point communication, less compartmentalized forms of communication are demonstrated by extrasynaptic (volumetric) release of neurotransmitters that act via receptor complexes outside of the synaptic cleft

(Vizi et al. 2010). Such interactions may occur through activation of peri-synaptic receptors that lie outside of the synaptic cleft but spatially close to it (Oláh et al. 2009; Vizi et al. 2010), or via distant receptors (Fuxe et al. 2013). This communication channel is slower than the point-to-point mechanisms described above (seconds-minutes) and takes place over distances as great as 1 mm from the release site. Thus, the effector region of this type of communication is sufficient to modulate circuit behaviors in a manner analogous to that described in invertebrate systems (DeLong and Nusbaum 2010).

The cellular elements of the brain communicate on different time scales using a wide variety of neurotransmitters whose effects are magnified by their interaction at a large number of receptors with different structures and postsynaptic actions. The fundamental processing unit of the brain is the neural circuit—aggregates of cellular elements and their synaptic and extra-synaptic contacts. Such circuits are formed at multiple levels of complexity, but fundamentally form dense inter-circuit connections with a smaller number of connections to other circuits with which they communicate resulting in the hierarchical architecture noted above for neural systems. To characterize a neural circuit fully would include a full description of the circuit wiring diagram and the neural elements embedded within that structural web, a full understanding of the neurochemical systems by which information was transferred and the time-frame on which such interactions depended together with a comprehensive description of the input–output function of that circuit under the recognition that its behavior is highly likely to be non-linear. Thus, a full description of even a 'simple' neural circuit has not yet been achieved; although a number of models and research studies have pointed to the complex behaviors such circuits are capable of producing (Ahrens et al. 2013; Guertin 2012; Kaneko 2013).

The hierarchical structure of the brain leads us beyond the 'simple' neural circuit, to the complex of circuits that together form the large-scale networks described using neuroimaging methods such as functional magnetic resonance (fMRI) and positron emission tomography (Barch et al. 2000; Dosenbach et al. 2007; Just et al. 2007). Using these methods provides a global view of brain connections during behavior in which interactions encompassing large brain areas connected over long distances can be linked to cognitive behaviors such as learning, memory and attention. Recently, a new area of research into large-scale brain connectivity has been developed based upon imaging of active brain circuitry when the subject is not performing any task, a condition termed 'the resting state' (Biswal et al. 1995; Cohen et al. 2008; Fox et al. 2005; Mennes et al. 2010). The linkage of brain structural connectivity to the functional organization definable during the resting state provides a new window on the organization and function of the brain (Deco et al. 2013).

Human Social Communication

Human communication structures exist at multiple scales, from small groups where contact is frequent, to increasingly distributed interactions where contact is less frequent. Humans transmit information in the form of both oral interactions and via the more permanent and globally accessible forms of written communication. Particularly in oral communication, transmitted information content is often modulated by emotional content or non-verbal communication in the form of body-language cues. While visual modulatory cues are not present in written communication, they are often inferred by the reader.

Human social groups cluster at multiple levels, with small groups (cliques, clans, tribes, etc.) having high degrees of internal communication but little communication with other groups (Bryden et al. 2011), an organization termed community structure (Girven and Newman 2002). This organization, described for many aspects of human social interactions, imparts a modular structure to the large-scale network in which communities are richly interconnected locally, but only sparsely connected to other communities in the global networks (Gulati et al. 2012).

Studies examining social network behavior in organizations note that highly local and isolated networks tend toward a homogeneous knowledge and decision base, making it desirable to seek outside contact to drive creativity and innovation (Gulati et al. 2012). The current emphasis on knowledge as a commodity in modern society has led to an increased interest in better understanding the means by which knowledge is disseminated in human social networks (Dupouët and Yıldızoğlu 2006; Morone and Taylor 2004). Human actors can accumulate knowledge by individual learning or through processes of interactive learning, processes that can be carried out both under formal learning conditions such as educational institutions or under informal conditions. An interesting result of simulation studies suggests that widely divergent levels of knowledge within a network tends to lead to a gap in knowledge dissemination, leading to community divisions into a highly knowledgeable, a group that is attaining greater knowledge at a slower rate, and a marginalized group that could be considered ignorant (Morone and Taylor 2004). Moreover, this division does not arise from community structure per se, as communities in which knowledge levels are not highly variable tend to disseminate knowledge efficiently and more equitably (Morone and Taylor 2004).

A sea change in human communication mechanisms was driven by the global introduction of computer-enhanced methods such as email, communication platforms such as Facebook and Twitter, and the interactive informational 'bloggersphere'. An important feature of social communication networks is the interrelationships between them—such that the network of friends, colleagues, and trade-partners influence responses of any individual agent to all networks to which that agent belongs (Szell et al. 2010). While social media can be seen to provide an unprecedented mechanism for the global exchange of knowledge, information, and opinion, to fully comprehend its reach requires a much fuller understanding of these complex inter-relationships.

As is true of the brain, the hierarchical and dynamic properties of human social—and, by extension, economical, technological and political—interactions lead to unpredictable emergent behaviors at multiple levels. Network theory provides a method by which such complexities may be evaluated in both space and time.

Network Theory Links Neural and Social Communication Systems

We have seen that the brain is a complex dynamic system (Amaral et al. 2004) consisting of on the order of 10^{11} neurons and 10^{15} synaptic connections (Sporns et al. 2005). In common with other complex dynamic systems, the brain exhibits critical dynamics (Chialvo 2010; Poil et al. 2008) and scale-free behavior (as explained below). Human social systems are also complex dynamic systems, with a global population of approximately 7×10^9 human beings according to the US Census Bureau (www.census.gov).

Complex systems exhibit non-random linkages over multiple temporal and spatial scales, a relationship captured by the popular 'six degrees of freedom' concept (Watts 2004). Although not without controversy, many such systems are described as scale-free or scale-invariant and follow power law distributions (Kello et al. 2010). Scale-free systems are characterized by the property of criticality; that is, they sit on the cusp between completely predictable (rigid) and completely unpredictable (chaotic) behavior. This is precisely the state we noted above as useful for a system that needs to be both highly adaptive and yet stable; these properties have been described in brain networks at multiple scales, from local and large-scale circuits (Fiete et al. 2010; Kitzbichler et al. 2009; Rubinov et al. 2011) to cognitive behaviors as complex as language (Kello et al. 2010; Steyvers and Tenenbaum 2005), online collaborative interactions (Woolley and Hashmi 2013—this volume), and the phase shifts from wake to sleep (Bedard et al. 2006; Zempel et al. 2012).

Scale-free systems share a common architecture described in the seminal paper of Watts and Strogatz (1998) as a small world network. In this architecture, network elements (termed nodes) are linked by connections (termed edges) such that the majority of connections are local while there are only sparse linkages between distant elements (Butts 2009; Watts and Strogatz 1998). This architecture confers several important properties to the system, and points to interesting system behaviors. As it is this architecture that links human social organization and behavior to that of the brain network, a brief description of some of these properties will be provided along with references for those interested in learning more.

A characteristic of small world networks is the presence of hub elements—elements that are richly connected to other network elements—while the majority of elements are more sparsely connected (Eguiluz et al. 2005). This organizational feature has been shown to be present in the brain for both structural and functional linkages (Collin et al. 2013; van den Heuvel et al. 2012), and has formed the basis for designation of a set of linking hubs labeled as 'rich club' elements. The same feature has been shown to be critical to human social interactions, from dissemination of information via communication (Opsahl et al. 2008; van den Heuvel et al. 2012; Vaquero and Cebrian 2013) to the diffusion of disease epidemics (Christakis and Fowler 2008; Pastor-Satorras and Vespignani 2001; Zhang et al. 2011).

These hub elements are critical to communication in small world networks as they provide the links between modules or communities in the global network. While many studies have relied upon analysis of network interactions in stable periods, the interactions described are dynamic, with both the structure of local communities and the links that bind them in flux on multiple time scales. No single node, whether human or neural, is embedded in only a single community, so that its behaviors are the result of both its structural embedding and the multirelational networks in which it operates.

The Computational Power of Human Social Communication

The concept of harnessing human elements for computation is not new (Grier 2005), and the practice of using humans as computational elements can be found as early as the eighteenth century. Modern computing has been argued to have developed from the intersection of scientific problem solving, technological innovation, and the social practice of computing teams (Rall 2006). Human computers calculated solutions to problems, often using pen and pencil but in later periods augmented with simple adding machines. In some instances, the human computers were well trained, but this was not always the case (Grier 1998, 2005; Rall 2006). While the period of human computers focused on calculating solutions to problems, as has been noted by others, the modern view of human computation rests on a partnership between electronic—or perhaps quantum—computers and humans in which each provides a unique skill set (Heylighen 2013).

One similarity remains as essential to the new view of human computation as it was to earlier views and that is the need to clearly and carefully define the problem at hand and the solution space within which it resides. While crowd-sourcing and citizen science are clear paths toward social modes of computation, they do not erase the need for expert knowledge and successful implementation of human computation will require a solid understanding of the social interrelationships needed to interleave expert and unskilled team members. This is not to suggest that, for example, all such teams are comprised of non-expert members—teams may also be composed of teams of interlinked experts in different arenas. However, regardless of the team composition, from the sheer number of individuals and computers involved to the skill sets of individual agents, social interaction and cultural biases must be understood to optimize any solution. Network analysis is one tool that may aid in this endeavor.

References

Ahrens MB, Huang KH, Narayan S, Mensh BD, Engert F (2013) Two-photon calcium imaging during fictive navigation in virtual environments. Front Neural Circuit 7:104

Amaral LA, Diaz-Guilera A, Moreira AA, Goldberger AL, Lipsitz LA (2004) Emergence of complex dynamics in a simple model of signaling networks. Proc Natl Acad Sci USA 101(44): 15551–15555

Barabási A-L, Albert R, Jeong H (2000) Scale-free characteristics of random networks: the topology of the world-wide web. Phys A Stat Mech Appl 281(1):69–77
Barch DM, Braver TS, Sabb FW, Noll DC (2000) Anterior cingulate and the monitoring of response conflict: evidence from an fMRI study of overt verb generation. J Cogn Neurosci 12(2):298–309
Bassett DS, Bullmore E (2006) Small-world brain networks. The Neuroscientist 12(6):512–523
Bedard C, Kroeger H, Destexhe A (2006) Does the 1/f frequency scaling of brain signals reflect self-organized critical states? Phys Rev Lett 97(11):118102
Biswal B, Zerrin Yetkin F, Haughton VM, Hyde JS (1995) Functional connectivity in the motor cortex of resting human brain using echo planar MRI. Magn Reson Med 34(4):537–541
Brown J, Broderick AJ, Lee N (2007) Word of mouth communication within online communities: conceptualizing the online social network. J Interact Mark 21(3):2–20
Butts CT (2009) Revisiting the foundations of network analysis. Science 325(5939):414–416
Chialvo DR (2010) Emergent complex neural dynamics. Nat Phys 6(10):744–750
Christakis NA, Fowler JH (2008) The collective dynamics of smoking in a large social network. N Engl J Med 358(21):2249–2258
Cohen AL, Fair DA, Dosenbach NU, Miezin FM, Dierker D, Van Essen DC, Schlaggar BL, Petersen SE (2008) Defining functional areas in individual human brains using resting functional connectivity MRI. Neuroimage 41(1):45
Collin G, Sporns O, Mandl RC, van den Heuvel MP (2013) Structural and functional aspects relating to cost and benefit of rich club organization in the human cerebral cortex. Cereb Cortex, epub ahead of print, PMID 23551922, DOI: 10.1093/cercor/bht064
Davidsen J, Ebel H, Bornholdt S (2002) Emergence of a small world from local interactions: modeling acquaintance networks. Phys Rev Lett 88(12):128701
Deco G, Jirsa VK, McIntosh AR (2013) Resting brains never rest: computational insights into potential cognitive architectures. Trends Neurosci 36(5):268–274
DeLong ND, Nusbaum MP (2010) Hormonal modulation of sensorimotor integration. The J Neurosci 30(7):2418–2427
Dosenbach NU, Fair DA, Miezin FM, Cohen AL, Wenger KK, Dosenbach RA, Fox MD, Snyder AZ, Vincent JL, Raichle ME (2007) Distinct brain networks for adaptive and stable task control in humans. Proc Natl Acad Sci 104(26):11073–11078
Dupouët O, Yıldızoğlu M (2006) Organizational performance in hierarchies and communities of practice. J Econ Behav Organ 61(4):668–690
Eguiluz VM, Chialvo DR, Cecchi GA, Baliki M, Apkarian AV (2005) Scale-free brain functional networks. Phys Rev Lett 94(1):018102
Felleman DJ, Van Essen DC (1991) Distributed hierarchical processing in the primate cerebral cortex. Cereb Cortex 1(1):1–47
Fiete IR, Senn W, Wang CZ, Hahnloser RH (2010) Spike-time-dependent plasticity and heterosynaptic competition organize networks to produce long scale-free sequences of neural activity. Neuron 65(4):563–576
Fox MD, Snyder AZ, Vincent JL, Corbetta M, Van Essen DC, Raichle ME (2005) The human brain is intrinsically organized into dynamic, anticorrelated functional networks. Proc Natl Acad Sci USA 102(27):9673–9678
Fuxe K, Borroto-Escuela DO, Romero-Fernandez W, Agnati LF (2013) Volume transmission and its different forms in the central nervous system. Chin J Integr Med 19(5):323–329
Garmestani AS, Allen CR, Gunderson L (2009) Panarchy: discontinuities reveal similarities in the dynamic system structure of ecological and social systems. Pap Nat Res 166. Ecology and Society 14(1):15. [online] URL: http://www.ecologyandsociety.org/vol14/iss1/art15/
Grier DA (1998) The math tables project of the work projects administration: the reluctant start of the computing era. Ann Hist Comput, IEEE 20(3):33–50
Grier DA (2005) When computers were human. Princeton University Press, Princeton
Guertin PA (2012) Central pattern generator for locomotion: anatomical, physiological, and pathophysiological considerations. Front Neurology 3:183

Gulati R, Sytch M, Tatarynowicz A (2012) The rise and fall of small worlds: exploring the dynamics of social structure. Organ Sci 23(2):449–471

Haas JS, Landisman CE (2012) Bursts modify electrical synaptic strength. Brain Res

He Y, Chen ZJ, Evans AC (2007) Small-world anatomical networks in the human brain revealed by cortical thickness from MRI. Cereb Cortex 17(10):2407–2419

Heylighen F (2013) From human computation to the global brain: the self-organization of distributed intelligence. In: Michelucci P (ed) The handbook of human computation. Springer, New York

Holling CS (2001) Understanding the complexity of economic, ecological, and social systems. Ecosystems 4(5):390–405

Just MA, Cherkassky VL, Keller TA, Kana RK, Minshew NJ (2007) Functional and anatomical cortical underconnectivity in autism: evidence from an FMRI study of an executive function task and corpus callosum morphometry. Cereb Cortex 17(4):951–961

Kaneko T (2013) Local connections of excitatory neurons in motor-associated cortical areas of the rat. Front Neural Circuits 7:75

Kello CT, Brown GD, Ferrer-i-Cancho R, Holden JG, Linkenkaer-Hansen K, Rhodes T, Van Orden GC (2010) Scaling laws in cognitive sciences. Trends Cogn Sci 14(5):223–232

Kitzbichler MG, Smith ML, Christensen SR, Bullmore E (2009) Broadband criticality of human brain network synchronization. PLoS Comput Biol 5(3):e1000314

Mennes M, Kelly C, Zuo X-N, Di Martino A, Biswal B, Castellanos FX, Milham MP (2010) Inter-individual differences in resting state functional connectivity predict task-induced BOLD activity. Neuroimage 50(4):1690

Meunier D, Lambiotte R, Bullmore ET (2010) Modular and hierarchically modular organization of brain networks. Front Neurosci 4

Morone P, Taylor R (2004) Knowledge diffusion dynamics and network properties of face-to-face interactions. J Evol Econ 14(3):327–351

Nagy JI, Dudek FE, Rash JE (2004) Update on connexins and gap junctions in neurons and glia in the mammalian nervous system. Brain Res Rev 47(1):191–215

Oláh S, Füle M, Komlósi G, Varga C, Báldi R, Barzó P, Tamás G (2009) Regulation of cortical microcircuits by unitary GABA-mediated volume transmission. Nature 461(7268): 1278–1281

Opsahl T, Colizza V, Panzarasa P, Ramasco JJ (2008) Prominence and control: the weighted rich-club effect. Phys Rev Lett 101(16):168702

Pastor-Satorras R, Vespignani A (2001) Epidemic spreading in scale-free networks. Phys Rev Lett 86(14):3200–3203

Poil SS, van Ooyen A, Linkenkaer-Hansen K (2008) Avalanche dynamics of human brain oscillations: relation to critical branching processes and temporal correlations. Hum Brain Mapp 29(7):770–777

Rall DN (2006) The 'house that Dick built': constructing the team that built the bomb. Soc Stud Sci 36(6):943–957

Rubinov M, Sporns O, Thivierge J-P, Breakspear M (2011) Neurobiologically realistic determinants of self-organized criticality in networks of spiking neurons. PLoS Comput Biol 7(6):e1002038

Scemes E, Suadicani SO, Dahl G, Spray DC (2007) Connexin and pannexin mediated cell—cell communication. Neuron Glia Biol 3(3):199

Sporns O, Tononi G, Kötter R (2005) The human connectome: a structural description of the human brain. PLoS Comput Biol 1(4):e42

Spruston N (2008) Pyramidal neurons: dendritic structure and synaptic integration. Nat Rev Neurosci 9(3):206–221

Steyvers M, Tenenbaum JB (2005) The large-scale structure of semantic networks: statistical analyses and a model of semantic growth. Cogn Sci 29(1):41–78

Szell M, Lambiotte R, Thurner S (2010) Multirelational organization of large-scale social networks in an online world. Proc Natl Acad Sci 107(31):13636–13641

Theis M, Giaume C (2012) Connexin-based intercellular communication and astrocyte heterogeneity. Brain Res

van den Heuvel MP, Kahn RS, Goñi J, Sporns O (2012) High-cost, high-capacity backbone for global brain communication. Proc Natl Acad Sci 109(28):11372–11377

Vaquero LM, Cebrian M (2013) The rich club phenomenon in the classroom. Sci Rep 3:1174

Vizi E, Fekete A, Karoly R, Mike A (2010) Non-synaptic receptors and transporters involved in brain functions and targets of drug treatment. Br J Pharmacol 160(4):785–809

Wang XF, Chen G (2003) Complex networks: small-world, scale-free and beyond. Circuits Syst Mag IEEE 3(1):6–20

Watts DJ (2004) Six degrees: the science of a connected age. WW Norton, New York

Watts DJ, Strogatz SH (1998) Collective dynamics of ‘small-world’ networks. Nature 393(6684): 440–442

Wilkinson D (2002) Civilizations as networks: trade, war, diplomacy, and command-control. Complexity 8(1):82–86

Woolley AW, Hashmi N (2013) Cultivating collective intelligence in online groups. In: Michelucci P (ed) The handbook of human computation. Springer, New York

Zempel JM, Politte DG, Kelsey M, Verner R, Nolan TS, Babajani-Feremi A, Prior F, Larson-Prior LJ (2012) Characterization of scale-free properties of human electrocorticography in awake and slow wave sleep states. Front Neurol 3:76

Zhang J, Xu X-K, Li P, Zhang K, Small M (2011) Node importance for dynamical process on networks: a multiscale characterization. Chaos An Interdiscip J Nonlinear Sci 21(1): 016106–016107

Zhou C, Zemanová L, Zamora G, Hilgetag CC, Kurths J (2006) Hierarchical organization unveiled by functional connectivity in complex brain networks. Phys Rev Lett 97(23):238103