Epistemological Constraints when Evaluating Ontological Emergence with Computational Complex Adaptive Systems

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Abstract. Natural complex adaptive systems are of particular scientific interest in many domains, as they may produce something new, like structures, patterns, or properties, that arise from the rules of self-organization. These novelties are emergent if they cannot be understood as any property of the components, but as a new property of the system. One of the leading methods to better understand complex adaptive systems is the use of their computational representation. In this paper, we make the case that emergence in computational complex adaptive systems can only be epistemological, as the constraints of computer functions do not allow for the creation of something new, as required for ontological emergence. As such, computer representations of complex adaptive systems are limited in producing emergence, but nonetheless useful to better understand the relationship between emergence and complex adaptive systems.

Keywords: complexity, epistemological emergence, ontological emergence

1 Introduction

Complex adaptive systems are of interest to many scientists and researchers in many domains. Buckley was among the first using the term complex adaptive system [6]. He applied systems research methods to better understand behavior in social systems, as the often used linear, categorical descriptions of processes and interactions did not sufficiently explain the complex nature of the subject of discourse. Of particular interest to Buckley was the observation of emergence in such systems.

The recent developments of computational methods supporting scientific research have led to the rise of a variety of computational science disciplines, and in particular to the increased use of computational methods to evaluate complex adaptive systems, as discussed in significant detail in [14,1,23]. In particular, agent-based modeling is often used to implement, computationally, complex adaptive systems; thus, allowing one to observe emergent macro-level system behavior that is not formulated explicitly, but rather results from the many micro-level interactions of the agents. As a result, agent-based models are often seen as the tool of choice for computational social science. As Bankes captures it in his introduction to the proceedings of the National Academy of Sciences on this topic:

> In social science, topics such as the emergence of cultural norms or institutions from the interaction of individual activity are indeed very important and not well addressed by competing modeling formalisms. So, the demonstrated ability of Agent Based Modeling to discover examples of such emergent dynamics from knowledge about the behavior of members of a society is potentially quite useful.[2]

However, many researchers in these application domains do not have a formal computer science education and are not fully aware of many of the underlying principles from the philosophy of science. As a result, they do not only use simulation as a reference to study complex adaptive systems, rather they interpret observations of computationally instantiated complex adaptive systems to fully and equally represent their natural counterparts. In their perception, the simulation "replaces" the real system. Knowledge gained from the computational experiments is mapped directly to insights and applications of the real systems. Studying the computational representation becomes equivalent to studying the underlying system in the real world rather than as the generation of sufficiency theorem [1] related to the real world system.

Based on the research conducted in support of [32], this paper gives examples of natural and computational complex adaptive systems and observable emergence, introduces a critical review of the categories of emergence from the philosophy of science perspective, and concludes that there are *significant epistemological constraints* when computational methods are used for evaluating emergence.

2 Complex Adaptive Systems

The literature agrees that simple systems behave in a straightforward, mechanical, usually linear, and, most of all, easy to predict and manner: they behave as expected. A complicated system is composed of many often nonlinearly interacting parts that can be studied using reductionist and probabilistic models and statistical methods. It is still predictable, but it usually requires experts who are highly educated and experienced and have a tailored tool set available.

For the definition of complex systems, in [29] the authors propose the following definition after a review of systems engineering-relevant literature from complexity science:

> Complex systems are systems that do not have a centralizing authority and are not designed from a known specification, but instead involve disparate stakeholders creating systems that are functional for other purposes and are only brought together in the complex system because the individual "agents" of the system see such cooperation as being beneficial for them.

Complex systems are not easily predictable, and the principles of reductionism do not bear fruit when laboring to understand them, as system behavior emerges on all levels of the system. Although they are not fully knowable, within reason there may be some prediction possible.

Complex *adaptive* systems add the element of self-organized adjustment of some or all of its components and of the system itself. For its definition, the focus very often is the agent metaphor for the system components, as compiled in [9] and revisited in [5]. One of the insights drawn from these overview articles is that the diversity of definitions suggests one should focus on properties of such systems, as elaborated in detail within Holland's seminal contributions to the unified theory of complex adaptive systems [15], which contained a particular focus on aggregation – complexity emerges from the interaction of smaller components, which themselves may be the products of systems – and nonlinearity – agents interact in dynamical and non-linear ways.

The reason we use computational science in general, and in the context of this paper computational complex adaptive systems, is that they help us to understand natural systems. There are legions of examples of natural complex adaptive systems that have been evaluated using computational support. Without claiming completeness, some examples include, *inter alia*:

- society [6],
- the ecosystem and biosphere [19],
- supply networks [8],
- human language [3,33],
- product development environments [22],
- health care[28],
- climate change [17], and
- urban hazard mitigation [12].

All these systems are not fully knowable and often quite hard too predict. Moreover, it is often difficult to even collect useful data about these systems. Unfortunately, all of these systems (and many others) are very important, so we cannot ignore them. We must try to get a better understanding of their dynamics and causal structures, and we want to provide decision makers a better foundation with which to make informed decisions. Currently, the most powerful tool to do this is the use of computational representations of these systems and to simulate their dynamics [7].

As already discussed in the introduction, computational science disciplines, such as computational physics, computational biology, computational chemistry, computational social science, and many more, explore the use of computer models and simulation in direct support of their research. The discipline of complex systems research benefit significantly from these developments, as computers amplify our abilities to model, simulate, and evaluate the *computational representations* of the systems of interest [31].

The principle steps of such a computational study of complex adaptive systems was captured in detail by [14] and professionalized by many authors since then. The Santa Fe Institute and other similar organizations dedicate their work to the multidisciplinary study of the fundamental principles of complex adaptive systems, including physical, computational, biological, and social systems. These multidisciplinary scholars and students are experts in their fields and come together to use computational complex adaptive systems in support of their research, and the resulting studies are impressive, such as studies conducted to prevent collapse of tropical forests [13], or new insights into how evolution works [26], just to name a few.

These studies are generally understood to prove the enormous value of computational complex adaptive systems, in particular when it comes to emergent behavior, which is a characteristic property of complex systems: system behavior that does not depend on its individual parts, but on the multiple relations and interactions on all system levels. The next section will provide a short overview of the different forms of emergence from a philosophical, as well as, from a systems engineering perspective.

3 Categories of Emergence

We understand emergence as an unpredictable macro-level behavior that dynamically arises from the spatio-temporal and multilevel interactions between the parts down to the micro-level of the system. These interactions may be a constraint on various levels within the system. Natural systems are open systems exposing emergent behavior to the observer. This novel, irreducible, and unpredictable macro-behavior adds further complexity to the system when it causes itself changes at the micro-level, which then can result in new behavior emerging on the macro-level. Overall, the system may adapt to a new environment by developing new multi-level interactions and feedback loops [18].

Philosophy has dealt with the challenge of emergence for more than a century, starting with George Henry Lewes foundational work [20], long before any computational system existed to support them. Philosophers distinguish between epistemological and ontological emergence. Of the two, ontological emergence became a far more active research thread than did epistemological emergence [30].

3.1 Epistemological and Ontological Emergence

Epistemology is the theory of gaining knowledge, its methods, validity, and its scope. Knowledge is understood as the scientifically justified belief in something. In the epistemological view, emergent properties and laws are systemic features of complex systems. This system is governed by true, law-like generalizations within a special science that is irreducible to fundamental physical theory for conceptual reasons. What is hidden to the researchers are this laws, resulting in the unpredictability of the emergence. As such, this view characterizes the concept of emergence in terms of limits of the human knowledge about the laws governing complex systems. The exposure of novel properties and behaviors is a characteristic of the system, but the unpredictability is a matter of knowledge.

The ontological view is quite different. Essentially, the ontological view of emergent properties are premised upon the idea that they are independent of the human knowledge. Instead they are novel, fundamental types of properties in and of themselves. Something new emerges that was not there before, and that cannot be explained by the components and their interactions and relations alone. The occurrence of emergent properties is not in any sense constituted by the occurrence of more fundamental properties and relations of the object's parts. Something really new is emerging from the system that has not been there before.

A detailed discussion on the philosophical views of emergent properties and their interpretation under epistemological and ontological viewpoints is presented in [25]. For the purposes of this paper, we will use a rather simple view, specifically: that epistemological emergence can be reduced by gaining more knowledge about the system, while ontological emergence cannot, because it is an inherit characteristic of the system.

3.2 Maier's Emergence Categories

This section introduces a systems engineering perspective. Mark Maier is known for his contributions to the discussion about systems of systems. In [21], he defined four categories of emergence, depending upon how well the emergence observed in the natural system can be reproduced and explained through a computational system.

- Simple emergence: The emergent property or behavior is predictable by simplified models of the system's components.
- Weak emergence: The emergent property is readily and consistently reproduced in simulation of the system but not in reduced complexity non-simulation models of the system, that is, simulation is necessary to reproduce it.
- Strong emergence: The emergent property is consistent with the known properties but, even in simulation, is inconsistently reproduced without any justification of its manifestation.
- Spooky emergence: The emergent property is inconsistent with the known properties of the system and is impossible to reproduce in a simulation of a model of equal complexity as the real system.

As implied by the terms used above, systems engineers normally do not like emergent phenomena as it results in behavior that is unforeseen and unpredictable. Consequently, Maier's viewpoint is written from the position that emergence is be avoided or, at least, controlled. In contrast, as engineers of complex adaptive systems, we seek to enable and leverage emergence [24].

In [32] we observe that simple emergence corresponds with congruent computable systems, and weak emergence with complicated computable system, where both system categories are predictable, at least in hindsight. Strong emergence falls into the category of unpredictable complex systems, while Maier's "spooky" emergence lies even outside of our system thinking boundaries, referencing real ontological emergence phenomena. Simple and weak emergence are epistemological, strong and spooky are ontological.

4 Epistemological Constraints of Computational Systems

In the light of this discussion, it seems to be fair to look at how we can gain insight and knowledge from the application of computational systems, such as modeling and simulation, and, in particular, agent-based approaches.

The famous Artificial Intelligence researcher Huber L. Dreyfus is well known for his two books on the limits and constraints of computers: "What Computers Can't Do: The Limits of Artificial Intelligence" [10] and "What Computers Still Can't Do: A Critique of Artificial Reason" [11]. Dreyfus points to known limits that are founded in the nature of computers as captured in the works of Turing, Church, Gödel, and other pioneers of computer science that were often overlooked by his colleagues. These constraints are, of course, still valid for computational platforms in general despite the advances in hardware and software that have been made over the years. Furthermore, these constraints extend to systems represented within a computational platform, including representations of complex adaptive systems.

The essential constraint remains: computers transform input parameters into output parameters using computable functions to do so. As a result, computers cannot create something new out of nothing, as everything that is produced by a computer must be in the input data or the transforming algorithm. As Boden points out in her paper, we can model combinational, exploratory, and transformational forms of creativity [4]. However, all these forms creativity are discovering through rearrangement and transformation, not creating something new that was not there before.

As such, the question arises if computational systems can indeed be complex in the sense of producing emergence? They can be complicated, even extremely complicated, but in principle, it boils down to the transformation of input parameters into output parameters using computational (computable) functions. That is true for all computations, including agent-based models. These are insights covered by peer reviewed, often foundational publications and as such important for computational complex adaptive systems as well.

5 Discussion

These observations raise the question if computational complex adaptive systems cannot produce ontological emergence, are they still useful? As observed by Rouse in [27], the borders between the system categories - simple, complicated, and complex - are often fuzzy and depend on the education and experience of the team. What looks complex and unpredictable to a novice may turn out to be complicated at best for an expert team. This view is true without question for epistemological emergence: if we increase the human knowledge, we reduce the epistemological emergence, so the application of computational complex adaptive systems is very useful!

In the best case, we can close all knowledge gaps, resulting in a significant reduction of complexity, comparable to moving from an epicycle model of the solar system to a Copernican and Kepler model. If all we observe in natural complex adaptive systems can be explained using computational representations, that would be a tremendous accomplishment. Humphreys shows in [16] how we use computational means to extend our abilities to gain knowledge and produce new scientific insights. We just have to be careful to remember that this insight does not come by exactly reproducing natural complex adaptive systems, but they help to reduce epistemological emergence by increasing our knowledge.

Finally, as discussed in [32], complexity is often a multivariable and multidimensional phenomenon within the space-time continuum. Multivariable implies an often-large number of variables with sometimes incomplete knowledge about their interdependencies. Multidimensional implies possibly multiple vantage points that are dependent on the frame of reference when observing the phenomenon. These vantage points are not mutually exclusive, but rather focus different facets. Furthermore, the phenomenon may manifest over time or over space in the space-time continuum, requiring methods allowing for spatio-temporal analysis instead of exclusively looking at local snapshots.

Where does this leave us and our ability to study and understand complex systems? Given the aforementioned characteristics, when analyzing complex adaptive systems using computationally-based modeling and simulation methods are still the best options we have today. However, given the fundamental limits to computational systems, and indeed any formal system, it is likely that there are classes of complex systems that cannot be usefully represented in a computational (Turing machine) form.

While that may be true, in most cases complex systems and their emergent phenomena come from understood components and interact in knowable ways. This being the case, for most purposes complex systems can be meaningfully studied by computational methods. However we must keep in mind that these are models, not the real system. What we create are "sufficiency theorems" [1]. We are deducing an outcome from an input and set of transformation rules, these rules may or may not be how nature actually works. Essentially, we can use computational methods to create deductions that can then be collected for inductive conclusions to solve abductive problems. But, just like all analytic methods, these are models of the real system in question. At the other extreme, one may argue if true ontological emergence in which something new emerges out of nothing is not magic, but rather some hidden law(s) we do not yet understand. As Arthur C. Clarke formulated this idea in his third law: *"Any sufficiently advanced technology is indistinguishable from magic."* Maybe computers can help us to advance the technology, but they will not produce ontological emergence.

Here we made the argument that, while there are fundamental limits to computation that puts a hard constraint on the complex systems that may be fruitfully represented within a computational system, many complex systems may be represented and studied with computational methods. However, we must not fall victim to the methods and remember that they are simply models that should be used to improve our understanding of complex systems. As all claims in this paper are based on accepted and peer reviewed - and often foundational - literature, additional experimental proofs are not necessary.

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