Moving Forward (and Beyond) the Modularity Debate. A Network Perspective

1. Introduction. At least since Fodor's (1983) *The Modularity of Mind*, the notion of modularity has been one of the most important concepts used to articulate an account of the human cognitive architecture. An account of the human cognitive architecture provides us with an encompassing theory (a "blueprint") of the nature, arrangement, and form of the structures and processes that are responsible for cognition and adaptive behavior. This should be distinguished from a theory of the origins of cognitive architectures, which is concerned with the evolutionary and developmental history of the structures and processes that are responsible for cognition and adaptive behavior.

There has been little agreement on how the concept of modularity should be characterized, and on how we should study the extent to which the human cognitive architecture is modular. This disagreement has arguably hindered advancement in our understanding of the human cognitive architecture. There are two main reasons why researchers have often argued at cross-purposes in debates about modularity. First, different researchers have often used the term 'modularity' in significantly different ways (for discussion of different notions of modularity see Segal 1996; Samuels 2000). Second, questions about the nature, arrangement, and form of the structures and processes responsible for cognition have been often conflated with questions about the value and problems of (some form of) adaptationism as a view about the role of natural selection in the evolution of our cognitive traits, in the construction of explanations of our cognitive faculties, and in the definition of the goal of research on the evolution of such faculties (cf. the history of modularity in Barrett and Kurzban 2006, 628-629; or the exchanges between

Fodor 2000, and Pinker 2005; between Lickliter and Honeycutt 2003a, 2003b, and Tooby, Cosmides and Barrett 2003; and between Buller 2005, and Machery and Barrett 2007).

Because of mere terminological disputes,[1] vagueness surrounding putative central features of modularity such as functional specialization, domain specificity and informational encapsulation, and especially because of little agreement about the proper empirical methods for discovering and justifying the existence of candidate modules (cf. the controversy around the cheater-detection module: e.g. Fodor 2000; Sperber and Girotto 2003; Cosmides and Tooby 2008a, 2008b; Fodor 2008), the modularity debate in the cognitive science and philosophy of psychology has often been frustratingly fruitless. If the debate could be moved forward and re-focused on substantive issues about our cognitive architecture, that would mark significant progress.

The goals of this paper are twofold. The first goal is to diagnose why the modularity debate risks to remain stagnant. The second goal is to suggest an effective remedy. Such a remedy is the theoretical framework of network science, which provides the basis of a more productive research program on the human cognitive architecture. Network science rests on bottom-up methods, which use large amounts of available and

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[1] Twyman and Newcombe write: “Given this lack of agreed-upon definition, the modularity position becomes analogous to the Hydra, the many-headed monster that Heracles found difficult to combat because there were too many heads to take on simultaneously, and, worse, because other heads grew while he addressed a specific one” (2010, 1317).

reliable data about brains, rather than on highly controversial methods, which partly draw on speculation about the evolutionary origins of cognitive mechanisms.

The paper is in four sections. In Section 2, I provide a critical overview of the two main accounts of modularity. These accounts have been respectively developed by Jerry Fodor, and by post-Fodorian researchers such as Clark Barrett, Peter Carruthers, Leda Cosmides, Robert Kurzban, Dan Sperber, and John Tooby. I explain why the notions of domain specificity and functional specialization as characterized within these two accounts do not facilitate theoretical and empirical progress. In Section 3, after having introduced the basics of networks science, I explain what modularity is from a network science perspective. I outline current methods for discovering modularity in systems of interest, and I argue that conceptual resources and methods from network science will help us move the modularity debate forward. In Section 4, I concisely review some of the evidence recently gathered within network neuroscience, about the modularity of the human cognitive architecture. Section 5 concludes.

A disclaimer about the scope of this paper is in order before moving on. Philosophers and many cognitive scientists have paid little attention to network science, and particularly to network neuroscience. It is not my aim to give a formal treatment of this field (see e.g. Rubinov and Sporns 2010). Nor is my aim to discuss in detail the theoretical and methodological foundations of network science. The paper will raise many questions—I shall be barely scraping the surface of this exciting field. Nonetheless, I hope to say enough about network science to convey philosophers and cognitive scientists a sense of the theoretical opportunities it affords, and of the problems it raises.

2. What is a Module? Current philosophical and psychological literature includes two prominent types of characterizations of modularity: one put forward by Fodor's (1983, 2000), and the other shared by post-Fodorian accounts such as Carruthers's (2006) and Barrett and Kurzban's (2006).

According to Fodor (1983), there are nine features that collectively individuate modules: domain specificity, mandatory operation, limited central accessibility, fast processing, informational encapsulation, "shallow" outputs, fixed neural architecture, characteristic and specific breakdown patterns, and characteristic ontogenetic timetables. For my purposes, three points are noteworthy about Fodor's account. First, Fodor is not so much concerned with the *evidential* status of the modularity of cognition: "This monograph—he writes—is about the current status of the faculty psychology program; not so much its evidential status (which I take to be, for the most part, an open question) as what the program is and where it does, and doesn't, seem natural to try to apply it" (1983, 1). So, Fodor's focus is on the nature and scope of a particular research program in cognitive science, which he calls "faculty psychology." This is "the view that many fundamentally different kinds of psychological mechanisms must be *postulated* in order to explain the facts of mental life" (Ibid., emphasis added). Second, Fodorian modules are intended to characterize a fragment of the human cognitive architecture. Fodor maintains that only peripheral (i.e. perceptual and motor) and linguistic systems are modular; the architecture of central systems supporting such cognitive capacities as reasoning and decision-making is instead non-modular (1983, 2000). Third, according to Fodor, a cognitive architecture counts as modular, if it is modular “to some interesting extent,” if it possesses most of the nine features singled out above to an appreciable degree (1983, 37). Hence, whether a cognitive architecture is modular (in Fodor’s sense) involves some vagueness. This vagueness is mitigated by the fact that some of the features of modularity, such as information encapsulation and domain specificity, are more important than others (Ibid.). If we find that a mechanism is informationally encapsulated and domain specific to some interesting extent, then we have good grounds to believe that it is a Fodorian module.

However, it is also a matter of degree whether a mechanism is informationally encapsulated or domain specific. For consider the definitions of an informationally encapsulated mechanism, and of a domain specific mechanism. A mechanism is informationally encapsulated to the extent that it is less open or permeable to information stored elsewhere in the system over the course of its processes. A mechanism is domain specific to the extent that it has a restricted subject matter. “[D]omain specificity has to do with the range of questions for which a device provides answers (the range of inputs for which it computes analyses)” (Fodor 1983, 103). From these characterizations, it is unclear to which extent a mechanism should be impermeable to information stored elsewhere in order to count as informationally encapsulated, and it is unclear how narrow the range of inputs that a mechanism can process should be for it to count as domain specific. Hence, both informational encapsulation and domain specificity are vague notions, which do not reliably help us to precisely identify modules.

More recently, many cognitive scientists, evolutionary psychologists, and philosophers have rejected Fodor’s notion of modularity. Barrett argues that Fodorian modularity “has been perhaps *too* influential, because it has foreclosed ways of thinking about modularity other than the very specific model [Fodor] proposed in his 1983 book” (2005, 260). Ermer, Cosmides and Tooby claim that “Fodor’s (1983) concept of a module is neither useful nor important” (2007, 153). Carruthers characterizes modularity by dropping some central features of Fodorian modules: “modules might be isolable function-specific processing systems, all or almost all of which are domain specific, whose operations aren’t subject to the will, which are associated with specific neural structures (albeit sometimes spatially dispersed ones), and whose internal operations may be inaccessible to the remainder of cognition” (2006, 12).

Although there are differences between particular post-Fodorian accounts of modularity, most post-Fodorian theorists agree that modules should be understood as functionally specialized cognitive mechanisms (Barrett and Kurzban 2006; Carruthers 2006; Coltheart 1999; Pinker 2005; Sperber 1994; Tooby and Cosmides 1992). Accordingly, to say that the human cognitive architecture is modular is to say that it consists of a number of isolable mechanisms specialized to carry out some function. A mechanism, in turn, can be understood as “a structure performing a function in virtue of its component parts, component operations, and their organization. The orchestrated functioning of the mechanism is responsible for one or more phenomena” (Bechtel and Abrahamsen 2005, 423). Hence, to say that a cognitive mechanism carries out some function is to say that it transforms some set of inputs into some set of outputs as a result of the organized set of operations performed by its component parts. It should be clear that the structural features of a mechanism—that is, the causal, spatial, and dynamical features of the components it comprises—are relevant to the function it carries out. In order to reliably identify the function carried out by some putative cognitive module, evidence about neuroanatomical and neurophysiological constraints can be relevant.

On this view, the defining feature of modular mechanisms is *functional specialization*. As Barrett and Kurzban put it, “functionally specialized mechanisms with formally definable informational inputs are characteristic of human (and nonhuman) cognition and… these features should be identified as the signal properties of ‘modularity’” (2006, 630). Functional specialization concerns the types of processes carried out by a mechanism. A cognitive mechanism is functionally specialized to the extent that it carries out a restricted range of types of processes that successfully apply to certain problem domains—where domains are individuated by the formal properties of input representations to the mechanism (Ibid.). Accordingly, a module would be a specialized input-output mechanism that accepts inputs of a particular form, performs specialized transformations (or processes) on them, and yields outputs, whose format makes them usable for other cognitive mechanisms (cf. Barrett 2005, Section 3).

Two points are noteworthy here. First, this characterization involves some vagueness, since it does not answer the question of how many functions a mechanism should carry out for it to cease to be functionally specialized. Second, that a module is individuated in terms of its functional specialization does not imply that there is a single, distinct anatomical structure in the brain that is responsible for the processes carried out by the module. Modules can correspond to distributed circuits of neural networks that do not neatly map onto any single anatomical structure.

2.1 Why Current Characterizations of Modularity Have Not Facilitated Progress. There is one important problem shared by Fodorian and post-Fodorian accounts of modularity. They do not offer reliable methods to identify either domain specificity or functional specialization in cognitive mechanisms. If domain specificity or functional specialization is essential to modularity, and we lack reliable ways to identify them, then we lack reliable ways to identify modules. If we lack reliable ways to identify modules, then the concept of modularity risks to hinder understanding and fruitful debate, rather than being a useful concept for articulating a theory of cognitive architecture.

The difficulty in identifying domain specificity and functional specialization partly depends on the vagueness of these two notions, which is acknowledged by both Fodor and post-Fodorian modularists. It also depends on the type of top-down methodology employed to define these features. This type of methodology—which I shall explain in a moment—is not directly concerned with using data and information from the brain sciences. To justify disregard for data and information from the brain science, it can be argued that modularity concerns a more abstract explanatory level than the level of neuroscience. Modularity would be a concept proprietary of the familiar Marr's (1982) computational and algorithmic levels, which are supposedly unconstrained by evidence about the neural level of implementation. If modularity is a concept proprietary of such levels, then modular architectures in cognitive systems can be identified and studied, while remaining agnostic about how defining features of modularity such as functional specialization are implemented in the brain (cf. Barrett and Kurzban 2006, 642).

In contrast to this conclusion, one of the convictions that motivate this paper is that data and information from the brain sciences are relevant to developing an empirically and theoretically fruitful account of modularity, and, more generally, a theory of cognitive architecture. A theory of cognitive architecture should draw on available and reliable data about structural, anatomical, and neurophysiological features of the brain, which are likely the bases of a much more productive research program.

Three reasons can be given in support of this conviction. First, the view that an empirically and theoretically fruitful account of modularity can disregard data and information from the brain sciences relies on a misguided understanding of Marr's (1982) three-level framework. Although in some passages Marr emphasises that "the three levels are only rather loosely related" (1982, 25), thereby suggesting some sort of autonomy between them, he also recognizes that accounts of particular cognitive capacities such as human vision should be ultimately assessed in terms of how well the computational and algorithmic specifications they include fit known neurobiological properties and details of the human visual system (1982, Ch. 3-4; see also Marr, Ullman and Poggio 1979, 916). Hence, Marr himself embraced a form of *co-evolutionary* research ideology, whereby concepts, models, and theories put forward at one level should be susceptible to correction and reconceptualization in light of discoveries, conceptual refinements, and methods available at some different level (Churchland 1986).

Second, both the Fodorian and most post-Fodorian accounts of modularity do refer to the brain sciences. For example, Fodor emphasises "the intimate association of modular systems with neural hardwiring," and draws on "form/function correspondences" between certain patterns of neural connectivity and modularity to argue that input systems processes, but not central processes, are modular (e.g. Fodor 1983, 117-119). Sperber (1994, 40) defines a cognitive module as “a genetically specified computational device in the mind/brain.” Cosmides and Tooby (1995) refer to modules as “neurocognitive” adaptations. Carruthers sometimes refers to specific features of modularity as features of the “mind/brain,” and draws upon anatomical as well as neurophysiological evidence to make a number of arguments about the organization of the mind of non-human and human animals (2006, Chapter 2). This overview indicates that many cognitive scientists and philosophers working on modularity draw on information from the brain sciences because this information can be relevant to developing, and assessing an account of modularity.

Third, and more important, *even if* developing an account of modularity and, more generally, a theory of cognitive architecture without paying attention to data and information from the brain sciences might not be a hopeless project, it is a significant advantage if such a research program finds data and information from the brain sciences relevant. One should not profess agnosticism about the neural implementation of functional specialization, insofar as neural evidence is available that is relevant to constrain hypotheses about cognitive specializations. In fact, not every functional analysis of a system is equally adequate to play an explanatory role. And one way to assess the explanatory grip of a given functional analysis is to consider the extent to which it is informed by known facts about the human brain. This might not be the only way, but is useful and congenial to the development of a fruitful account of modularity.

I now turn to the methodology widely adopted by many cognitive scientists and philosophers to identify modularity. Fodor (1983) does not elaborate on it, partly because—as noted above—he is not much concerned with the evidential status of the modularity of cognition. Most of the post-Fodorian literature, instead, addresses the methodological issue of how we should study modularity within an adaptationist framework. A type of top-down, evolutionary/functional methodology is generally adopted. Accordingly, the basis for studying the architecture of the human cognitive system, and the extent to which it is modular consists in the identification of the types of computational problems that the human cognitive system faced over its evolution (Pinker 1997; Tooby and Cosmides 2005).[2] These kinds of problems, called *adaptive problems*, consist of situations such that different variants of some phenotypic trait contribute differently to reproductive fitness. The search for the structures and processes that can plausibly constitute our cognitive architecture is deferred until an adaptive problem—which could be solved by the organized operations of those structures—is identified (see e.g. Barrett and Kurzban 2006; Cosmides and Tooby 1995). Pursuing this approach, domain specificity is defined in terms of sets of input stimuli characteristic of the adaptive problems faced by our ancestors (Barrett 2009; Carruthers 2006; Ermer, Cosmides and

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[2] Buller explains this methodology thus: “Reverse engineering is a process of figuring out the design of a mechanism on the basis of an analysis of the tasks it performs. Evolutionary functional analysis is a form of reverse-engineering in that it attempts to reconstruct the mind’s design from an analysis of the problems the mind must have evolved to solve” (2005, 92).

Tooby 2007; Sperber 1994). Functional specialization is defined similarly, in terms of adaptive problems solved by the cognitive systems of our ancestors. Accordingly, to say that a mechanism is functionally specialized is to say that it carries out a restricted range of types of processes that could solve the types of adaptive problems “that caused the propagation of its genetic basis relative to that of alternative mechanisms” (Ermer, Cosmides and Tooby 2007, 153).

If domain specificity and functional specialization are to be understood within an adaptationist framework, then some reliable way to individuate adaptive problems is necessary in order to identify modules in our cognitive architecture. However, the reliable individuation of adaptive problems is far from straightforward. It involves problematic methods, which have given rise to controversy about the status of evidence in evolutionary psychology used for establishing that a given cognitive mechanism is an adaptation, or is adaptive. Although the research program in evolutionary psychology is clearly not doomed a priori, it is currently very challenging to reliably test adaptationist hypotheses about our past and about the origins of our cognitive architecture (cf. Atkinson and Wheeler 2004; Buller 2005; Lloyd and Feldman 2002; Kaplan 2002; Richardson 2007; Schulz 2011; Sterelny and Griffiths 1999; Machery Forthcoming provides a more positive assessment of the status of evidence in evolutionary psychology). In the face of such methodological challenges, if the search for modularity mainly depends on our ability to individuate adaptive problems, *and* disregards the structural constraints and neurophysiological dynamical patterns that more apparently shape our cognitive architecture, then the worry that researchers are too unconstrained to suppose any module for any imaginary adaptive task becomes serious.

This worry should not suggest that an adaptive understanding of domain specificity and functional specialization is unimportant to articulating a full account of our cognitive architecture. My point is about the counter-productiveness of adopting a top-down evolutionary/functional analysis as the basis of a research program on modularity and cognitive architecture. If “the language of modularity affords useful conceptual groundwork in which productive debates surrounding cognitive systems can be framed”—as claimed by Barrett and Kurzban (2006, 644)—then the utility of such a language in moving the debates forward will be greater if the notion of a module is *not* cashed out in adaptationist terms, but instead is understood within an evolutionarily-neutral framework.

Network science offers such a framework. Understanding modularity from a network science perspective can enable us to integrate neurophysiological and structural information about cognitive mechanisms, while freeing the notion of functional specialization from adaptationism. Concepts and methods from network science can make the language of modularity more conducive to productive theoretical and empirical debates about the form and organization of the architecture of cognitive systems such as the human brain.

3. What a Module Is: A Network Science Perspective. The brain is a complex system composed of intricately interconnected, interacting elements. The organized activity of such elements is responsible for cognitive capacities and behavior. Network science offers a conceptual framework, methods, and a set of mathematical and statistical techniques, whereby we can understand the architectural organization of brain networks, and how such organization is responsible for cognition.

The explanatory targets of network science are complex networks and the phenomena they display. Complex networks can be engineered, biological, and social systems. In order to understand the organization of the structures and informational relationships that characterize complex systems, network science relies on concepts and methods from fields such as graph theory, statistics, information theory, machine learning, measurement theory, and dynamical system theory (Börner, Sanyal and Vespignani 2007).

Graph theory is the primary analytical framework used in network science. Graphs are sets of nodes and edges, which allow us to represent complex network systems such as the World Wide Web, mafia gangs, or the brain. Nodes represent elements, or components of the system. Edges represent connections between pairs of nodes. Edges can be directed or undirected, and they can be binary (i.e. they are either present or absent) or weighted (i.e. they can take on fractional values). Nodes can be connected directly by single edges, or indirectly by intermediate nodes and edges. Network measures include degree, strength, and centrality. Degree and strength of a node measure the extent to which the node is connected to the rest of the network. The degree of a given node is the number of connections that link the node to the rest of the network; a node with high strength makes strong connections—where strength is equal to the sum of connection weights. The minimum number of edges that must be travelled to go from one node to the other defines the path length between two nodes. The centrality of a node measures how many shortest paths between other parts of the network pass through that node. Nodes with high degree and high centrality are called “hubs.” Hubs are crucial for efficient communication between different nodes, as they facilitate global connectedness and integration of information within the network. All these measures refer to the *topology* of the network. So, two nodes of a network can be physically distant, but topologically close, as short path length between two nodes does not imply close physical proximity between them.

In cognitive science, network science is the basis of two main projects. The first project aims to describe the patterns of connectivity displayed by the multiscale networks that constitute nervous systems. The second aims to reveal the organizational principles behind the architecture of the networks of the brain understood as a type of information processing system. More generally, network neuroscience asks how brain networks, spanning the microscale of individual cells and synapses, and the macroscale of embodied and embedded cognitive systems, are responsible for cognition (Sporns 2011).

If we consider a graphical description of a brain network, network nodes can represent neural elements such as cells, populations of neurons, or cortical and subcortical regions, while network edges can represent structural connections between nodes such as synapses or axonal pathways. There are three modes of connectivity between the nodes comprised by a brain network. Besides structural connectivity, there are functional and effective connectivity (Sporns 2007).

Structural connectivity refers to the pattern of physical or anatomical connections linking neural elements. A representation of the structural connectivity of the brain corresponds to the “wiring diagram of the brain,” or *connectome*, which provides a map of the anatomical connections between neural structures (Sporns, Tononi and Kötter 2005). *Functional connectivity* refers to patterns of symmetrical statistical association between activities in different neural elements. Measured in terms of correlation or covariance, mutual information, or spectral coherence between activities in neural elements—regardless of whether they are structurally connected—functional connectivity captures neurophysiological dynamics (Friston 1994). Information about functional connectivity tells us how activity in one neural node affects the correlations between activities in all the other nodes over time. A third mode of connectivity is *effective connectivity*, which refers to patterns of causal effects among neural elements. Measured through structural equation modeling, Granger causality, and other methods, it describes directed relationships between neurophysiological events (Friston 2011).

Information about these three modes of brain connectivity constitutes an important part of a theory of cognitive architecture. This should be obvious if we recognize that a theory of the architecture of a cognitive system should provide us with information about how the system is structured, and how the organized activity of its elements is responsible for cognitive phenomena and behavior. Information about structural, functional, and effective connectivity helps us describe the anatomical organization of the brain. It enables us to precisely identify the topological, statistical, and information-theoretical principles that might lie behind the architecture of a cognitive system such as the brain. Furthermore, information about these three types of connectivity advances our understanding of how certain causal transactions that take place among certain neural elements produce specific cognitive phenomena.

Bullmore and Sporns (2009, 187) outline four basic steps that are common to most approaches to identify brain networks:

1. Define network nodes.
2. Define edges.
3. Represent the complete set of nodes and edges with a "connection matrix" that specifies which pairs of nodes are directly connected by an edge.
4. Analyze the resulting network with appropriate network-theoretical tools.

Each step requires researchers to make choices that will impact their results. This does not mean, however, that researchers' choices are arbitrary, or that most results across studies are incoherent. Appropriate choices depend on the research question under investigation, on the researchers' pragmatic ends and interests, on background knowledge of the system, and on available techniques. For example, if we consider the first step, appropriate parcellation of a given system into neural nodes can rely on histological, anatomical, electrophysiological, receptor distribution, or imaging data, depending on the research question and scale at which the researchers intend to investigate the system. At the level of large-scale brain system, nodes are better defined as coherent anatomical regions on the basis of prior anatomical criteria and functional imaging data (e.g. Cohen et al. 2008). Unsupervised, data-driven methods can be used to define and/or validate previously identified boundaries between coherent brain regions (Golland et al. 2008). The idea behind such data-driven methods is—*very* roughly—that nodes can be defined by searching sets of anatomical or imaging data for clusters of data, which emerge as coherent regions.

Analyses of several different types of brain networks, carried out with different techniques, have shown that some characteristic features of the human cognitive architecture can be detected with high reliability and robustness. One such feature is modularity. *Modularity* is topologically defined in terms of specific patterns of connectivity between neural nodes. Modules are “communities of nodes that share greater numbers of mutual connections within each community and fewer connections between them” (Sporns 2011, 113).

If you suspect that this notion is ridden with vagueness as much as the notions of modularity of the Fodorian and post-Fodorian accounts, this suspicion will be dispelled in a moment. Before turning to this issue, two aspects of modularity as characterized within network science are worth pointing out. First, in many complex systems, modularity is a property of architectures that span multiple scales. Many complex systems, including the brain, display the fractal property of *hierarchical* modularity, where “roughly the same kind of community structure is expressed repeatedly at different hierarchical levels or topological scales of the network” (Meunier et al. 2010, 2). Second, the distinction between structural, functional, and effective connectivity allows us to distinguish between structural, functional (i.e. statistical), and effective (i.e. causal) modularity. Based on patterns of structural connections in the system, structural modules consist of groups of densely anatomically interconnected nodes that are only sparsely connected with the rest of the network. Similarly, based on the patterns of statistical (and causal) dependencies displayed by the system, modules are individuated by clusters of densely functionally (and effectively) interconnected nodes.

Let us now examine how modules are identified in complex systems, and whether the network-scientific notion of modularity is as vague as the traditional notions. A system displays a modular architecture, if the nodes comprised by the system cluster in communities such that the nodes in each community are densely connected and the nodes between communities are sparsely connected. How dense? How sparse? There are a number of methods to answer these questions, each of which uncovers in an automated way the modules comprised by the system, quantifying how modular its architecture is (see Fortunato 2010, for a review). Each of these methods gives a precise answer to the questions about the number and size of modules in the system. These answers are not necessarily the same. Despite differences, however, most available methods yield coherent results that validate each other.

Currently, one of the most prominent measures of modularity has been developed by Newman's (2006) (see also Newman and Girvan 2004). The basic idea is that the modularity of a network is identified on the basis of "the number of edges falling within groups [of nodes] minus the expected number in an equivalent network with edges placed at random" (Newman 2006, 8578). Modularity corresponds to "statistically surprising arrangement of edges" in the network (Ibid.). Network-scientific measures of modularity such as this, *unlike* the notions of modularity underlying Fodorian and post-Fodorian accounts, have received a mathematical formulation. Each of these measures is an objective method, whose assumptions are explicitly laid out, and can be independently evaluated in light of empirical results.

A characterization of modularity within network neuroscience has several advantages over the Fodorian and post-Fodorian accounts. First, the bottom-up and data-driven methods used to identify and measure modularity make it a precise concept, and a quantifiable property, which can help us integrate information about different levels of organization in the brain. Second, the focus is on architectural features of our cognitive system, instead of on their origins, or on their being adaptations. Third, features such as functional specialization are not matters of stipulation, nor are they labelled in an intuitive manner; rather, they can be rigorously characterized and discovered, drawing upon network-theoretical analyses of patterns of brain connectivity. I conclude this section by articulating each claim in turn.

From a network-scientific perspective, modularity "is the result of an objective analysis of network connectivity and not based on intuitive or subjective classification criteria for network elements or on their intrinsic characteristics" (Sporns 2011, 113). Pursuing bottom-up, data-driven methodologies, network science eschews the use of concepts such as domain specificity and functional specialization to define modularity, whose vagueness makes it relatively more problematic to reliably identify modules. Bottom-up, data-driven methods deliver measurements of modularity, which quantify to what extent a given cognitive system is modular. Furthermore, a modularity analysis of connection datasets can provide us with a precise, quantitative characterization of the relationship between structural properties, and neurophysiological dynamics of a target brain network. While facilitating us to connect different levels of structural, functional, and causal organization in the brain, modularity analyses can also uncover whether certain organizational principles (e.g. topological efficiency, global efficiency of information transfer, robustness,…) are conserved “over different scales and types of measurement, across different species and for functional and anatomical networks” (Bullmore and Sporns 2009, 196).

Second, from a network science perspective, whether the properties endowed by a modular architecture are adaptive, or evolved because of their fitness benefits to our ancestors are separate, secondary questions (Bullmore and Sporns 2012). The question “How modular is the brain?” is not the same question as “How many adaptations does the brain contain?” or “How functionally differentiated is the brain?” And these questions should not be conflated.

Although there is growing appreciation that a network analysis of the topological properties of a biological system is congenial to the study of the “evolvability” of the system (Wagner, Pavlicev and Cheverud 2007), network science by itself does not answer questions about the evolutionary forces by which modular architectures could be selected (Sporns 2011, Ch.7).[3] Modular architectures, for example, have been shown to display robustness. Their topological properties tend to be resilient to perturbations such as the

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[3] The “evolvability” literature does not have exactly the same definition of modularity as the network definition. According to this literature, a system is modular to the degree that different parts of it can be shaped independently by selection. Hence, modularity here is similar to the inverse of pleiotropy. Nonetheless, also this notion of modularity—where the relevant networks are genetic and epigenetic networks—can be understood within network science. Thanks to Clark Barrett for drawing my attention to this point.

removal, or lesion of nodes or edges. Since systems that display a degree of robustness have been shown to possess a fitness advantage, the evolution of modularity might be linked to a topological property such as robustness (Wagner, Mezey and Calabretta 2005). However, network modularity and “evolvability” can diverge in their empirical implications. It is possible that a highly modular neural network does not exhibit a high degree of within-network evolvability, in the sense that evolutionary forces did not shape different parts of the neural network separately.

Similarly, within network neuroscience questions about the degree of modularity of the brain are distinguished from questions about the degree to which modules have been selected to carry out distinct functions. This is how it should be, since the answers to those questions are not necessarily the same. Barrett’s (2012) discussion of the relationship between increasing brain size, network-modularity, and the evolution of brain specializations illustrates this point nicely. Barrett considers two distinct (non-necessarily mutually exclusive) hypotheses (2012, 10737-10738). According to one hypothesis, the evolutionary force behind increasing brain size was selection for increased neural processing power. This could have led to increasing modularity purely as an architectural by-product of increasing network size. The resulting more modular brain is not necessarily more functionally differentiated, as the more modular architecture did not undergo selection for new specializations. According to another hypothesis, the evolutionary force behind brain increase was selection for increased specialization. “If the best way to produce new specialized regions is to increase brain size… then selection for specialization could have favored mutations that increased overall brain volume, thereby increasing modularity” (2012, 10737). In this case, but not in the former, a more modular brain is evidence for more functional differentiation/increased specialization. Examples such as this bear out that, while network neuroscience can be relevant to some questions about the origins of our cognitive architecture (by e.g. identifying organizational principles of complex brain networks, or neural wiring rules), it does not substitute for other approaches for those interested in those questions.

Finally, from a network perspective, features such as functional specialization, informational integration, and segregation are not matters of stipulation or of intuitive labeling. Especially within post-Fodorian/evolutionary psychologists’ accounts of modularity, intuitive labels such as “tool-use module” or “friendship module” have been used to characterize the function of many putative modules (Tooby and Cosmides 1992, 113). One problem with this type of characterization is that it does not allow us to predict structures from functions, or functions from structures. Intuitive labeling does not allow us to predict what type of structural organization, or what type of topology a target mechanism will display, given knowledge of the cognitive functions it performs; and it does not help understand what types of cognitive functions a target mechanism can perform, given knowledge of its structural organization and topology. Part of the reason is that this type of labeling ignores all mode of neural connectivity, which can constrain and bootstrap *functional ontologies* for cognition (Bilder et al. 2009; Price and Friston 2005).

Let me single out a number of approaches, where network-theoretical analyses of connectivity, or measures such as modularity bear on our understanding of cognitive function. First, modularity and connectivity analyses provide grounds for distinguishing networks of the brain, which, in the investigation of structure-function relationships, can be regarded as more appropriate structural units than brain regions considered in isolation from the broader neural context (Klein 2012; McIntosh 2000). Hampshire et al. (2012), for example, addressed the question of whether human intelligence is a single unitary general ability or a set of multiple independent abilities, by relating different brain networks to population differences in performance in a range of cognitive tasks that could yield a measure of general intelligence (IQ). A data-driven method (exploratory factor analysis) was used to identify functional networks from whole-brain imaging data of participants who performed a battery of cognitive tasks. Reasoning, short-term memory, and verbal processing were respectively found to load most significantly on three distinct functional networks, which best explained cross-task correlations in performance in a larger population sample. The relationships between dissociable functional brain networks, specific cognitive abilities, and general intelligence scores could then be used to support the view that intelligence is not unitary.

According to a second approach, descriptions of structure-function relationships can be validated and constrained by examining the extent to which a given structural network exhibits similar neural dynamics (i.e. functional connectivity) in similar cognitive tasks. Passingham et al. (2002), for example, showed that each cytoarchitectonic area has unique patterns of cortico-cortical connections that reliably indicate differences in neural activity during distinct cognitive tasks. This type of evidence suggests that specific patterns of structural connectivity partly determine the types of processes carried out by a given structure, and thereby can afford constraints on the types of cognitive functions that the structure can perform.

Furthermore, information about functional connectivity can provide an independent test of whether a cognitive function is supported by a target structure. Different functional modular arrangements may be observed during different cognitive tasks, suggesting that "the flow of cognition is a result of transient and multiscale neural dynamics, of sequences of dynamical events that unfold across time" (Sporns 2011, 206). Changes in patterns of functional modularity are highly sensitive to the perturbations caused by sensory input, task-specific demands, or lesion. Functional connectivity of a target network can show dynamic changes in modularity predicted by experimentally controlled manipulations in some task. The evidence provided by the extent to which those dynamic changes track specific experimental manipulations bears on two questions. First, in which classes of tasks is the target structure involved? Second, to what extent do the processes carried out by the structure make a difference to whether some cognitive capacity is displayed? These questions are obviously important to describe structure-function relationships underlying functional ontologies for cognition (Friston and Price 2011).

While particular measures in a task can be associated with patterns of functional modularity (i.e. with sequences of dynamical events in the brain), functional networks maintain stable, global topological characteristics (Bassett et al. 2006). The persistence of global topological properties along with the peculiar dynamical-functional changes associated to certain sensory input or particular measures in a cognitive task afford insights about how the variety of cognitive phenomena are determined by the architecture of the networks of the brain (Sporns 2011, Ch. 8).

Further insights about structure-function relationships, and, particularly, about how modules relate to cognitive function, are provided by the organizational principles characteristic of certain types of architectures. Two such principles are “functional segregation” and “functional integration.” Modular architectures display a higher degree of locally *segregated* processing (or functional segregation), according to which different modules selectively capture different statistical regularities in their inputs—while their activities are statistically independent from each other. If a cognitive architecture displays a high degree of segregation, it will tend to display specialized local processing carried out by different modules, and little “cross-talk” between modules, which reduces both wiring costs and the propagation of noise in the global processing of the system. In light of segregation, a module’s functional specialization appears not only to be the result of the intrinsic biophysical properties of the module, but also of its extrinsic interactions within the network. “Specialization is not an intrinsic property of any region, but depends on both forward and backward connections with other areas” (Friston and Price 2001, 275). Functional specialization, therefore, becomes meaningful only in the context of global features of networks’ connectivity. It cannot be identified by considering a target mechanism in isolation from the processes carried out by other mechanisms with which it interacts, and from the global features of the system in which it is embedded. Globally *integrated* processing (or functional integration) is another organization principle displayed in varying degrees by different types of architectures. If a cognitive system generates unified cognitive phenomena and coherent behavior, then relevant information processed by segregated modules must be integrated. Globally integrated processing can be achieved in a modular system courtesy of hub nodes, which can enable efficient communication between modules and integrate information processed locally, as well as of topological arrangements such as *small-worldness*, where high local clustering is combined with short paths that connect all nodes of the network facilitating direct cross-talk among several modules (Gallos, Makse and Sigman 2012).

Finally, information about modularity and modes of connectivity can be used to build neural models, which can offer testable hypotheses about structure-function relationships, while performing cognitive functions. Eliasmith et al. (2012), for example, built a 2.5-million-neuron model of the brain that could perform almost as well as humans at a number of tasks. One of the added-values of models such as this is that they offer a "set of hypotheses regarding the neural mechanisms and organization that may underlie basic cognitive functions" (2012, 1205). Part of the explanation for the success of this model is that its structural and functional connectivity embodies constraints motivated by information about real brains' modularity and connectivity. The model captured several aspects of neuroanatomy and neurophysiology, and showed how they could give rise to different cognitive functions and adaptive behavior.

As highlighted by this discussion of network-centered approaches to understanding cognitive function, it may well be misguided to ask which module is necessary (and/or sufficient) for a particular cognitive task. The relationship between modularity and cognitive function should be studied in a context-sensitive way. More attention should be paid to the dynamic patterns of (structural, functional, and effective) connectivity of modules engaged in particular cognitive tasks, rather than to the cognitive function of individual modules.

4. To What Extent the Human Cognitive Architecture is Modular. A growing number of studies of structural and functional connectivity in the human brain agree that our cognitive architecture comprises "a set of interconnected communities of structural and functionally related elements, arranged on multiple scales from cells to systems" (Sporns 2011, 114). Among such communities, modular structures are prominent. Modules identified in the architecture of neural systems present common features: they are likely to share pathways, if they are spatially close; they are typically connected through hub nodes and naturally tend to form small-world arrangements. Here is a brief survey of the evidence.

Hagmann and colleagues (2008) analyzed the structural connectivity in the human cerebral cortex at high spatial resolution. They considered cortical networks of 998 brain regions of interest (with average size of 1.5 cm^2) in six human subjects. Their modularity analyses revealed a set of regions of cortex that are highly central, and highly connected. This set of regions appears to form a structural core of the human brain. Six structurally distinct modules interconnected by highly central hubs were also identified. While the structural core was located predominantly within the posterior medial cortex, the six modules consisted of densely connected, spatially contiguous structures spanning frontal, temporoparietal, and medial cortical regions. The connector hubs that linked these modules were located along the anterior-posterior medial axis of the cortex, including the rostral and the caudal anterior cingulate, the paracentral lobule, and the precuneus. More fine-grained analyses revealed additional hierarchically nested modular arrangements: two segregated clusters corresponding to the dorsal and ventral pathway were found in the visual cortex.

Chen and colleagues (2008) carried out a different modularity analysis of the structural connectivity of the human cortex at high spatial resolution, considering 45 regions. They identified six modules, each of which comprised between four and ten cortical regions. These modules were located in anatomically distinct areas known to carry out processes supporting auditory/linguistic, strategic/executive, sensorimotor, visual, and mnemonic capacities. Chen and colleagues also identified several connector hubs, predominantly located in multimodal or association areas, which receive convergent inputs from multiple cortical regions.

Findings from studies on functional connectivity, adopting different methodological approaches, confirm the results concerning the multi-scale modular architecture of structural brain networks. Meunier et al. (2009), for example, studied the modular organization of functional networks under resting (i.e. no-task) conditions at several hierarchical levels. Their results show that functional networks in the human brain have a hierarchical modular organization. At the highest level of the hierarchy, they identified fewer and larger modules, including a somatosensorimotor module, a parietal module, and occipital modules. Hubs were identified in the association and cortical areas. At lower levels of the hierarchy, each of these larger modules was found to comprise several smaller sub-modules, and sub-sub-modules.

He et al. (2009) confirmed that functional networks of the human brain present a highly organized modular architecture. Consistent with previous findings, the modules they identified under resting conditions comprised somatosensory, motor, auditory, occipital, and parieto-frontal regions. Highly connected and highly central hubs were identified in the association and limbic/paralimbic area. He and colleagues also found that each of the modules they identified presented unique patterns of internal organization, which suggests that different modules at the same hierarchical level can present idiosyncratic network-properties.

What does this brief survey indicate? Different network-scientific methods consistently show that both structural and functional brain networks display modularity. Modular networks are likely to involve nested hierarchies, ranging from coarse modules to more fine-grained ones, where different modules can present characteristic topological properties. Modularity appears to be a highly conserved organizational feature of the architecture of complex brain networks.

5. Conclusion. I hope to have convinced you that network science provides a more rigorous and tractable concept of modularity than the Fodorian or post-Fodorian accounts, which portends to lead to significant insight into the topological organization of the human cognitive architecture, brain function, and possibly brain evolution. The theoretical framework of network science can be the basis of a more productive research program on the human cognitive architecture.

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