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Brain networks, structural realism, and local approaches to the scientific realism debate

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ABSTRACT

We examine recent work in cognitive neuroscience that investigates brain networks. Brain networks are characterized by the ways in which brain regions are functionally and anatomically connected to one another. Cognitive neuroscientists use various noninvasive techniques (e.g., fMRI) to investigate these networks. They represent them formally as graphs. And they use various graph theoretic techniques to analyze them further. We distinguish between knowledge of the graph theoretic structure of such networks (structural knowledge) and knowledge of what instantiates that structure (nonstructural knowledge). And we argue that this work provides structural knowledge of brain networks. We explore the significance of this conclusion for the scientific realism debate. We argue that our conclusion should not be understood as an instance of a global structural realist claim regarding the structure of the unobservable part of the world, but instead, as a local structural realist attitude towards brain networks in particular. And we argue that various local approaches to the realism debate, i.e., approaches that restrict realist commitments to particular theories and/or entities, are problematic insofar as they don't allow for the possibility of such a local structural realist attitude.

1. Introduction

Brain networks are one of the primary objects of study in cognitive neuroscience. These networks are characterized by the ways in which brain regions are anatomically and functionally connected with one another. Cognitive neuroscientists use a variety of noninvasive techniques (e.g., fMRI) to study these connections. They use graph theory to represent these networks formally as graphs, where the nodes of the graph correspond to brain regions, and the edges correspond to connections between regions. And they use a variety of graph theoretical measures to analyze the ways in which brain networks are organized.

Our goal in this paper is to examine this work in cognitive neuroscience, determine the kind of epistemic commitment towards brain networks that this work licenses, and draw some conclusions about the scientific realism debate based on our analysis of this work.

In order to determine the appropriate kind of epistemic commitment, we examine the scientific practices involved in the study of brain networks and the attitudes that cognitive neuroscientists take towards brain networks as a result of engaging in those practices. We consider two possible kinds of epistemic commitment. Since cognitive neuroscientists represent brain networks as graphs, one possibility is that this work licenses an epistemic commitment to the graph theoretic structure of brain networks, without giving us knowledge of what instantiates that structure. We call this possibility *structural knowledge of brain networks*.[1] Alternatively, if this work gives us knowledge of what instantiates that structure, then we have what we call *nonstructural knowledge of brain networks*. We argue that this body of work in cognitive neuroscience gives us structural knowledge of brain networks.

In order to draw our conclusions regarding the realism debate, which concerns issues like the truth of our best theories and the existence of the entities that they posit, we focus on two positions within that debate. The first is structural realism, which is most often understood as a global position regarding our best theories in general, according to which those theories latch onto the structure of the unobservable part of the world. We argue that our claim regarding structural knowledge of brain networks should not be

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[1] If knowledge is too much of a loaded term, we can put the same point in terms of belief or epistemic commitment.

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understood as an instance of a global structural realist claim regarding our best theories in general. Instead, it ought to be understood locally, with no presumption that what goes for this work in cognitive neuroscience will generalize to other branches of science. The second position is what we call a local approach to the scientific realism debate. Unlike global structural realists, proponents of local approaches restrict their realist conclusions to particular theories and/or entities (Fitzpatrick, 2013; Magnus & Callender, 2004). We argue that these approaches can be problematic insofar as they involve a choice between realism and anti-realism regarding a particular theory or entity; adopting a kind of local structural realist attitude, as we do towards brain networks, is not an option. And we discuss how Saatsi's (2015) exemplar realism allows for this possibility, in which case our conclusions regarding brain networks fit most comfortably within that position.

The approach that we take in this paper involves a careful examination of the practices involved in the study of brain networks, and this approach has both strengths and limitations. One strength is that our conclusions are grounded in actual scientific practice. Another strength is that we bring a relatively novel case to bear on issues in the realism debate. While cognitive neuroscience, and work on brain networks in particular, features in the philosophy of science more generally (Bechtel, 2015; Colombo, 2013; Zednik, 2015), it has not played much of a role within the realism debate. And by bringing this case into the realism debate, we're able to explore a relatively unexplored possibility within that debate, namely, the possibility of adopting a kind of local structural realist attitude. However, the fact that our conclusions are so closely grounded in scientific practice is a double-edged sword, since it may turn out to be the case that cognitive neuroscientists are on the wrong track regarding the kind of epistemic commitment that this work licenses. That said, we still take it to be worth considering what kinds of philosophical conclusions can be drawn from this work on the assumption that cognitive neuroscientists are on the right track.

We proceed as follows. In section 2, we discuss the background and significance of this work in cognitive neuroscience. In section 3, we distinguish between two kinds of brain networks that cognitive neuroscientists investigate, namely, anatomical networks and functional networks. In section 4, we provide more detail regarding the noninvasive and graph theoretic techniques that they use to investigate these networks. In section 5, we argue that the application of these techniques provides structural knowledge of brain networks. In section 6, we discuss structural realism. And in section 7, we discuss various local approaches to the realism debate.

2. Modeling brain networks

For some time, neuroscientists have worked towards constructing models of neural connections, and recent technological advances in data acquisition, analysis, and visualization methods have allowed cognitive neuroscientists to construct models of neural connections in the human brain (Hagmann et al., 2008; Sporns, 2013; Sporns, Tononi, & Kötter, 2005; Wedeen et al., 2008). These technological advances led to the formation of the so-called Human Connectome Project (HCP) in 2010. As Van Essen et al. (2013, p. 62) put it, "to systematically explore the human connectome [is] to generate maps of brain connectivity that are 'comprehensive' down to the spatial resolution of the imaging methods available." They characterize one of the primary goals of HCP as "a systematic effort to map macroscopic human brain circuits and their relationship to behavior in a large population of healthy adults" (2013, p. 62). It's worth noting that other connectomic projects proceed at scales below the macroscale of brain regions, i.e., the meso- and microscales. For example, Bock et al. (2011) report a microscale connectome of a group of neurons in the mouse primary visual cortex using two-photon calcium imaging and large-scale electron microscopy. And Varshney, Chen, Paniagua, Hall, and Chklovskii (2011) build on previous work by White, Southgate, Thomson, and Brenner (1986) in order to produce a model, at the microscale of individual synapses, of the neuronal network of *Caenorhabditis elegans*. However, in this paper, our focus will be on the set of techniques that cognitive neuroscientists use to study human brain networks at the macroscale. Given the importance of techniques to HCP and other related research, any adequate understanding of this work, along with the models that this work produces, will have to pay particularly close attention to those techniques.

3. Structural/anatomical and functional brain networks

Our next task is to distinguish between two kinds of brain networks, namely, structural/anatomical networks and functional networks. In order to do so, we'll begin by distinguishing between two kinds of neural connections, namely, structural/anatomical connections and functional connections.

Structural connections are anatomical connections that link neural elements. These connections are often referred to as neural pathways or neural tracts. They consist of white matter, i.e., of bundles of mylenated axons that connect regions of gray matter in the brain. While the brain's structural/anatomical connectivity is relatively stable over the course of minutes, it can change over the course of hours or days (Sporns, 2013, p. 248). In what follows, we'll use the term 'anatomical' when referring to the kinds of connections and networks that cognitive neuroscientists label as 'structural.' Since we'll devote a fair amount of discussion to the implications of our case study for structural realism in section 6, we'll reserve the term 'structural' to refer to the more abstract, relational structure of interest to structural realists.

Anatomical connections contrast with another kind of neural connection that cognitive neuroscientists investigate, namely, functional connections. Functional connections are "patterns of statistical dependence among neural elements" (Sporns, 2013, p. 248; see also Smith, 2012). For example, if activity in one brain region occurs when some other brain region is active, and vice versa, there is a functional connection between those two regions, in which case they exhibit functional coupling. Functional connectivity is not nearly as stable as anatomical connectivity, and can change in the course of tens of milliseconds.

There is a corresponding distinction between two kinds of brain networks, namely, anatomical networks and functional networks (Bullmore & Sporns, 2009; Sporns, 2013; Wig, Schlaggar, & Petersen, 2011). Anatomical networks constitute the brain's anatomical connectivity, while functional networks constitute its functional connectivity. Cognitive neuroscientists use graph theory in order to represent these networks formally as undirected graphs. In general, a graph is made up of a set of nodes and edges, as shown in Fig. 1. The nodes are brain regions. In an anatomical network, the edges are anatomical connections, while in a functional network, the edges are functional connections. Hence, when cognitive

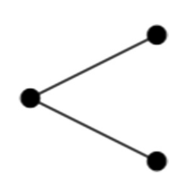

Fig. 1. A graph with three nodes and two edges.

neuroscientists construct models of brain networks, those models are graphs.

In what follows, we'll use the terms 'network' and 'system' to refer to concrete entities in the world, for example, brain networks; and we'll use the terms 'graph' and 'model' to refer to the abstract or formal entities used to represent those concrete entities. A graph represents such a network accurately when the nodes of the graph correspond to the brain regions of the network, and when the edges of the graph correspond to either anatomical or functional connections between those regions. Given this representational relationship, for the sake of convenience, we'll refer to both graphs and networks as being made up of nodes and edges, though these should be understood as formal entities in the case of graphs and features of concrete entities in the case of networks.

4. Techniques for studying brain networks

Our goal in this section is to introduce the techniques that cognitive neuroscientists use to study brain networks. We'll distinguish two kinds of techniques: noninvasive techniques for collecting data regarding such networks, and graph theoretic techniques which use those data to construct and analyze models of brain networks.

The noninvasive techniques include diffusion tensor imaging (DTI), electroencephalography (EEG), magnetoencephalography (MEG), and functional magnetic resonance imaging (fMRI). Cognitive neuroscientists employ DTI to collect data regarding anatomical networks. DTI allows them to study the neural tracts that constitute anatomical connections indirectly, by examining the diffusion of water molecules in the human brain. They also use tractography to take the data from DTI and produce models of neural tracts. They employ EEG, MEG, and fMRI to collect data regarding functional networks. These techniques yield time series data, which provide information regarding the times at which various brain regions are active. They thus provide information regarding statistical patterns in the interactions among neural elements, i.e., functional connections. In this way, cognitive neuroscientists collect data that they subsequently use to construct models of the two kinds of brain networks.

In order to apply the noninvasive techniques, cognitive neuroscientists must first parcellate the brain into regions that correspond to the nodes of a network (Power et al., 2011; Rubinov & Sporns, 2010; Sporns, 2013, 2014; Stam & Reijneveld, 2007; Stam & van Straaten, 2012). Sporns (2013, p. 249) describes two standard methods for deriving the nodes of a network: "by parcellating cortical and subcortical gray matter regions according to anatomical borders or landmarks, or by defining a random parcellation into evenly spaced and sized voxel clusters." However, these are not the only methods, and Sporns (2014, pp. 652–653) reviews a variety of additional parcellation schemes. Cognitive neuroscientists then use the datasets provided by the noninvasive techniques in order to determine the edges among the nodes.

Once the nodes and edges are determined, cognitive neuroscientists construct graph theoretic models of brain networks, and they use a number of graph theoretic measures to analyze those models. These measures can be classified in terms of three broad categories, namely, those that measure segregation, integration, and influence (Sporns, 2013, pp. 249–251). First of all, segregation amounts to the extent to which the nodes of a network form clusters that are relatively insulated from other such clusters. One important measure of segregation is a network's clustering coefficient. The clustering coefficient of a node measures the connections among that node's neighbors, and the clustering coefficient of a network is obtained by averaging the clustering coefficients of all of its nodes. Secondly, integration amounts to a network's ability to exchange information, and depends on the way in which a network is interconnected. One important measure of integration is a network's characteristic path length. In order to calculate the characteristic path length, one must first determine the distance (or shortest path length) that separates each pair of nodes in the network. Distance can be determined by either the number or the length of the edges that connect one node to another. Characteristic path length is then obtained by averaging all of the distances. Finally, influence concerns the centrality of individual nodes and edges to the functioning of the network. One important measure of the influence of a node is obtained by determining the degree of the node, i.e., the number of edges attached to it. The most influential nodes are referred to as hubs.

These measures come into play when characterizing the ways in which brain networks are organized (Sporns, 2013, pp. 251–254; Sporns, Honey, & Kötter, 2007). Measures of segregation relate to the extent to which a network can be decomposed into distinct clusters or modules, and much of the work on brain networks attempts to determine their modular organization. Brain networks have been found to exhibit small-world organization, which strikes a balance between segregation and integration. Such networks are characterized by both high clustering and short path lengths. Brain networks have also been found to exhibit rich club organization, which occurs when hubs located in distinct clusters or modules are themselves densely interconnected with one another, as shown in Fig. 2.

5. Structural knowledge of brain networks

At this point, we can consider what kind of epistemic commitment these noninvasive and graph theoretic techniques license. We'll consider two possibilities, namely, structural knowledge of brain networks, and nonstructural knowledge of brain networks. Cognitive neuroscientists represent brain networks as sets of interconnected nodes and edges within the framework of graph theory. We'll understand *structural knowledge of brain networks* as knowledge of how the nodes and edges of brain networks fit together, i.e., knowledge of the relational structure that the nodes and edges instantiate. More generally, we'll refer to this kind of relational structure, regardless of how it is instantiated, as *graph theoretic structure*. And we'll understand *nonstructural knowledge of brain networks* as knowledge of the individual nodes (qua brain regions) and edges (qua connections) that instantiate that graph theoretic structure.

While cognitive neuroscientists do consider what kind of epistemic commitment these techniques license, they don't frame this issue in terms of a distinction between structural and nonstructural knowledge of brain networks. This issue often arises in the context of addressing various methodological challenges that cognitive neuroscientists face in the course of studying brain networks. In section 5.1, we'll examine the ways in which they attempt to overcome these challenges, and the conclusions that they draw regarding the extent to which they succeed in modeling brain networks. On this basis, we'll argue that the techniques they use give us structural knowledge of brain networks. We'll discuss anatomical networks in section 5.2 and functional networks in section 5.3. Finally, in section 5.4, we'll argue that various graph theoretic techniques used in the analysis of brain networks also gives us structural knowledge of those networks.

5.1. Methodological challenges

To begin with, we'll focus on some methodological challenges that result from the fact that different parcellation schemes can yield different sets of nodes, and therefore different graphs. A

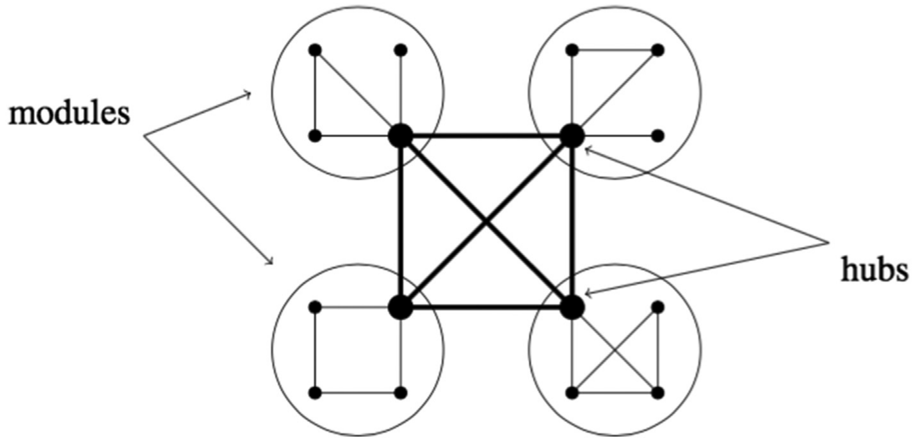

Fig. 2. Hubs in distinct modules are densely interconnected with one another, thus forming a rich club which is represented by the thick lines.

number of cognitive neuroscientists have observed that, in order to conclude that a graph accurately represents a brain network, one must have some confidence that the nodes in the graph correspond to real items in the brain network (Butts, 2009; Power et al., 2011; Smith et al., 2011; Wig et al., 2011). When different parcellation schemes yield different sets of nodes, cognitive neuroscientists must determine the extent to which these parcellation-relative nodes correspond to real items. The challenge that they face here is not restricted to the nodes. Since edges are investigated only once nodes are well-defined, the edges and the resulting graphs are also parcellation-relative. In contrast, the brain networks that cognitive neuroscientists seek to investigate are presumed to exist independently of the choice of parcellation scheme—a real network must be parcellation-independent. The challenge, then, is to determine the extent to which parcellation-relative graphs accurately represent a parcellation-independent brain network.

In general, the way in which cognitive neuroscientists attempt to overcome this challenge is to construct distinct graphs using alternative parcellation schemes and identify common features that these graphs share. As Sporns (2014, p. 653) puts it, "[o]ne way in which this issue has been addressed involves network construction and analysis across different parcellation schemes and spatial scales to identify network attributes that are robustly expressed." Sporns goes on to note some success in this regard: "Indeed, it appears that many qualitative characteristics of network structure are relatively stable across different parcellations." The basic idea is that, when we find that distinct graphs share certain attributes, we have some good converging evidence that those attributes correspond to real attributes of brain networks.

Some examples should help to clarify this general strategy. Sporns (2014, p. 653) reports that "studies of brain networks using a variety of parcellations … have converged on a set of fundamental attributes of human brain organization that are largely consistent with those found in nonhuman primates." These attributes include the existence of network hubs located at certain brain regions. Convergence in this case provides some evidence that the graph theoretic models in question accurately represent the hubs of the network. To take another example, Power et al. (2011) construct two novel brain-wide graphs using alternative parcellation schemes. In order to determine the accuracy of these graphs, they compare subgraphs of these graphs with some antecedently well-understood functional networks and with each other. They conclude that "despite great differences in network size and definition, the subgraphs are remarkably alike and contain many subgraphs corresponding to known functional systems, bolstering confidence in their accuracy" (2011, p. 666). Once again, this convergence among the subgraphs indicates that they accurately represent real features of brain networks.

According to cognitive neuroscientists themselves, this work licenses an epistemic commitment to the characteristics of brain networks that are robustly expressed across a number of distinct, parcellation-relative graphs. Or as Sporns (2014, p. 653) puts the point, "many qualitative characteristics of network structure are relatively stable across different parcellations." Given Sporns's focus on network structure, we'll now argue that this work gives us structural knowledge of brain networks. Sporns's remark aside, it's worth emphasizing that this is not a conclusion that cognitive neuroscientists themselves explicitly draw regarding our knowledge of brain networks. That said, we'll argue that the techniques that they use to collect data, construct and analyze models, and attempt to overcome various methodological challenges strongly suggest that this work gives us structural knowledge of brain networks.

5.2. *Structural knowledge of anatomical networks*

We'll turn our attention to anatomical networks first. Noninvasive techniques like DTI are used to study anatomical connections by examining the diffusion of water molecules along the neural tracts that constitute those connections. They thus presuppose the existence of neural tracts, which seem to be things about which we could have nonstructural knowledge. Moreover, anatomical connections are parts of brain anatomy that can be investigated rather directly, in some cases by direct observation, through the use of invasive techniques like autopsy and the dissection of human cadaver brains. Such invasive techniques may give us nonstructural knowledge of particular anatomical connections. Since anatomical networks seem to be concrete entities that exist independently of whatever graph theoretic structure they happen to instantiate, it's a bit difficult to show that work in cognitive neuroscience gives us structural knowledge of those networks. But that is exactly what we will now argue.

While invasive techniques may give us nonstructural knowledge of particular anatomical connections, they do not thereby give us nonstructural knowledge of in vivo anatomical networks. Nonstructural knowledge of anatomical networks requires quite a bit of knowledge regarding individual connections and regions and how they fit together to constitute such a network. And even if invasive techniques yielded such knowledge, it would be nonstructural knowledge of ex vivo anatomical networks, as opposed to the in vivo networks studied by means of noninvasive techniques.

Noninvasive techniques like DTI and tractography constitute a rather indirect way of investigating in vivo anatomical networks, and this fact opens up the possibility that the knowledge that these techniques yield is structural knowledge. As Sporns (2013, p. 253) puts it: “Importantly, diffusion imaging and tractography deliver inferential and statistical models of fiber anatomy but cannot directly trace or visualize anatomical connections.” Cognitive neuroscientists investigate such connections in the in vivo human brain indirectly, without observing them. In order to do so, they must overcome a number of methodological challenges. One, which we’ve already discussed, results from the existence of alternative parcellation schemes. Another, to which we now turn, is what is known as the “crossing fiber” problem (Landman et al., 2012).

The crossing fiber problem results from the fact that, within a single voxel, there may be multiple neural tracts (fibers) with distinct orientations. For example, in cases where there are two fiber orientations within a voxel, DTI yields the erroneous result that there is one fiber with an orientation intermediate between the two actual fiber orientations (Tuch et al., 2002, p. 581). Cognitive neuroscientists have developed a number of techniques designed to resolve this problem, for example, multi-tensor analysis (Tuch et al., 2002) and diffusion spectrum magnetic resonance imaging (Wedeen et al., 2008). One of the primary ways in which they defend the use of such techniques is to show that they yield data consistent with antecedently known anatomical networks. In other words, they use converging evidence, in which case the way in which they address this methodological challenge is similar to the way in which they address the challenge that results from alternative parcellation schemes.

This use of converging evidence from different techniques and different parcellation schemes strongly suggests that the knowledge of anatomical networks that these techniques yield is structural knowledge. Suppose that some particular graph were a completely faithful representation of a particular anatomical network. Such a graph would yield both structural knowledge and nonstructural knowledge of that anatomical network. The problem is that, due to the methodological challenges that we’ve discussed, cognitive neuroscientists tend not to put too much faith in the representational capacities of a single graph. Instead, they consider such graphs collectively, and conclude that they accurately represent an anatomical network to the extent that they are similar to one another and consistent with what is already known about the network. Importantly, similarity and consistency do not require that graphs, or even subgraphs, are identical, or that they match other data perfectly. Instead, what cognitive neuroscientists are looking for are cases where different graphs express the same qualitative characteristics of network structure, for example, the existence of network hubs in particular brain regions. Graphs that are not strictly identical to one another may be similar enough for cognitive neuroscientists to conclude that hubs exist in particular regions. In other words, two graphs may diverge from one another when it comes to individual nodes and edges, and yet both indicate hubs in the same regions. Hence, such graphs are not best understood as yielding knowledge of the individual nodes qua brain regions and edges qua connections that together constitute anatomical networks (i.e., nonstructural knowledge). Instead, they’re best understood as yielding knowledge of the approximate graph theoretic structure that those nodes and edges instantiate (i.e., structural knowledge).

The fact that our knowledge of anatomical networks is structural knowledge is due to our epistemic limitations, as opposed to the nature of such networks. They consist of bundles of white matter that connect regions of gray matter in the brain, and they are best understood as concrete entities that exist independently of whatever graph theoretic structure they happen to instantiate. But given the noninvasive techniques that cognitive neuroscientists currently use to investigate in vivo anatomical networks, our knowledge of them is limited to their graph theoretic structure.

5.3. Structural knowledge of functional networks

We now turn to functional networks. Nodes in a functional network are brain regions or populations of neurons. Noninvasive techniques like EEG, MEG, and fMRI do not really tell us much about the nature of these nodes. Deriving the nodes via some parcellation scheme or other is a precondition for applying these techniques in the first place. Moreover, as we’ve already discussed, different parcellation schemes can yield different nodes, in which case the nodes are parcellation-relative. But even if we assume that cognitive neuroscientists are working with a parcellation scheme that yields nodes that correspond to real items in a brain network, applying these techniques doesn’t tell us what the nodes are. Instead, it tells us what the edges are, given some antecedent method of identifying the nodes.

Edges in a functional network are functional connections. Functional connections are unlike anatomical connections, since functional connections are patterns in brain activity as opposed to parts of brain anatomy. And while functional connectivity depends on anatomical connectivity, the relationship between the two is not a straightforward one. One reason for this nontrivial relationship is that brain regions can be functionally coupled in the absence of a direct anatomical connection linking those regions (Sporns, 2013, p. 256). In that case, functional connections do not ultimately reduce to anatomical connections in the brain. Moreover, there is nothing inherently causal in the notion of a functional connection, since such connections merely reflect patterns in activation (Sporns, 2013, p. 248). Detecting a functional connection, then, allows cognitive neuroscientists to represent that connection as an edge in a functional network without supplying them with knowledge of the anatomical connections that make such activation patterns possible.

Since functional connectivity amounts to patterns in brain activity, it is best understood structurally; and the techniques that cognitive neuroscientists use to investigate it therefore provide us with structural knowledge of functional networks. The fact that our knowledge in this case is structural is not due to an epistemic limitation, but to the nature of functional networks. Since such networks are best understood structurally, our knowledge of them must be inherently structural.

5.4. Graph theoretic techniques

Our final goal in this section is to argue that the application of various graph theoretic techniques is best understood as providing structural knowledge of brain networks. These techniques involve the study of networks qua formal objects of graph theory. The use of such techniques is not unique to the study of brain networks. They are employed throughout network science to investigate any kind of network that can be represented within the framework of graph theory, regardless of how it is instantiated, for example, brain networks, social networks, and so on. Network scientists study such networks in terms of the graph theoretic measures that we discussed in section 4, for example, the clustering coefficient of a network and its characteristic path length; and in terms of the different ways in which networks can be organized, for example, small worlds and rich clubs. These measures, along with the ways in which networks can be organized, are examples of what

Huneman (2010) calls "topological properties." Huneman defines such properties as "properties that are either proper to subsets in a topological space or to some graphs and networks" (2010, p. 217). A network has a particular topological property if a graph that provides an accurate representation of that network has that topological property. Since topological properties are defined as properties of mathematical objects, they're best understood as purely structural properties. So when cognitive neuroscientists conclude that a brain network has a particular topological property like small-world organization, they are characterizing the structure of that network. Hence, these graph theoretic techniques are best understood as yielding structural knowledge of brain networks.

However, some of the conclusions that cognitive neuroscientists draw from the application of these graph theoretic techniques may seem to go beyond structural claims. For example, they use characteristic path length as a measure of integration, which they characterize as a network's ability to exchange information (Sporns, 2013, pp. 249–250). Specifying this ability seems, on its face, to go beyond a merely structural description of a network. In order to respond to this objection, it will be necessary to clarify the relationship between integration and its measures. To do so, we'll employ Huneman's account of a "topological explanation," which is "an explanation in which a feature, a trait, a property or an outcome X of a system S is explained by the fact that it possesses specific topological properties T_i" (2010, p. 216). In the case of brain networks, cognitive neuroscientists use topological properties like characteristic path length in order to explain information exchange. They thereby offer a topological explanation of this feature. Does this explanation thereby supply us with nonstructural knowledge of brain networks? The explanans itself is limited to topological properties, which are purely structural. And a more precise description of the explanandum in this case is the efficiency of information exchange. Explaining how a network is capable of exchanging information in the first place would presumably go beyond a merely structural description, and would appeal to properties of the things that instantiate the network. But if this capability is taken as given, one can explain efficiency in terms of structural properties like characteristic path length. So while claims about information exchange can presumably go beyond structural claims, we can understand the efficiency of information exchange in structural terms.

Finally, the way in which cognitive neuroscientists overcome the methodological challenges that we discussed in section 5.1 suggests that our knowledge of brain networks is deeply structural. In order to conclude that a graph provides an accurate representation of a network, cognitive neuroscientists compare that graph with other graphs, and search for network attributes that are robustly expressed across those graphs. This search amounts to determining the extent to which these graphs share certain topological properties. So it is really structural similarity among graphs that grounds claims about whether a particular graph provides an accurate representation of a particular network.

Before moving on, it will be useful to sum up our conclusions from this section. We've examined some noninvasive techniques and graph theoretic techniques that cognitive neuroscientists use to investigate brain networks, and we've argued that the application of these techniques can provide only structural knowledge of brain networks. In that case, the application of these techniques licenses an epistemic commitment to the graph theoretic structure of brain networks.

6. Structural realism

Our goal in the remainder of the paper is to discuss the significance of our case study for the scientific realism debate. Given that we've focused on the structure of brain networks, we'll begin by considering how our case study is related to structural realism. Structural realists claim that, when it comes to the unobservable reality that our best theories purportedly describe, we ought to be realists about its structure, but not about anything that purportedly goes beyond that structure. Our claim that the application of various techniques in cognitive neuroscience licenses an epistemic commitment to the structure of brain networks may seem to be an instance of a more global structural realist claim. However, we'll now argue that this is not the best way to understand our claim. In short, we take issue with the tendency to defend structural realism as a global position about our best theories in general. We take our realist conclusions to apply much more locally to brain networks, without any presumption that these conclusions will generalize to the whole of science. In order to explain why, we'll draw on our case study as well as some recent literature from the realism debate, especially a recent paper by Saatsi (2015).

But before we do so, it's worth emphasizing the global nature of structural realism as it is usually defended. Structural realist positions come in a number of different varieties, but their proponents usually defend those positions as global positions about our best theories in general. Saatsi (2015) notes this global tendency among a number of structural realism's most prominent defenders, including Worrall, Ladyman and Ross, and French. Worrall (1989, p. 99) aims to "adopt some sort of realist attitude towards presently accepted theories in physics and elsewhere." Ladyman and Ross's (2007) information-theoretic structural realism is a metaphysical view regarding what exists in the world, and is therefore completely global in scope. French (2014) defends his form of structural realism in global terms as well, and draws examples from across the physical and biological sciences to support his position. To be sure, though, there are exceptions to this global tendency. For example, Frigg and Votsis (2011, p. 269) mention the possibility that structural realism be defended, not as a global position, but as an approach to fundamental physics in particular, since much of its support comes from case studies in fundamental physics. That said, there is a fair amount of work that applies structural realism to cases from other sciences, including economics (Ross, 2008), the social sciences (Kincaid, 2008), the biological sciences (French, 2014, ch. 12), and the history of chemistry (Ladyman, 2011). This body of work attempts to show the applicability of structural realism to other branches of science, and the most widely held view among structural realists is that structural realism is a global position that applies to our best theories in general. We'll call this view global structural realism.

One of the primary reasons that structural realists have defended their position as a global position is that they take such a position to be the best way of reconciling the no-miracles argument (NMA) and the pessimistic meta-induction (PMI). According to NMA, the success of our best theories would be miraculous unless those theories latch onto some unobservable reality. PMI begins with the observation that we've rejected all past theories as false, and concludes on inductive grounds that our current best theories are false as well, especially when it comes to the claims they make about the unobservable. Regarding PMI, structural realists concede that in cases of theory change, theoretical content (i.e., content regarding the unobservable) is not completely preserved. But they argue that something is preserved over theory change even at the theoretical level, namely, claims about the structure of the unobservable part of the world. And the fact that our best theories capture the structure of reality at the unobservable level yields an explanation of why those theories are as successful as they are, thereby accommodating NMA. Reconciling these two arguments constituted Worrall's (1989) initial defense of structural realism, and subsequent defenses (e.g., Ladyman & Ross, 2007, ch. 2) have also emphasized this point. Insofar as both NMA and PMI concern our best theories in general, their scope is global, and so the only kind of position that holds any promise for reconciling these two arguments is a global one—hence the tendency to defend structural realism as a global position.

In our view, structural realists have succeeded in showing that it is often fruitful to restrict our epistemic commitments to the structure of particular theories, entities, and phenomena; and their case studies contain powerful illustrations of this fruitfulness. However, we take it that there are some problems with defending global structural realism, and in the remainder of the section, we'll focus on the ways in which different characterizations of structure threaten global structural realism.[2]

In order for structural realism to qualify as a global position, structural realists must employ a notion of structure that is univocal, precise, and applicable to different domains investigated by different branches of science at different stages of history. Even if one is impressed by the diversity of case studies that structural realists have used to support their position, these case studies could only support a global position if the same notion of structure is operative in all of the case studies. If a structural realist were to claim that realism about structure amounts to different things in different cases, that would require abandoning the prospects of defending structural realism as a global position in favor of the kind of local approach to the realism debate that we motivate at the end of this section and in section 7.

We hold that there are problems with this aspect of global structural realism, and in order to show why, we'll rely on two arguments that Saatsi (2015) makes against this position. First of all, he observes that structural realists have proposed a number of abstract characterizations of structure. These include characterizations in terms of Ramsey sentences and model theoretic characterizations in terms of the semantic view of theories. When these characterizations are defended in the abstract, without appeal to particular cases from the sciences, Saatsi claims there is no reason to expect that any single characterization will turn out to provide a way to delineate our realist commitments in general. Secondly, he goes on to note that these abstract characterizations are often illustrated in terms of concrete examples—for example, Worrall's (1989) discussion of Fresnel's wave theory and Ladyman's (2011) discussion of the phlogiston theory. However, Saatsi has his doubts about the prospects of generalizing from a few particular examples to a global position, and about the usefulness of a notion of structure that amounts to whatever these and other examples that structural realists discuss have in common. As Saatsi (2015, p. 7) puts it, "structure as the 'common denominator' threatens to become so vague (or disjunctive) that [it] fails to pin down realist commitments in the way it is purportedly meant to do." All together, Saatsi's arguments give us some reason to doubt that one and the same notion of structure will be applicable to all of the cases that global structural realists hope to subsume.

Global structural realists might try to respond to Saatsi's arguments by defending the idea that the various characterizations of structure are actually different ways of characterizing the same structure. The problem with this response is that it seems to require that these characterizations are somehow equivalent to one another, and it's far from clear that this is the case. To complicate matters, it's worth pointing out that Saatsi mentions only a few of the extant characterizations of structure available in the literature, namely, characterizations in terms of Ramsey sentences (Worrall, 2011) and in terms of the semantic view of theories, whether via partial structures (Bueno, French, & Ladyman, 2002) or in modal terms (Ladyman & Ross, 2007). But there are also characterizations in terms of category theory (Bain, 2013), group theory (French, 2014), and frame theory (Votsis & Schurz, 2012). In some cases, structural realists explicitly deny that these characterizations should be understood as alternative ways of characterizing the same structure. For example, Ladyman & Ross's (2007) advocacy of the semantic view is premised on a rejection of the Ramsey sentence view.

To complicate matters even further, in our case study, we characterized structure in yet another way, namely, in terms of graph theory. Ultimately, a graph or network is just a set of nodes and edges. One might use a set theoretical model similar to the kind that proponents of the partial structures approach (e.g., Bueno et al., 2002) often use to characterize structure, and represent a network as an ordered pair $\langle D, R\rangle$, where D is the set of nodes and R is the set of edges. However, there are a number of properties of networks that are not properties of set theoretical models more generally. Such properties include the topological properties that we discussed in section 5.4. Examples of such properties include the clustering coefficient of a network and its characteristic path length. While networks can be characterized in terms of their clustering coefficients and characteristic path lengths, set theoretical models in general cannot. This is because such models can be used to represent much else besides networks, and it only makes sense to inquire about characteristic path length when discussing networks. The fact that networks have topological properties that set theoretical models more generally can lack indicates that there is a structural difference between networks and set theoretical models. Similar considerations apply to the other characterizations of structure mentioned in the previous paragraph, insofar as such characterizations can be used to represent things other than networks. In that case, the graph theoretic notion of structure adds something not already found in at least some of the other abstract characterizations of structure found in the literature. To put the point another way, not everything is a network, and we therefore shouldn't expect that characterizing the graph theoretic structure of a network will be the same as characterizing the structure of things that are not networks.

Another way in which global structural realists might try to respond to Saatsi's arguments is to attempt to find a sufficiently precise 'common denominator' among the case studies structural realists have presented. In order to evaluate this possible global structural realist response, it's worth examining some cases in slightly more detail, and so we'll compare our case study with Ladyman's (2011) discussion of the phlogiston theory. Ladyman understands the sense in which the phlogiston theory captures the structure of the unobservable reality qualitatively, in terms of a classification of various types of chemical reactions. Phlogiston theorists conceived of a number of chemical reactions as instances of either phlogistication or dephlogistication, and understood these kinds of reactions as the inverse of one another. Ladyman claims that "[t]his is a prime example of a relation among the phenomena which is preserved in subsequent science even though the ontology of the theory is not; namely the inverse chemical reactions of reduction and oxygenation" (2011, p. 99). In contrast, cognitive neuroscientists represent relations among brain regions, not in terms of qualitative descriptions, but in terms of graphs. There is a common denominator here, namely, relations among phenomena. But presumably, the structural realist cannot simply claim that any relations that obtain among any phenomena count as structure since phenomena bear all kinds of arbitrary and accidental relations to one another. This common denominator is therefore insufficient for concluding that Ladyman's 'inverse of' relation and the graph theoretic relations from our case study both fall under some more

[2] Another problem for global structural realism concerns whether NMA and PMI are fallacious. See Magnus and Callender (2004).

general category of 'structure' that is important for delineating our realist commitments.

Saatsi's arguments against global structural realism are also meant to motivate Saatsi's own position, which he calls exemplar realism. Exemplar realism is the view that we ought to determine our epistemic commitments by examining particular theories and models, and attempting to account for their successes by identifying the particular ways in which those theories and models latch onto reality. Moreover, exemplar realism amounts to a kind of pluralism about how such theories and models can latch onto reality. As Saatsi (2015, p. 6) puts it, "empirical success can be due to getting 'structure' right, getting right some of a system's less-specific features, getting right the fundamental causal contributors, and so on." Saatsi calls these "realist recipes," and in his view, even if no recipe can apply to all cases, each recipe may fit some limited number of cases. In Saatsi's view, structural realists may be correct about how some particular theories or models latch onto an unobservable reality; but global structural realists engage in unwarranted generalization from those particular cases to the whole of science. We take exemplar realism to be a promising position, and we'll devote some additional discussion to it in section 7.

For now, we wish to motivate another possibility that is suggested by Saatsi's exemplar realism, but that Saatsi himself does not consider explicitly, namely, that 'structure' amounts to different things in different cases. For example, it's possible that Ladyman is correct about the phlogiston case and that we are correct about the case of brain networks. Intuitively, it seems that both Ladyman's 'inverse of' relation and our notion of graph theoretic structure are examples of structure. But when philosophers repeatedly fail in their attempts to articulate a single notion of structure that is both sufficiently precise and applicable to all of the cases that structural realists have discussed, why not conclude that there are different notions of structure operative in different cases? Just as the different realist recipes can function as different ways in which a theory or model can latch onto reality, so can the different abstract characterizations of structure. One theory or model may latch onto Ramsey sentence structure, while another latches onto model theoretic structure, while yet another latches onto graph theoretic structure, and so on. But if so, we lack a univocal account of structure, and so we ought to reject global structural realism. In that case, our claim regarding brain networks should not be understood as an instance of a global structural realist claim, but instead as a local claim.

7. Local approaches to the scientific realism debate

Given the fact that we've rejected global structural realism in favor of a more local claim regarding structural knowledge of brain networks in particular, perhaps our case study actually provides support for what we'll call a local approach to the scientific realism debate. According to this kind of approach, we ought to resolve whether to adopt a realist attitude towards a particular theory, claim, or entity by examining the first-order evidence that scientists have used to support it. The problem with these approaches is that they tend to be absolutist, in the sense that the only options regarding a particular scientific theory, claim, or entity are realism and anti-realism. They don't allow for the kind of local structural realist attitude that we take regarding brain networks. However, Saatsi's (2015) exemplar realism does, and we'll discuss how our case study fits with Saatsi's position.

To begin with, it will be necessary to go into a bit more detail regarding what constitutes a local approach to the realism debate. Proponents of local approaches argue that we should abandon attempts to settle the realism debate at the global level of our best theories collectively. Instead, we ought to conduct the debate at the local level of individual theories, claims, and entities. Rather than asking whether our best theories are approximately true, we ought to ask whether to adopt a realist attitude towards particular theories and/or components of theories. Moreover, any attempt to answer this latter question will have to be grounded in the first-order scientific evidence that convinced scientists of the truth of particular claims, and of the existence of particular entities. Proponents of local approaches thus transform realism and anti-realism from global positions regarding our best theories in general to local commitments regarding this or that particular theory, claim, or entity.

When it comes to determining our epistemic commitments, we agree with proponents of these approaches that we should go local. But when it comes to the nature of our epistemic commitments, local approaches tend to be absolutist in the sense that one must choose between a realist attitude and an anti-realist attitude regarding a particular theory, claim, or entity. For many cases, it's surely appropriate to take one of these two attitudes. But in our view, local approaches would be even more attractive if they allowed for epistemic commitments that fall somewhere between these two attitudes, for example, a structural realist attitude.

The local approaches due to Magnus and Callender (2004) and to Fitzpatrick (2013) provide a useful illustration of this state of affairs. According to Magnus and Callender's approach, "realism and anti-realism are options to be exercised sometimes here and sometimes there" (2004, p. 337), with the result that "[t]here may be good reasons to be a realist about neutrinos, an anti-realist about top quarks, and so on" (2004, p. 333). And according to Fitzpatrick's approach, which he calls the "local strategy," "the best foundation for a realist attitude towards a particular theoretical claim of modern science … is the weight of the particular first-order evidence that led scientists to accept the claim in the first place" (2013, p. 143). Moreover, Magnus, Callender, and Fitzpatrick are explicit in their rejection of structural realism. Magnus and Callender motivate their approach by arguing that arguments like NMA and PMI are fallacious. They conclude that "[w]ithout these [arguments], we lose the rationale for both *entity realism* and *structural realism*" (2004, p. 333). They presumably draw this conclusion because of the central place that Worrall (1989) assigns to these two arguments in his defense of structural realism. The important point is that, for Magnus and Callender, one can be a realist or an anti-realist about neutrinos, but not a structural realist. Fitzpatrick makes a similar point regarding structural realism. He criticizes Worrall's structural realism as being "overgeneralized" and "far too concessive to the anti-realist" (2013, p. 150). In particular, he writes: "While it may perhaps be true that all we are entitled to be optimistic about in current science are its implications about the abstract structure of nature, it seems bizarre to make this as a general claim, as Worrall does, on the basis of a few cases from nineteenth century physics" (2013, p. 150). Once again, it seems that we must choose between realism and anti-realism; structural realism is not an option.

It's clear that what Magnus, Callender, and Fitzpatrick reject is global structural realism, which we reject as well. However, in the course of rejecting global structural realism, they have neglected the possibility of taking a kind of local structural realist attitude towards a particular theory, claim, or entity. Once we conduct the realism debate locally, a look at the first-order evidence may show that our knowledge in that area is structural knowledge, as we've argued in the case of brain networks.

Fortunately, there is one local approach that explicitly allows for this possibility, namely, Saatsi's exemplar realism. Saatsi characterizes exemplar realism in terms of a "realist attitude … according to which the impressive empirical success of science is by and large down to theories latching onto reality in ways that make them empirically successful" (2015, p.8). But exemplar realism still counts as a local approach insofar as Saatsi claims that "[a] realist gains her epistemic commitments when she applies her realist attitude locally, in a piecemeal way, to particular theories in particular disciplines and domains of science" (2015, p. 8). As we discussed in section 6, exemplar realism amounts to a kind of pluralism about the ways in which a theory or model can latch onto reality. In some cases, latching onto reality amounts to getting the structure right, while in other cases, it may amount to getting something else right. Exemplar realism thus provides the resources for us to be clearer about what we mean by adopting a local structural realist attitude. When one concludes that the way in which a particular theory or model latches onto reality is by getting the structure right, then one is adopting a local structural realist attitude. Our claim regarding brain networks is that the graph theoretic models that cognitive neuroscientists construct latch onto reality by getting the structure of brain networks right. In other words, we adopt a local structural realist attitude towards brain networks.

8. Conclusion

In this paper, we've examined a body of work in cognitive neuroscience that investigates brain networks, and we've argued that this work yields structural knowledge of those networks. More specifically, it yields knowledge of the graph theoretic structure of those networks, without providing knowledge of the individual nodes qua brain regions and edges qua connections that instantiate that structure. Moreover, we've explored the significance of this conclusion for some recent work in the scientific realism debate. In particular, we've argued that our conclusion should not be understood as an instance of a global structural realist claim regarding our best theories in general. Instead, it ought to be understood locally, and we've argued that various local approaches to the realism debate are problematic insofar as they tend not to allow for such a local structural realist attitude. Finally, we've argued that the conclusions that we've drawn regarding brain networks fit most comfortably within exemplar realism.

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References

Bain, J. (2013). Category-theoretic structure and radical ontic structural realism. *Synthese, 190*, 1621–1635. http://dx.doi.org/10.1007/s11229-011-9896-6.

Bechtel, W. (2015). Generalizing mechanistic explanations using graph-theoretic representations. In P.-A. Braillard, & C. Malaterre (Eds.), *Explanation in biology: An enquiry into the diversity of explanatory patterns in the life sciences* (pp. 199–225). Dordrecht: Springer. http://dx.doi.org/10.1007/978-94-017-9822-8_9.

Bock, D. D., Lee, W.-C. A., Kerlin, A. M., Andermann, M. L., Hood, G., Wetzel, A. W., et al. (2011). Network anatomy and in vivo physiology of visual cortical neurons. *Nature, 471*, 177–182. http://dx.doi.org/10.1038/nature09802.

Bueno, O., French, S., & Ladyman, J. (2002). On representing the relationship between the mathematical and the empirical. *Philosophy of Science, 69*, 452–473. http://dx.doi.org/10.1086/342456.

Bullmore, E., & Sporns, O. (2009). Complex brain networks: Graph theoretical analysis of structural and functional systems. *Nature Reviews Neuroscience, 10*, 186–198. http://dx.doi.org/10.1038/nrn2575.

Butts, C. T. (2009). Revisiting the foundations of network analysis. *Science, 325*, 414–416. http://dx.doi.org/10.1126/science.1171022.

Colombo, M. (2013). Moving forward (and beyond) the modularity debate: A network perspective. *Philosophy of Science, 80*, 356–377. http://dx.doi.org/10.1086/670331.

Fitzpatrick, S. (2013). Doing away with the no miracles argument. In V. Karakostas, & D. Dieks (Eds.), *EPSA11 perspectives and foundational problems in philosophy of science* (pp. 141–151). Switzerland: Springer. http://dx.doi.org/10.1007/978-3-319-01306-0_12.

French, S. (2014). *The structure of the world: Metaphysics and representation*. Oxford: Oxford University Presshttp://dx.doi.org/10.1093/acprof:oso/9780199684847.001.0001.

Frigg, R., & Votsis, I. (2011). Everything you always wanted to know about structural realism but were afraid to ask. *European Journal for Philosophy of Science, 1*, 227–276. http://dx.doi.org/10.1007/s13194-011-0025-7.

Hagmann, P., Cammoun, L., Gigandet, X., Meuli, R., Honey, C. J., Wedeen, V. J., et al. (2008). Mapping the structural core of human cerebral cortex. *PLoS Biology, 6*, e159. http://dx.doi.org/10.1371/journal.pbio.0060159.

Huneman, P. (2010). Topological explanations and robustness in biological sciences. *Synthese, 177*, 213–245. http://dx.doi.org/10.1007/s11229-010-9842-z.

Kincaid, H. (2008). Structural realism and the social sciences. *Philosophy of Science, 75*, 720–731. http://dx.doi.org/10.1086/594517.

Ladyman, J. (2011). Structural realism versus standard scientific realism: The case of phlogiston and dephlogisticated air. *Synthese, 180*, 87–101. http://dx.doi.org/10.1007/s11229-009-9607-8.

Ladyman, J., & Ross, D. (2007). *Every thing must go: Metaphysics naturalized*. Oxford: Oxford University Press (With Spurrett, D. & Collier, J) http://dx.doi.org/10.1093/acprof:oso/9780199276196.001.0001

Landman, B. A., Bogovic, J. A., Wan, H., ElShahaby, F. E. Z., Bazin, P.-L., & Prince, J. L. (2012). Resolution of crossing fibers with constrained compressed sensing using diffusion tensor MRI. *NeuroImage, 59*, 2175–2186. http://dx.doi.org/10.1016/j.neuroimage.2011.10.011.

Magnus, P. D., & Callender, C. (2004). Realist ennui and the base rate fallacy. *Philosophy of Science, 71*, 320–338. http://dx.doi.org/10.1086/421536.

Power, J. D., Cohen, A. L., Nelson, S. M., Wig, G. S., Barnes, K. A., Church, J. A., et al. (2011). Functional network organization of the human brain. *Neuron, 72*, 665–678. http://dx.doi.org/10.1016/j.neuron.2011.09.006.

Ross, D. (2008). Ontic structural realism and economics. *Philosophy of Science, 75*, 732–743. http://dx.doi.org/10.1086/594518.

Rubinov, M., & Sporns, O. (2010). Complex network measures of brain connectivity: Uses and interpretations. *NeuroImage, 52*, 1059–1069. http://dx.doi.org/10.1016/j.neuroimage.2009.10.003.

Saatsi, J. T. (2015). Replacing recipe realism. *Synthese, Online First*, 1–12. http://dx.doi.org/10.1007/s11229-015-0962-3.

Smith, S. M. (2012). The future of FMRI connectivity. *NeuroImage, 62*, 1257–1266. http://dx.doi.org/10.1016/j.neuroimage.2012.01.022.

Smith, S. M., Miller, K. L., Salimi-Khorshidi, G., Webster, M., Beckmann, C. F., Nichols, T. E., et al. (2011). Network modelling methods for FMRI. *NeuroImage, 54*, 875–891. http://dx.doi.org/10.1016/j.neuroimage.2010.08.063.

Sporns, O. (2013). Structure and function of complex brain networks. *Dialogues in Clinical Neuroscience, 15*, 247–262.

Sporns, O. (2014). Contributions and challenges for network models in cognitive neuroscience. *Nature Neuroscience, 17*, 652–660. http://dx.doi.org/10.1038/nn.3690.

Sporns, O., Honey, C. J., & Kötter, R. (2007). Identification and classification of hubs in brain networks. *PLoS One, 2*, e1049. http://dx.doi.org/10.1371/journal.pone.0001049.

Sporns, O., Tononi, G., & Kötter, R. (2005). The human connectome: A structural description of the human brain. *PLoS Computational Biology, 1*, e42. http://dx.doi.org/10.1371/journal.pcbi.0010042.

Stam, C. J., & Reijneveld, J. C. (2007). Graph theoretical analysis of complex networks in the brain. *Nonlinear Biomedical Physics, 1*, 3. http://dx.doi.org/10.1186/1753-4631-1-3.

Stam, C. J., & van Straaten, E. C. W. (2012). The organization of physiological brain networks. *Clinical Neurophysiology, 123*, 1067–1087. http://dx.doi.org/10.1016/j.clinph.2012.01.011.

Tuch, D. S., Reese, T. G., Wiegell, M. R., Makris, N., Belliveau, J. W., & Wedeen, V. J. (2002). High angular resolution diffusion imaging reveals intravoxel white matter fiber heterogeneity. *Magnetic Resonance in Medicine, 48*, 577–582. http://dx.doi.org/10.1002/mrm.10268.

Van Essen, D. C., Smith, S. M., Barch, D. M., Behrens, T. E. J., Yacoub, E., & Ugurbil, K. (2013). The WU-Minn human connectome project: An overview. *NeuroImage, 80*, 62–79. http://dx.doi.org/10.1016/j.neuroimage.2013.05.041.

Varshney, L. R., Chen, B. L., Paniagua, E., Hall, D. H., & Chklovskii, D. B. (2011). Structural properties of the *Caenorhabditis elegans* neuronal network. *PLoS Computational Biology, 7*, e1001066. http://dx.doi.org/10.1371/journal.pcbi.1001066.

Votsis, I., & Schurz, G. (2012). A frame-theoretic analysis of two rival conceptions of heat. *Studies in History and Philosophy of Science, 43*, 105–114. http://dx.doi.org/10.1016/j.shpsa.2011.10.010.

Wedeen, V. J., Wang, R. P., Schmahmann, J. D., Benner, T., Tseng, W. Y. I., Dai, G., et al. (2008). Diffusion spectrum magnetic resonance imaging (DSI) tractography of crossing fibers. *NeuroImage, 41*, 1267–1277. http://dx.doi.org/10.1016/j.neuroimage.2008.03.036.

White, J. G., Southgate, E., Thomson, J. N., & Brenner, S. (1986). The structure of the nervous system of the nematode *Caenorhabditis elegans*. *Philosophical Transactions of the Royal Society of London B: Biological Sciences, 314*, 1–340. http://dx.doi.org/10.1098/rstb.1986.0056.

Wig, G. S., Schlaggar, B. L., & Petersen, S. E. (2011). Concepts and principles in the analysis of brain networks. *Annals of the New York Academy of Sciences, 1224*, 126–146. http://dx.doi.org/10.1111/j.1749-6632.2010.05947.x.

Worrall, J. (1989). Structural realism: The best of both worlds? *Dialectica, 43*, 99–124. http://dx.doi.org/10.1111/j.1746-8361.1989.tb00933.x.

Worrall, J. (2011). Underdetermination, realism and empirical equivalence. *Synthese, 180*, 157–172. http://dx.doi.org/10.1007/s11229-009-9599-4.

Zednik, C. (2015). Heuristics, descriptions, and the scope of mechanistic explanation. In P.-A. Braillard, & C. Malaterre (Eds.), *Explanation in biology: An enquiry into the diversity of explanatory patterns in the life sciences* (pp. 295–318). Dordrecht: Springer. http://dx.doi.org/10.1007/978-94-017-9822-8_13.