The Fundamentals of Complex Adaptive Systems

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2 authors:

Ted Carmichael
University of North Carolina at Charlotte

Mirsad Hadzikadic
University of North Carolina at Charlotte

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Ted Carmichael and Mirsad Hadžikadić

Abstract Complex Adaptive Systems (CAS) is a framework for studying, explaining, and understanding systems of agents that collectively combine to form emergent, global level properties. These agents can be nearly anything, from ants or bees, to brain cells, to water particles in a weather pattern, to groups of cars or people in a city or town. These agents produce emergent patterns via correlated feedbacks throughout the system, feedback that create and fortify a *basin of attraction*: a persistent pattern of behavior that itself is outside of equilibrium.

There is also an ever-growing understanding that similar features in complex systems across a diversity of domains may indicate similar fundamental principles at work, and as such there is often utility in using the key features of one system to gain insight into the workings of seemingly distinct fields. Here we also include a brief review of multiple models that attempt to do exactly this, including some of our previous work. Though there is not complete agreement on all aspects and definitions in this field, this introduction also summarizes our understanding of what defines a CAS, including the concepts of complexity, agents, adaptation, feedbacks, emergence, and self-organization; and places this definition and its key features in a historical context. Finally we briefly discuss two of the common biases often found that the tools of CAS can help counteract: the hierarchical bias, assuming a strong top-down organization; and the complexity bias, the tendency to assign complicated features to agents that turn out to be quite simple.

Ted Carmichael
University of North Carolina at Charlotte, Department of Software and Information Systems, 9201 University City Blvd, Charlotte, NC 28223; *and*
TutorGen, Inc., 1037 S Ft Thomas Ave, Fort Thomas, KY 41075. e-mail: tedsaid@gmail.com

Mirsad Hadžikadić
University of North Carolina at Charlotte, Department of Software and Information Systems, 9201 University City Blvd, Charlotte, NC 28223 e-mail: mirsad@uncc.edu

1 Overview

Most interesting collective phenomena in natural and social systems can be described as having stable and persistent states, often outside of equilibrium. The term *basin of attraction* has been used to describe such systems, capturing the idea of correlated feedbacks among the agents of a system that create these identifiable and distinct patterns. These systems are so defined because they are resilient in the face of external forces, but can nevertheless also exhibit tipping points: situations where the stable system finally crosses some threshold, and begins a rapid transition to a new state. These thresholds can be characterized as a qualitative change in system characteristics: a change in sign or abrupt change in magnitude (either enduring or a spike) in the first or second derivative of a system variable.

Threshold effects are found all around us. In economics, this could be movement from a bull market to a bear market; in sociology, it could be the spread of political dissent, culminating in rebellion; in biology, the immune system response to infection or disease as the body moves from sickness to health. Companies, societies, markets, or even humans represent such persistent states that can change rapidly at any time. Both endogenous and exogenous feedbacks can cause sudden, non-linear shifts in system behavior, ensuring that the future of these systems are often unknown and challenging. How do events unfold? When do they take hold? Why do some initial events cause an avalanche of change while others do not? What characterizes system stability and resilience? What are the thresholds that differentiate a sea change from negligible variations?

Complex Adaptive Systems (CAS) has proven to be a powerful framework for exploring thresholds and resilience, and other related phenomena. As the name implies, a CAS is a system of agents that interact among themselves and/or their environment, such that even relatively simple agents with simple rules of behavior can produce complex, emergent behavior. The key to CAS is that the system-level properties generally cannot be understood, or often even defined, at the level of the individual agent description. Therefore, these systems must be studied holistically, as the sum of the agents and their interactions.

1.1 Defining CAS

We characterize a general CAS model as having a significant number of self-similar agents that:

- Utilize one or more levels of feedback;
- Exhibit emergent properties and self-organization;
- Produce non-linear dynamic behavior.

The CAS framework can be used to describe systems that encompass phenomena across many diverse environments and a wide range of disciplines. These systems are present at all scales of inquiry: from the movement of markets and economies to individual knowledge acquisition; from large-scale social interaction to small-scale cellular behavior. Advances in modeling and computing technology have not only led to a deeper understanding of complex systems in many areas but have also raised the possibility that similar fundamental principles may be at work across a wide variety of domains. This idea has led to several multidisciplinary conferences forming to allow the sharing of ideas across domains, including the annual Swarmfest meeting, and The Association for the Advancement of Artificial Intelligence (AAAI) CAS Fall Symposia series, from where the papers in this volume are drawn.

The overriding goal for these conferences is to create synergy and build connections amongst domain-specific experts. Often, complex systems from two distinct fields may seem different on the surface, but have quite similar underlying dynamics. We hypothesize that by modeling complex systems from many different areas, we can start to find the principles that show common causes and common effects across domains. In this way, the known causes and mechanisms in one domain are used to gain insight into the controlling properties of similar effects in other domains. As Neil Johnson writes:

> In particular, the connections between such systems have not been properly explored — particularly between systems taken from different disciplines such as biology and sociology. Indeed it is fascinating to see if any insight gained from having partially understood one system, say from biology, can help us in a completely different discipline, say economics [14, p. 16].

Put another way, Epstein writes:

> Generality, while a commendable impulse, is not of paramount concern to agent-based modelers at this point [10, p. 1602].

And so we believe that by bringing these researchers together, who study different fields but use the same tools and techniques of CAS and Agent-based Modeling (ABM), we can overcome the natural tendency of scholars to work only within their own silos, and encourage fruitful and cross-disciplinary collaborations that successfully draw generalities across domains.

1.2 Common Models Across Diverse Domains

As an illustrative example consider the model found in Midgley, Marks, and Kunchamwar [17], one of numerous examples of using ABM to implement a CAS framework to further understanding of the dynamics found within a particular system. In this work, the authors construct a model that aims to reproduce a typical market structure by utilizing the properties of a supermarket setting. Their model incorporates three types of agents: consumers, retailers, and manufacturers. They have chosen ABM over more traditional methods of model construction that use game theory or analytical equations of system dynamics, due to the power and flexibility of CAS:

> [O]ne can more easily incorporate the existing knowledge about the nature of human-decision-making processes into AB models than into analytical equations. [...] AB models allow a flexibility of representation that is not present in more traditional approaches.

But Midgley et al.'s model was not designed with general applicability in mind. It may be that some of the agent attributes could reasonably be applied to other domains. For example, *chance of observing a store promotion* might be a stand-in for *vision*; *number of best promotions remembered* may be generalized as *memory*; and perhaps *satisfaction threshold* for an agent could represent any state-change threshold for any agent. But it has not been explicitly explored how these translations may be realized, or to what advantage, in a different system. Other attributes, such as *range of advertising levels* or *quarterly increment/decrement to mark-up*, may not have any obvious analogues. Further, the rules governing calculations that utilize these attributes also suffer a lack of generalizability or an explicit method for applying these rules to a new domain.

In [22] the authors present a more general economic model, utilizing only two agents: buyers and sellers. While this work is intended to demonstrate the utility of ABM in this context, it is quite clear that these agents may be easily applicable to many types of markets. However, as with [17], there is no discussion or representation of this models applicability to systems that are outside of economics.

Examples from other domains also follow this common pattern. Vries and Biesmeijer have created an ABM of honeybee foraging [7], which they expanded upon in [8]. While this work is intended to utilize enough flexibility to represent a broad range of variable values found in real-world honeybee colonies, it does not purport to show general adaptability to other fields. Similarly, ABM has been used to develop sophisticated tools for the study of traffic flow under a wide spectrum of environmental factors, such as weather, infrastructure, and changing demographics. [11] describes one such system; but again, limited to only a single domain.

There have also been examples of ideas or concepts of CAS taken from one domain and applied to one or more others. Schellings classic model on segregation [20] is an example of a fundamental property, one that may be readily applied to many systems, informing models found in sociology, biology, or economics. Flocking behavior has been studied in birds, fish, and crowds of people, and simple analogies between these diverse systems can be drawn [21]. Also, the collective intelligence of ants for determining the shortest path has proven to be useful in the engineering of decentralized flow control, such as in computer networks. In general, these examples illustrate how one system can inform study of another: either by drawing comparisons from one model to another, or by using certain properties found in one model to inform the construction of a second model.

In furthering this idea our prior work has explored using a single CAS tool to replicate key properties of complex systems as found in multiple domains: a single model with multiple applications. This model was developed and used to simulate the growth of cancer and the immune system response; and then used to show similarities in the growth of a social contagion effect in a polity, and the government response to this growing unrest [5]. We noticed that both of these systems exhibited properties of predators and prey, and so we adapted the model to also simulate a generalized predator-prey system, replicating key phenomena found in the ecosystem literature such as Gauses Law, the stepped pattern of biomass accrual, the Competitive Exclusion Principle [3]. With this model we also discovered some surprising limits on the Red Queen Effect: the idea that competitive populations will perform an arms race to continually outstrip the other group [4].

This endeavor is similar in scope to the work of Nicolis and Prigongine [18]. As described by [21], they were attempting to develop a rigorous theory of self-organizing behavior, and they were successful in showing that mathematical equations used to describe chemical reactions could also apply to the cyclical dynamics of a predator-prey model. However, their approach did not use a stochastic ABM method; rather, it relied on idealized equations which — though useful — are difficult for representing a diversity of agents and agent-attributes.

Our generalizability approach in [5] is most similar to that used previously by Axelrod et al. [1]. In this work, a model of political state-level alliances during World War II was successfully applied to an economics system of company-level alliances. In the political model there are five attributes — such as shared religion or border disputes — that were used as either attractors or repulsors in a pair-wise calculation of affinity across 17 countries. These affinity calculations — 65,536 in total — would then determine the alliances of each country (subsequently labeled either Allies or Axis). No matter what the initial conditions, only one of two final configurations appeared each time, one of which was correct for all 17 countries save one.

This same model was then applied to the case of eight computer companies choosing which coalition to support between two competing versions of the UNIX operating system. This application used the same theory as that for the political model, simply adapting the attributes and relative sizes of each actor, and the model successfully predicted the real-world strategic alliances that the computer companies formed.

The primary difficulty with [1] is that there are so few agents in each system: only seventeen for the political case and eight for the business case. This limitation opens up the model to criticism, in terms of agent attributes that could, perhaps, be easily calibrated to predict a known result. Also, this system is not intended to simulate the machinations of the countries or the companies over time; rather, it merely searches for a single end state. Further, it is unclear how a set of these weights in one domain — political alliances — would help inform similar weights in another domain, such as corporate alliances.

Nevertheless, the strength of their work is that the models interactions are translatable from one domain to another, particularly regarding the underlying theory used in both cases. Such cross-disciplinary applicability is the overarching goal of the symposia and conferences that we have organized over the years, including through the AAAI, and the annual Swarmfest meetings that are represented in this volume. Ultimately it would be more interesting and, perhaps, more useful if such trans-disciplinary models displayed similar characteristics and outputs not just at one moment in time, but over complete model runs, so that it is not just end-states that show similarities, but also the dynamics that get you there. This is a much more difficult goal to reach, of course, but perhaps also more significant and therefore more worthwhile to pursue.

2 Properties of Complex Adaptive Systems

This section looks at some of the earliest work used to formulate the paradigm of CAS and touches on the fundamental properties and key characteristics that define this paradigm.

2.1 Historical Context

In the 1960s researchers were trying to understand better the dynamics of slime mold: in particular, there was a persistent mystery in how it could transition between its active and its dormant states [15]. Biologists had long known about slime molds strange behavior, acting as a single organism under some conditions, and devolving into individual cells under other conditions. They knew that a chemical acrasin was somehow involved, and speculated that there were pacemaker cells which would produce an acrasin and thereby attracted the other cells to it. Years of study were conducted in the vain search for these pacemakers.

In the late 1960s a physicist and a mathematician (Evelyn Keller and Lee Segal) came across a paper by Alan Turing that described what he termed *morphogenesis*: the idea that organisms can form great complexity from simple roots. Published in 1952, it was one of the last papers he produced, and in it, he described a mathematical model whereby simple organisms, following just a few simple rules, could produce strikingly complex patterns [23].

Keller and Segal took the ideas in Turings paper and developed the mathematics to describe a system of slime mold, demonstrating that it is not necessary to account for pacemaker cells in such a model. Rather, all that was required to reproduce the properties of the system were two rules: that each cell simultaneously produces, and is attracted to, an acrasin. These two simple rules were sufficient to account for the molds strange behavior, and demonstrated how this collective interaction could allow numerous individual cells to form a multi-cellular organism, one that could move about its environment and act as a single living being. A third rule, that the cells produce the acrasin under certain environmental conditions, was sufficient to explain the transition from a dormant state to an active one.

In this way, the description of a slime-mold model exhibits all the classic properties of a CAS: the agents (cells) of the slime-mold affect each other via the feedback mechanisms inherent in the two rules; they also react to the influence of the changing environment, which is sufficient to activate these two rules; once activated, the cells self-organize as an emergent property of this system; and finally, the threshold change in behavior of the slime-mold organism represents the non-linear dynamics necessary to adapt to new environmental conditions.

This re-framing of the slime-mold behavior is indicative of a systems-level approach to studying complex phenomena. This framework was recognized as a new way to approach system-level phenomena in many other fields, such as the classic invisible hand that governs the marketplace, as found in the work of economist Adam Smith; or the contagion effect, found in social theory as well as epidemiology studies; or the study of traffic patterns and the movement of crowds. The subsequent founding of the Santa Fe Institute in 1984 by Murray Gell-Mann, a physicist; John Holland, a biologist; and others, is seen by many as the beginning of CAS as an explicit field of study [24]. They recognized the multidisciplinary nature of these phenomena, and thus brought together scholars from many different areas to begin the process of applying CAS to a wide variety of research questions.

2.2 Complexity

There is not yet a single, agreed-upon theory that describes complexity or a complex system equally for every situation. As with many things, it is often a matter of degree or perspective, rather than clear distinction, as to what is complex and what is not. However, we can distinguish some key characteristics of a complex system for our purposes here.

The most general distinction we use refers to Warren Weavers division of complexity into two types: disorganized complexity and organized complexity [25]. Disorganized complexity refers to a system of many even millions of parts that interact at random, producing aggregate effects that can easily be described using probability and statistical methods. The example he gives is that of a very large billiard table with millions of balls rolling in different directions, colliding with each other and with the walls. Even though the path of a single ball may be erratic, or even unknown, the system itself has measurable average properties. Clearly, there is feedback in such a system: one billiard ball strikes another, and then that ball can bounce around and strike back. But this does not suffice. There is something missing in this system, without which it cannot produce self-organizing behavior.

What we are concerned with here, then, is organized complexity. Organized complexity refers to a system with a sizable number of agents which have correlated interactions. And since these interactions are correlated, they can produce emergent, global-level properties for the system as a whole.

> An average quantity alone is not an emergent feature. Yet statistical quantities, which define properties of an aggregation, can be regarded as simple emergent properties if they depend on a relation of the particles to each other, i.e., if they do not make sense for a single particle [12, p. 8].

Correlation among the interactions in such a system implies two things: 1) that the agents of the system exhibit feedback mechanisms; and 2) that these feedback mechanisms are, by definition, endogenous to the system itself. In this way, the agents affect each other in a correlated manner.

2.3 Agents

The term *agent* tends to be an overloaded one. Some researchers, therefore, may use an alternative, such as *particle*, to describe the individual objects of a complex system [16]. While logically sound in the way Kennedy et al. present the term, it doesnt seem to capture the autonomy, or intent, of many agents; particularly those found in social systems. Thus we use the more conventional term *agent* in our description. But we distinguish between the somewhat overlapping conceptions of agents found in CAS relative to those generally described in a Multi-agent System (MAS) [27]. CAS agents possess simple rules and attributes; are largely autonomous with only local knowledge; and, as constituent parts of a larger system, are easily replaced by similar agents without disrupting the emergent features of that system. In contrast, MAS agents tend to be more autonomous and intelligent, more complicated, and fewer in number. MAS agents also tend to fall into a strict hierarchy, whereas CAS agents are easily replaced or switched around. Contrast all the individual parts of a car with, say, a colony of bees. Each bee is easily replaced with another, whereas each part of a car has a strict function and placement.

Finally, *emergence* in most MAS models is usually mentioned only as something to be avoided if possible, rather than as an inherent, key property of the system. In CAS, emergence is considered a feature, not a bug.

Put another way, building a car is *complicated*. The agents are specific, diverse, and fall into a strict hierarchy. Driving a car is *complex*: dynamic and ever-changing, with multiple levels of feedback and a loose hierarchy of replaceable agents.

In our work we also consider CAS agents to be self-similar, to use a term common in the literature; i.e., the agents are largely homogeneous. It is worth noting that many published works refer to these not as homogeneous agents, but as *heterogeneous* agents, such as in Epstein [9, pp. 5-6]. We believe the discrepancy is simply a difference in emphasis. As Epstein uses the term heterogeneous, he is referring to a differentiation regarding the agent attribute-values, not the agent specifications themselves. That is, his heterogeneous agents have a range of values for their attributes, not a range of attributes. While other authors may call such agents homogeneous due to their similarity, it is useful to understand that these authors are talking about the same thing. To avoid ambiguity, we use the term *self-similar*, while also recognizing that the agents of a complex system can be different — but not too different — in terms of the rules and attributes that relate to the emergent property in question.

These differences across agents do matter, in their variety, because a particular emergent property depends upon a degree of self-similarity within the system. Consider a simple model of traffic flow as an example, with the agents as cars moving along a highway. Each agent has two rules: slow down if the car ahead is too close, and speed up if it is too far away. Under some conditions, a wave-like pattern can emerge across the ebb and flow of the cars, as one car slows, causing the next in line to slow, also. In simulations, this can occur whether the rules for slowing down and speeding up are exactly the same across all cars, or if there is some slight variation for the activation of each rule (i.e., if they are heterogeneous in attribute-values). But if some agents have rules that allow them to stop completely, or crash, or drive off the road — if they are *too* heterogeneous in their attributes — then this chaotic behavior would disrupt the emergent patterns of traffic. The system breaks down if the agents diverge too far in their rules and attributes.

Similarly, if the flocking example found in [26] were adjusted so that some agents have wildly different attributes, then *flocking* may not be a reachable state for the system. If there is no correlated feedback among the agents, then an emergent property is impossible.

The degree to which agent must be similar depends upon the characteristics of the model being studied; specifically, it depends on the emergent behavior that is of interest. For example, the agents in the traffic pattern may be made much more complex, with many more attributes, than two simple rules of when to speed up and when to slow down. Each agents perceptions, disposition, reactive ability, and etc., could be included in the specifications. And many other agent attributes besides. But note that these attributes, and many more, only matter *to the degree that they relate to the two conditions that produce the emergent behavior*. No matter how complex the calculations that take into account perceptions, disposition, reaction times, and so forth, they ultimately determine only an expression of the two rules: when to speed up and when to slow down. The agents may be described as quite heterogeneous across all these attribute values, but they must be self-similar enough to produce an emergent traffic pattern that can be analyzed and compared to real-world data.

2.4 Agent-level vs. System-level Adaptation

Agent-level adaptation implies some sort of fitness function or selection criteria for agents, based on their attribute-values. This further implies some difference or capacity for change among the agents attribute-values; and more than just superficial differences, but rather functional and consequential heterogeneity. Agent-level adaptation becomes hard to distinguish under certain conditions, however. To illustrate the potential difficulty, imagine an economics model where agents sell a certain good at a certain price. The agents each have a rule that states: sell product X for no less than Y units of money. On one level, these two agents are exactly the same, in that their internal rules are the same, even if one agents current state for the value of Y is 10 dollars while another agent has his Y set to 11 dollars. The difference between the first and second agent is not the difference in rules or attributes, but in one attribute *value*. In this sense, these agents are still homogeneous, because they have the same type of rules, and they apply these rules in the same way. In another

— but very real — sense, these agents are heterogeneous, adapting individually as each adjusts his price point for maximum efficiency.

This sort of change in the agents state can be termed *learning*, or *adaptation*, or even *evolution*: all words that mean essentially the same thing, but fall along an implied continuum of persistence and complexity. *Learning* is the easiest, and fastest to change, while *evolution* tends to be on longer time-scales, and is more permanent. Thus, our hypothesized economic agents may *learn* a new price-point for selling, and this price point may be updated daily. Or, some of these agents may *adapt*, changing their internal algorithms used to update this price point. Or — going even further — the agents may *evolve*, perhaps changing their modes of behavior so that they not only sell product X, but can buy it as well.

In contrast to agent-level adaptation, system-level adaptation is when a group of agents changes in a correlated way, reacting holistically to the environment. In general, we label system-level adaptation as correlated changes in the attribute-values among a large group of connected agents. Agent-level adaptation, then, is a more substantial change in an individual agent, such as changes in the set of agent rules or attributes. And thus system-level adaptation could be represented by a flock of birds that sees a predator. The flock may shift and split apart as the individual birds try to avoid the predator, and these birds influence their neighbors to change direction as well. Even though no individual bird has changed how it reacts to seeing a predator — i.e., they haven't adapted or evolved — the flock itself can adapt to avoid the danger. It is this system-level adaptation that gives CAS its power: collectives reacting intelligently to the environment, with complex dynamics and versatility, even though they are comprised of very simple agents.

2.5 Feedbacks

Feedback, simply defined, means that the outputs of a system at time t affect the inputs of that system at time t+1. As the agents in a complex system interact, the results of some interactions may influence future interactions. It is this influence that represents the feedback within the system itself. In the previously mentioned model of traffic patterns along a highway, one car that slows down in response to the car in front of it may then produce a similar effect in the next car in line. This action/response that can easily produce a wave of congestion along the highway is due to feedback between the cars, from one to the next in line. It is worth pointing out that the term *wave* is apt in this case, as it describes a pattern of behavior across multiple agents, much like a wave in the ocean, even though the agents participating in the pattern change over time. This matches well with how Holland and others have described emergence in complex systems:

> Emergent phenomena in generated systems are, typically, persistent patterns with changing components [13, p. 225].

Note also the distinction between this organized feedback as compared to the disorganized complexity of our billiard table. While it is true that one collision between two balls alters the course of future collisions, it does not affect the course of future collisions *persistently*; that is, if one colliding ball happens to bounce to the north, it does not mean that the next ball struck will also bounce northward.

> Relationships in these systems are mutual: you influence your neighbors, and your neighbors influence you. All emergent systems are built out of this kind of feedback [15, p. 120].

The key point here is that such reciprocal influence among neighbors is more significant when it creates measurable, global properties. The action/reaction patterns represent the correlations within the system that make up these global properties. While our traffic pattern example may have measurable statistical properties — such as how many cars traverse the highway in a given day — these measurements do not fully capture the wave-like behavior of the system. It is by identifying the correlated feedback that we find a richer, and therefore more interesting, description of the system.

2.6 Endogenous vs. Exogenous Factors

One may want to consider the first action that sets the pattern in motion – is it an endogenous or exogenous instigator? While the resultant pattern is certainly endogenous to the system, the initiation of that pattern may be either. It can sometimes be difficult to characterize effects as one or the other, and how the system itself is defined may further confuse the distinction. However, by defining correlated feedback as a key property of a CAS, we bypass this argument in favor of defining what the feedback represents, and what it tells us about the system.

If an external effect sets off a chain reaction of persistent patterns, then the underlying properties that allow this chain reaction to occur are of distinct interest for understanding the system. If, however, there is persistent and recognizable feedback that comes from outside of the system, then we consider this feedback to be significant regarding our understanding of the system properties. Therefore, when we define a system, we use the method and type of feedback as a key attribute.

Consider the example of a marketplace. Such a system may encompass agents that buy and sell products, or stock in companies; it may include the concept of wealth, earnings, inflation, etc.; and it may also be affected by regulatory bodies, such as the Federal Reserve. If one defines the system as only the agents and how they interact with each other, then the actions of a Federal Reserve would be exogenous to this system. However, these actions by the Federal Reserve — whatever they may be — are clearly influenced by the state of the market. Furthermore, they are likewise designed to influence the future state of that market. This is a significant level of feedback that should be accounted for when studying the system, i.e., the market.

Another way of determining whether certain factors are exogenous or endogenous to the system is to consider whether or not the feedback goes both ways: the agents affect the environment even while the environment affects the agents. This is distinct from a model of, say, an ecology which has sunlight as an external factor. The sun cycles through day and night, as well as annual cycles of summer and winter, and these cycles generally affect the behavior of most ecological systems. But the agents in this system cannot truly affect the behavior of the sun. While defining what encompasses a system, and what potential factors are internal or external to that system, it is more important to note the level of feedback that exists between those factors, as this is both definitional and functional to the system being studied.

2.7 Emergence and Self-Organization

The term emergence, like complexity, has not yet reached a consensus definition. Some researchers distinguish between weak emergence and strong emergence, and use this definition as representing a fundamental law.

> If there are phenomena that are *strongly emergent* [emphasis added] with respect to the domain of physics, then our conception of nature needs to be expanded to accommodate them. That is, if there are phenomena whose existence is not deducible from the facts about the exact distribution of particles and fields throughout space and [time] (along with the laws of physics), then this suggests that new fundamental laws of nature are needed to explain these phenomena [6, p. 1].

This idea would seem to indicate that a strongly emergent property is similar to the idea of gravity: gravity is a fundamental law, a property of matter; but gravity is only apparent as one particle relates to another. In this view, it is not that the rule cannot be modeled by the agent, but rather it cannot be understood except in terms of other agents.

In our definition of emergent behavior, we adopt this idea of relations among agents in the system, as in the way we have previously defined correlated interactions. A traffic pattern cannot really exist with only one car, and a colony of ants cannot be said to find food if there is only one ant. In this way, emergent behavior is a property of a system that is at a different scale than the parts of the system [19]. In a similar vein, emergence is the macro-level behavior that is not defined at the macro-level, but rather depends upon the rules and interactions of agents defined at the micro-level.

Consider a few examples of typical emergent behavior. There are the cars as agents, in the example cited previously. There is also the example of bees or ants, following simple rules to forge for food or build a nest. Johnson talks at length about the city of Manchester, England, during the 19th century [15]. He uses it to illustrate how a city with tens of thousands of people, yet absolutely no central planning, still managed to organize itself in distinct patterns, such as areas of the working class separate from the nicer middle-class neighborhoods.

> The city is complex because it has a coherent personality, a personality that self-organizes out of millions of individual decisions, a global order built out of local interactions [15, p. 39].

The brain is also often cited as a complex, adaptive system, with intelligence (or even some sub-set of intelligence, such as vision) as an emergent feature. In our CAS models, we look at a number of emergent features, such as the self-organization of the agents and the aggregate behavior of the system [5, 3, 4].

The *self* in *self-organization* refers to the state of an individual agent in a complex system. This agent follows its own local rules, and uses its own own attributes in applying those rules. Let us consider a simple model of an ant colony. For the purposes of illustration, this model need not be realistic. Assume each individual ant has the same three rules: 1) search randomly across the environment for food; 2) if you find food, carry it back to the colony and leave a scent trail; 3) if you find a scent trail, follow it until you find food.

If one ant finds food, then this new attribute — "I have food" — activates the rule to carry a piece of the food back to the colony and leave a scent trail. Now, by leaving the scent trail, this ant can affect the current state of any other ant that happens upon that trail. A new ant, finding the scent trail, will activate its own rule to follow that trail to the food source, at which point it will also carry a piece back to the colony, and add to the trail. In this way, a significant subset of the ant colony organizes itself to systematically collect the food and bring it back to the colony. The individual agents — in this case, the ants — are acting with limited knowledge and simple rules. But by providing feedback to other agents, and influencing them to act in similar ways, they produce the correlations of behavior that represent the organization of the overall system; i.e., the self-organization that emerges from these interactions, defining the local increase in complexity.

2.8 Natural Biases of Complex Systems

The framework of CAS directly challenges two distinct biases that tend to affect our understanding of the agents in a complex system: 1) a hierarchical bias; and 2) a complexity bias. A hierarchical bias can be illustrated by the tendency to view a complex system in terms of a leader directing the activities of all the other agents. As Johnson points out, colonies of ants have previously been viewed as the queen controlling the colony as a whole; however, this fails to capture the amount of autonomy present among the other ants [15]. And, with a little reflection, it becomes obvious that a queen ant simply would not have the bandwidth necessary to communicate to all the other ants, and direct them in their daily tasks. Fundamentals of information theory demonstrate that such would be impossible. Most ants do not come into contact with the queen, and they do not have much to say when they do. Only a few things can be communicated via pheromones that ants exchange, and complicated task lists are not among them.

In much the same way, the growth of Manchester previously mentioned, and the distinctions that emerged between, say, rich and poor neighborhoods, was deeply surprising to those who thought that such patterns of growth could only be achieved by directed action, through some sort of governing body.

These strange phenomena — global properties of systems as represented in the growth of Manchester, or Smiths invisible hand theory — did not go unnoticed or unstudied. However, as with the peculiar behavior of the slime mold, researchers struggled to frame a model that could explain these global effects using a hierarchy that they intuitively felt must exist. The development of CAS tools and models, therefore, represent a new methodology to remedy the shortcomings of previous methods. We no longer have to assume that the behavior is directed in a hierarchical fashion. Distributed intelligence and decision-making does not require a central governing authority. Correlated feedbacks among autonomous agents are enough to describe and model these behaviors.

CAS methods of analysis also help resist the *complexity* bias for hypothesized agents that is often found when studying complex systems. This is closely related to the hierarchical bias, in that leader-agents are assumed to be more complex, to account for the level of control needed in a leadership model. In other words, the leader must be smarter: more capable and more complicated. Also, the required network among such agents would be, by necessity, more complicated and long-reaching, to allow for instructions to be passed to each agent in the system. If one is to assume a hierarchical system in, say, an ant colony, then the modeler must answer the question: how are orders conveyed to each worker ant? The consequences of a complexity bias is a more unwieldy, computationally expensive, and fragile model.

A CAS is inherently simpler. Each ant does not need instructions; rather, they can be programmed with just a few rules of behavior. In such a model, the ants do not even have to be aware of the state of the colony as a whole; they only need to know their own current state and apply that information to their current environment. Similarly, a slime-mode model doesnt require a complex pacemaker cell if a simpler CAS model is able to replicate the organisms complex behavior without it.

This release from both the hierarchical bias and complexity bias in the agent-level description of a system is more satisfying, as it follows Occams Razor: the simplest explanation for a phenomenon is the preferred one. And the beauty of this paradigm is also found in the fact that the simpler explanation — the emergent, distributed explanation — is also less expensive to implement. Fitness functions that are inherent in nature are always pushing the system, any system, toward more efficient use of resources. And thousands of autonomous, simple ants that dont require constant instruction are surely more efficient — and more robust — than a model that has one central, complicated, irreplaceable, and over-worked queen.

3 Conclusions

The assumptions inherent in Complex Adaptive Systems have allowed us to more productively study challenging and complex phenomena, in both nature and society. It has allowed us to uncover intriguing similarities across domains that are seemingly far apart. And it allows us to focus on the agent primitives in our models, as direct analogues to real-world behavior. This inherent transparency is a key feature of Agent-based Modeling, as an antidote to black box simulations that may be correct, but are by definition obscure and hard to analyze.

By using the CAS paradigm, with correlated feedbacks among simpler agents, then the features of the system of interest are allowed to emerge from dynamic agent interactions, as they do in the real world, rather than be dictated in a top-down, complicated manner. Ultimately, this gives our models the inherent flexibility needed to simulate systems even when conditions are different than expected. This flexibility makes our models more fundamentally robust, able to adapt to a variety of environments, only some of which may be anticipated. Thus, the CAS approach, and its inherent flexibility and distributed robustness, creates models that can capture results we did not already expect to see.

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