Classification of Emergence and its Relation to Self-Organization

Emergence is a difficult concept to describe clearly. It has been characterized in the literature in a number of ways, none of which are easy to understand or describe clearly how other concepts in complex systems science are related to emergence. We provide a simple, clear description, and classification of emergence in terms of self-organization. This provides a framework for understanding how concepts such as thermodynamic equilibrium, nonlinearity, and computability are related to emergence. © *2008 Wiley Periodicals, Inc. Complexity 00:00–00, 2008*

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1. INTRODUCTION

Two fundamental concepts in complex systems science are emergence and self-organization. Many systems in the natural world are self-organized and exhibit emergent behavior. Self-organization and emergence are intimately related, and the aim of this work is to describe how emergence may be characterized in terms of self-organization. As emergence is still relatively poorly understood, we aim to provide a simple, clear classification of emergence that is applicable across all scientific disciplines. Our description also provides a framework onto which other concepts related to emergence (including nonlinearity, computability, equilibrium) can be positioned.

Emergence is a useful but difficult concept that has generated an extensive, and not particularly congruent literature [e.g. [1–11]]. It is typically described as a property of a system that is not reducible to, nor readily predictable from the properties of individual system components. Such properties may therefore appear surprising or unexpected, at least from a reductionist perspective. Aristotle, two millennia ago captured the concept as "the whole is something over and above its parts, and not just the sum of them all . . ." Complex systems research adopts a holistic perspective that is complementary to the traditional reductionist paradigm. In particular, systems biology is moving in this direction and we may be witnessing a paradigm shift in understanding the Universe, as we realize that some laws of nature cannot be deduced by delving deeper into details [12].

The relatively abstract nature of emergence has resulted in numerous ways of defining and classifying it being proposed. Emergence still lacks a clear, standard and widely accepted definition [3, 9, 13, 14]. To some, the general concept describes an unproblematic relation among perfectly ordinary entities or proper-

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ties, whereas to others it evokes a sense of mystery [6]. In this article, we provide a very simple and intuitive classification of types of emergent phenomena. It is vital that complex systems science adopt simple definitions that apply universally and can be communicated easily across disciplines.

2. CLASSIFICATION OF EMERGENCE—ROLE OF SELF-ORGANIZATION

2.1. Intrinsic Emergence and the Role of an Observer

Emergence is a phenomenon that can exist across many scales of organization, ranging from the microscopic (atoms and molecules) to the macroscopic (organisms, species, and ecosystems). It is therefore possible to envision a continuum of emergence spanning these scales, ranging from the simplest phenomenon that can be considered emergent to the most complex and esoteric processes in existence. Emergent properties are intrinsic to a given system, and invariably reflect real physical phenomena. We argue that they exist regardless of whether or not we observe them, although some theorists suggest the contrary [3]. A possible exception is the special case where an observer comprises part of the system, and the emergent property exists as part of the observer's mind. The complication arises because the emergent phenomenon is internal to the observer, and intimately involved in the ultimate perception and/or utility of the emergent property. However, it could also be argued that the functioning of real, biochemical processes in the brain generates properties that are emergent, regardless of whether or not the observer is conscious of them.

Although all emergent properties are real phenomena, their measurement and exploitation always requires an observer, as we discuss below. This view of the role of the observer in emergence is broadly congruent with that of Crutchfield [15] who distinguishes two kinds of emergence: intrinsic and pattern formation, which exists only when observed.

2.2. Classification of Emergence Based on Self-Organization

Many authors associate emergence with nonequilibrium self-organization, although the term self-organization is not always used [1, 16–18]. However, it is also reasonable to apply the concept of emergence to collective properties of equilibrium systems, such as the pressure and temperature of a gas in a closed vessel. To reflect the two fundamentally different types of system in which emergence can be found (those at or near equilibrium and those far from equilibrium), we propose two broad classes of emergence: simple and complex. The simplest and most complex emergent properties represent the extremes of an emergence continuum.

We propose that the critical phenomenon defining the transition from simple to complex classes of emergence is the onset of self-organization, which is invariably associated with nonequilibrium pattern formation [19]. We define self-organization as a dissipative nonequilibrium order at macroscopic levels, due to collective, nonlinear interactions between multiple microscopic components. This order is influenced by interplays between intrinsic and extrinsic factors, and decays upon removal of the energy source (Halley and Winkler, submitted). A cartoon illustrating our concept of emergence, and the role of self-organization, is shown in Figure 1. Other related concepts such as computability, and equilibrium, can be accommodated by this conceptual framework.

2.2.1. Simple Emergence

Simple emergence occurs in systems at, or near thermodynamic equilibrium. Such systems are common in the physical world, and possess emergent properties that are collective or global, and derived from interactions of component parts. Simple emergence applies to gases in closed vessels, and many everyday objects, such as tables, rocks, and bottles of wine—the table exhibits stability, a rock possesses rigidity, and wine exhibits fluidity. Machines and self-assembled structures also exhibit simple emergence. Salthe [20] referred to this type of emergence as scalar or compositional.

Simple emergent properties are often able to be designed, are close to linear, are computable and relatively predictable from the properties of the components. However, as we will show later, simple emergent properties (like all emergent properties) can be modeled and predicted more efficiently at the system level than at the component level. For example, emergent properties of an ideal gas (temperature and pressure) can be predicted from the properties and interactions of the atomic or molecular components. However, prediction is more efficient at the system level as these properties can be described by a simple gas law equation. In summary, collective properties are simple emergent properties if they do not depend on nonequilibrium conditions and self-organization.

2.2.2. Complex Emergence

As the emergence continuum is traversed, starting from very simple emergent properties, the systems depart further from equilibrium. A point will be reached where the nonequilibrium nature and increasing nonlinearity of the system results in low-level self-organization. This may take the form of a phase transition or symmetry breaking bifurcation [21, 22]. We define this as the point where complex emergent properties come into being, and the point at which a system becomes "complex."

Complex emergence exists only in nonlinear systems driven far from equilibrium by the input of matter and/or energy. Countless natural sys-

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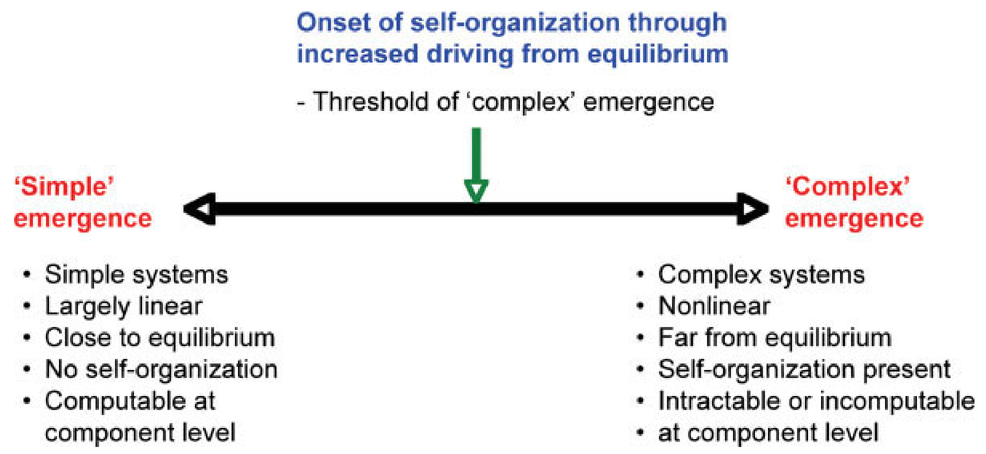
FIGURE 1



A simple diagram of the emergence continuum that ranges from the simplest emergent property to the most complex, esoteric property. The boundary between simple and complex emergence is defined by the onset of self-organization in the system. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com.]

tems are of this type, and many of them have been described as complex systems. Because self-organization requires reasonably constant energy input to maintain orderliness, complex emergent properties also require continual energy input. Consequently, as complex systems must involve self-organization, only these types of systems can generate complex emergence. Our concept of complex systems is different to that proposed recently by Crutchfield et al. [23] who provided counterexamples to the claim that complexity is synonymous with being out of equilibrium. However, these counterexamples were really self-assembled equilibrium systems rather than self-organized systems. We address the issue of self-organized versus self-assembled systems in a separate paper (Halley and Winkler, submitted).

Examples of complex emergent properties include regular hexagonal convection cells [19, 21, 24], selection of shortest pathways in ant mass-recruitment systems [25–27], and the dynamic instability of a population of microtubules attached to a microtubule organizing center in a cell [28]. Other, more complicated examples include weather patterns, ecosystems, and emotions. In examples such as consciousness and self-awareness, the assumption we make is that there is nothing vital or essentially mysterious in their emergence. In other words, as with other less esoteric systems, if we possessed adequate knowledge of physics, chemistry, biology, and other relevant sciences, we could in principle understand their emergence from the behavior and interaction of all relevant component parts.

As systems become more complex (the emergence continuum moves further toward the complex emergence extreme), self-organization appears at more than one level, possibly through repeated symmetry breaking bifurcations [21, 22]. Such systems have multiple, hierarchical levels of self-organization, and calculation of system level emergent properties from the component level rapidly becomes intractable and possibly incomputable—the shortest algorithm describing the system is the system itself [29–31].

In the next section, we discuss how coarse graining a system (i.e., viewing the system at an appropriate level of detail) enables one to build predictive models of emergent properties. The key to deeper understanding is finding the right level of detail and the relevant mechanisms of interaction [1].

3. DETECTING, QUANTIFYING, AND EXPLOITING EMERGENCE

3.1. Detection and Quantification

Although we argue that all emergent properties exist irrespective of any observer, the exploitation and use of emergent properties certainly requires an observer's participation. It is far from clear how to rigorously detect and quantify emergence. However, information theoretic approaches provide one method for detecting and possibly quantifying intrinsic emergence [32]. For example, Crutchfield and Shalizi [33] developed a description of emergence in terms of a parameter called relative predictive efficiency. The efficiency of prediction of a process is the ratio between its excess entropy and its statistical complexity, $e = E/C$. Excess entropy (E) is

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measure of the complexity of stochastic processes and it can be interpreted as the fraction of historical memory stored in the process that can inform us about the future (i.e. how well can the system be modeled). The statistical complexity (C) can be considered crudely as the size or complexity of the model of the system at a given level of description. If a system can be described at two levels of abstraction (a component or agent level, and a higher level derived from it) emergence exists if the higher level description of the system has a higher predictive efficiency than the lower level. That is, the derived process emerges from the underlying process. Predictive efficiency can be thought of as the ratio between how well the system can be modeled, and the complexity of the model or system description. Poorly predictive models, or those that predict well but are very complicated, will have a lower level of predictive efficiency. This information theoretic approach to detecting emergence is applicable to emergence at all scales and levels of complexity, from simple to complex, although it is far from clear how to calculate such values for some systems, particularly complex ones.

It is important here to again distinguish between intrinsic emergent properties that exist regardless of whether or not they are observed, and the act of detecting, measuring or exploiting emergence, which necessarily requires an observer. Crutchfield and Shalizi's computational paradigm allows intrinsic emergence to be quantified, a process that involves an observer in the building of models of emergent properties and in calculating the relative predictive efficiency (consciously or otherwise). These models are emergent properties themselves if present in the mind of an observer. For example, a chemist pondering the pressure and temperature relationship of an ideal gas forms a model of these emergent properties in his or her mind, but the actual physical properties of the gas that we label temperature and pressure exist regardless. In the absence of any knowledge of the ideal gas law, the chemist might estimate the relative predictive efficiency of the gas at both component and system levels. Such calculations would be onerous at the component level, as they require a fairly complex molecular dynamics framework and tracking of individual gas molecules. Although such a component level model may be capable of accurately predicting the thermodynamic properties of a gas (high E), the complexity of the model required to do so (very large C) causes the predictive efficiency (E/C) to be low. At a higher level there exists a simple relationship ($PV = nRT$) between certain key variables that can also accurately predict the thermodynamic properties of the system. In this case, E is high and C is relatively small so the predictive efficiency E/C is larger. This larger predictive efficiency at the higher level informs the observer that temperature and pressure are real emergent properties.

3.2. Exploiting Emergence

There is evidence from diverse sources that "coarse graining" of a complex system can make computationally intractable problems accessible while still capturing essential features of the emergent properties [29, 34]. Coarse graining is intimately involved with the process of modeling, as all models are abstractions that only include salient details. Models represent a simplified representation of reality. For example, visual coarse graining and perceptual modeling occurs in the brain, as much of the information we see is disregarded.

Coarse graining is also exploited in many conceptual or computational modeling situations. Crutchfield argued that emergence is ubiquitous in Nature as it has strong adaptive advantages for living systems that employ it [15, 29]. This idea is consistent with the idea of modeling at multiple levels of abstraction performed by an observer (essentially any organism with sensory and information processing capabilities that interacts with its environment). Crutchfield's suggestion that organisms utilize emergence to make sense of the world is congruent with Crutchfield and Shalizi's concept of emergence as a measure of relative predictive efficiency [33]. Organisms that exploit emergence to process sensory information use whatever information processing machinery they possess to develop simplified models (abstractions) of the world. Compared with organisms that respond to raw sensory information alone, or those that use less efficient models of their environment, such creatures should enjoy substantial competitive advantages.

4. HOW CAN WE USEFULLY MODEL EMERGENT PROPERTIES?

Organisms appear to regularly exploit emergent properties, capitalizing on several information processing capabilities including pattern recognition, coarse graining of information, and heuristics. Interestingly, researchers use analogous pattern recognition and evolutionary methods to investigate complex biological systems, methods that have shown considerable promise. Such complexity-based methods allow the system to be described and modeled from the top down at an appropriate level of detail or abstraction. Although the notion of top down modeling seems to contrast with the spirit of complexity science, which typically considers how emergent properties arise from the bottom up, such techniques exploit and rely upon the higher predictive efficiency of the emergent properties that they model. Importantly, just like models of emergence in an animal's brain, the internal architecture of top down complexity based models may bear little resemblance to the architecture of the

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systems they are modeling. However, in this context, it is not the internal architecture that matters, but rather the properties that emerge from this structure, i.e., the emergent properties being modeled.

For example, studies of quantitative structure–activity relationships derive simple, predictive models of the response of complex proteins, cells, organs, and organisms to molecules. This is achieved using a coarse-grained representation of the molecules and a highly flexible method of modeling nonlinear interactions (a neural network) to model emergent biological responses, such as binding affinity, differentiation fate, or animal response. The internal architecture of these models bears little resemblance to the internal architecture of, for example, a rat. Nonetheless, given sufficient training data, the model predictions come surprisingly close to predicting the response of a rat to particular chemicals.

Medicinal chemists have generated predictive models of properties of biological systems for a considerable time, but have only recently become aware of the emergent nature of these properties. This recognition allows complex systems-based methods such as neural networks and evolutionary methods to be used in a more disciplined, effective way. Appreciation of the complexity of biological systems enables us to consider such systems in insightful new ways. It also facilitates conscious exploitation of alternative, complexity-based techniques, such as agent based frameworks. In this way, complex systems science, with its particular reliance on modeling and simulation, should enable more rapid progress in the modeling and appreciation of complex systems.

5. CONCLUSIONS

We propose a simple framework on to which concepts, such as emergence, equilibrium, and computation, can be positioned. This framework is universal and simple enough to transcend scientific boundaries, an important consideration for complex systems science which regularly deals with phenomena that transcend such boundaries. The distinction we make between simple and complex concerns the onset of self-organization through increased driving from equilibrium. Simple systems are those that are at or near equilibrium and may exhibit simple emergent properties. Complex systems are nonequilibrium systems displaying self-organization, and the collective properties of these systems are complex emergent properties. Although complex and simple systems have been described by others (e.g. Collier and Hooker [35]) our use of the terms relates to how these describe emergence, and the transition between simple and complex emergence triggered by the onset of self-organization. Although all emergent properties are intrinsic and real, some depend upon an observer that uses its information processing abilities to construct the emergent phenomenon, which is an abstract model of pertinent features in its environment.

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