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Misconceptions Regarding Emergent Phenomenon Vary By Domain

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Abstract

Although the study of how learners approach emergent phenomena is relatively new, a consistent set of misconceptions associated with emergence have been documented. However, little consideration has been given as to whether some misconceptions manifest more frequently in one domain than another, or take on a different character depending on the agents or phenomenon involved. We examined participants' explanations of emergent phenomena from three domains. We found significant differences between domains, showing greater or lesser evidence of misconceptions. We propose that that novices bring prior knowledge, folk psychology, and folk biology to bear in determining the capabilities of the agents involved in a phenomenon, and that these beliefs guide their explanations. We believe that the study of how people perceive emergence would benefit from drawing upon research on folk theories, anthropomorphism, developmental constraints, and other areas that will help us understand how learners characterize agents, environments, and their interactions.

Keywords: emergence; complexity theory; misconceptions; science education; folk biology; folk psychology

Introduction

We live in a complex world. Not just in the everyday sense, but in a mathematical, or scientific, sense. Many of the phenomena we encounter in everyday life are of the emergent, or complex, sort. Emergent phenomena play a

central role in every scientific discipline. Color and convection are emergent phenomena, as are weather patterns, earthquakes, and the evolution of galaxies. The activities carried out by ant colonies, bee hives, and American voters exhibit emergence, as does the co-evolution of flowers and bees. There is, therefore, potential for great benefit in developing an understanding of how emergent systems arise and behave, but this is a difficult task for learners.

In non-complex, or "direct," systems, the overall behavior of the system and its outcomes tends to be deterministic, linear, and predictable, often organized by a centralized process or individual leader. The circulatory system (Chi, 2005, in press) follows a clear path, each step having a clear purpose in a system that is regulated by nerves keeping the heart beating at a regular pace. A problem in Newtonian mechanics, say, the building of a bridge, involves identifying forces that sum to indicate the stresses on a particular element of the bridge, stressors which can be offset directly by adding new elements in a cumulative way, or inventing new structures that alter how the forces sum.

In contrast, complex systems are unpredictable, nonlinear, and give rise to novel, or emergent, behavior (Holland, 1999). Even when the exact rules governing each agent are fully specified, the resulting phenomenon will be unpredictable and irreducible, and adding new elements multiplies the possible interactions between agents, leading to unexpected, non-replicable outcomes. There are no set

leaders or controllers; an agent may appear to have such powers, such as the lead goose in a flock, but they are in the lead simply because the other geese fell in line with them.

It is not surprising that the naïve learner struggles when faced with explaining and understanding emergent phenomena. Previous studies have well-documented the challenges that emergent systems present for learners (Jacobson, 2001; Hmelo-Silver & Azevedo, 2006). Learners new to emergent systems are likely to expect clear patterns of cause-and-effect, purposeful encounters between agents, and a central control system that oversees their movements and actions (Chi, 2005; Resnick, 1996). Complex systems introduce the notion that order can emerge out of random interactions; stochastic movements and actions are central to how emergent phenomena arise and evolve. This challenges the commonsense belief that ascribes purposefulness to events in the universe (Jacobson, 2001). In a deterministic, linear system, small changes to the starting conditions generally lead to small changes in outcomes. In a complex system, the smallest change can have a drastic effect on the outcome, as interactions amplify and reshape the actions of individual agents and their encounters with their environment. The learner tries to make sense of these patterns by invoking centralized control, in the form of a “queen” bee or other sort of leader, who has knowledge of the entire goings-on and can shift the pattern according to their needs or the needs of the group. But there is no leader to be found.

The study of how people perceive, explain, and understand emergent systems is a relatively new area, and both logistical considerations and underlying assumptions have led us, as researchers, to pursue our investigations through a close examination of single phenomenon (Chi, in press), a single self-contained ecosystem (Hmelo-Silver & Pfeffer, 2004), or a small set of phenomena within a single domain, such as chemistry (e.g., Talanquer, 2008; Rappoport & Ashkenazi, 2008) or evolution (e.g., Evans, 2001; Poling & Evans, 2004).

Logistically, this approach has been fostered by the fact there are only a few tools for modeling emergent systems (e.g., Colella, Klopfer & Resnick, 2001; Tisue & Wilensky, 2004), and creating such models is highly time-consuming. Data collection is similarly time-consuming, and research has focused heavily on case studies and close observation of small groups in complex settings (e.g., Charles & d'Apollonia, 2004; Wilensky & Resnick, 1999), or larger groups interacting with a single aspect of a phenomena. We have spent little time looking at whether and how learners' actions and ideas change from one domain to the next.

Theoretically, too, there is a basic reason why we might believe that, with time, these individual studies would come together to create a fuller account of how learners perceive, represent, and think about emergent systems. To be considered an emergent system, a phenomenon must meet specific mathematically-defined criteria. At the mathematical level, diffusion, chemical bonds, and traffic jams have a great deal in common; emergent phenomenon

belong to a class that is unaffected by features specific to a particular domain.

It remains to be seen, then, to what degree the abstract features and behaviors of an emergent system actually do cross domain boundaries for learners. If I become proficient in understanding diffusion, for example, will this make learning about traffic jams or chemical bonds any easier for me? We not only do not have such comparisons, we lack assessments that allow us to directly compare a learner's understanding of the principles of emergence in one domain to their understanding in another.

Our goal for the project we describe here was to create an assessment of key aspects of emergent systems that could be applied across topics. Learners' understanding of each phenomenon was assessed using an instrument that had identical stems representing each component of emergence, into which the particular phenomenon could be inserted. If learners respond to the basic patterns that underlie the phenomenon, they should show similar levels of understanding (or misunderstanding) across domains. If a person showed a low understanding of diffusion, they should show a similarly low understanding of geese flocking, as the same basic principles are needed to make sense of these two phenomena. Thus, we can determine whether their knowledge is tied to a particular system, or is available at a more abstract level.

If domain knowledge plays a role, however, then responses may be influenced by folk theories that ascribe greater capacity for volition, control, and decision making to certain sorts of entities, and less to others. A bacterium may be seen as relatively incapable of engaging in goal-oriented behavior, of communicating with other bacteria, or of choosing a course of action. A goose, given that it has a brain and nervous system, may be seen as more capable. The social behavior of ants, likewise, may cause us to assume they are more intentional and communicative, and less driven by instinct and environment. Given people's bias to find centralized, intentional causes for emergent patterns, it may be harder to believe that animals with greater neurological development are subject to random processes, do not engage in communication and group planning, and do not make choices when they act.

We therefore decided to test our domain-general stems in the context of three different domains: unicellular slime molds aggregating before sporing, ants, a social animal, foraging for food, and geese, the most “advanced” neurologically, flocking. These three entities not only come from different locations on the phylogenetic tree, they differ in the ways that we describe above.

We designed a study in which participants watched simulations of three phenomena. Participants responded to an open-ended written protocol that used the same questions for each domain, altered only to refer to the domain at hand. We then coded participants' responses and compared their conceptualizations of each phenomena.

If misconceptions arise due to the features that all emergent phenomenon have in common, we would expect

responses to our probes to be roughly the same across the simulations. If, however, domain-specific considerations come into play, we expect to see misconceptions arising more often in some domains than in others. In particular, we predicted that misconceptions would be invoked less often with regard to slime molds than ants or geese. In addition, we predicted ants would give rise to the greatest number of misconceptions due to the familiarity of their social nature.

Methods

Participants

Forty participants, undergraduates from a large Southwestern University, completed the written protocol, receiving \$20 in compensation. None had formal training in emergence or complexity theory. The protocol took approximately 60 minutes to complete.

Materials and Procedure

The participants completed a written protocol posing questions about three emergent phenomena: geese flocking, ants foraging for food, and slime molds aggregating to spore. The order in which the phenomena were presented was counterbalanced across participants.

Each phenomenon was illustrated with a NetLogo simulation that had been video-captured, so that the same run could be shown to all participants. Agents were represented by icons that captured the basic appearance of the real entity (i.e., ant, slime mold, goose), and participants were told before the simulation began what symbols would be used, and what they would mean.

Each simulation lasted approximately 90 seconds, and were roughly divided into three phases. First, there was a brief section that allowed participants to orient themselves to the simulation, the symbols used for the agents and environmental objects, and the agents' behavior. Next, the behavior began to develop emergent properties, i.e., patterns began to form at the group level. Finally, the simulation reached equilibrium (in the case of the flocking and slime mold simulations) or the agents achieved their goal (of finding food, in the ant simulation). Pilot runs of the simulations and the responses of the participants suggested that few had any difficulties mapping the real phenomenon onto the simulation.

There were a total of 7 questions. We began each of the three protocol sections with broad questions (e.g., #1 and #2 below), moving to more specific questions that capture key aspects of emergent phenomena (e.g., #3 and #4 below). The questions were designed to be as similar as possible across entities, substituting in the appropriate phrases:

1. Describe the patterns that the *ants/geese/slime mold organisms* make in as much detail as possible.
2. What do you think causes the *ants/geese/slime molds* to make the patterns you see?

3. Do you think that there are special leader *ants/geese/slime molds* that signal the others to *follow them/ follow them/ come to them and form clusters*?
4. If we make a new video with the same *ants and food/geese/slime molds* in the same starting positions, how similar do you think the patterns they form will be?

We instructed participants to write as much as they could, giving as much detail as they could provide. They were told to answer the questions in the order they were given, and not to go back and change any of their answers.

Results

To create the coding system used to categorize participants' answers, two of the authors (SKB and GSS), conducted an open coding of the data, allowing codes to emerge, rather than searching for codes based on existing expectations and hypotheses. We iteratively coded sections of the data and discussed our codes, coming to agreement on 13 themes that were present across all domains. No theme arose that was not present at least once in each domain. Two of the other authors (RR and BH) who did not have contact with GSS and SKB during the development of the codes, applied the codes to the data. Both were blind to the hypotheses regarding the relationship between a given domain and possible patterns for that domain. They applied the codes with 94.5% agreement, resolving disagreements through discussion. Less than 5% of the answers were deemed uncodable. Multiple codes could be applied to a single answer, if all of the criteria for each code was met.

Although we arrived at 13 themes, not all of these codes spoke to the issue of misconceptions about emergence. Some were not directly relevant (e.g. "descriptive," used when for a play-by-play description of the simulation, without interpretation, or "external factors," when characteristics of the simulation itself were the focus, instead of the content.) Other codes proved complex and potentially misleading because they captured different concepts for different individuals (this is further discussed below).

We chose to focus on the codes that, based on prior research, are most central to identifying whether participants hold a misconception or correct representation. We chose four that directly invoke misconceptions well-documented in the literature, and two providing evidence that the participant held a correct representation of the phenomenon (see Table 1 for a description of the codes, and a sample response). Regarding the misconceptions, people tend to assume that there is a controlling force directing the agents, that the agents are communicating and cooperating, that certain agents have special powers that allow them to direct the pattern, and that all of the agents are acting out of a sense of purpose. In contrast, the last two suggest understanding of two basic principles of emergence: the

lack of centralized control, and the role of stochastic processes.

Table 1: Codes Used in The Analysis

Code	Description	Example
Centralized Control	Reference to a group member determining, directing, or guiding the actions of the rest of the members.	<i>The slime mold that produces more pheromones will signal the others to come and cluster around them.</i>
Cooperation	Agents cooperatively determine their behavior, or work together as a group.	<i>Each geese are telling each other where to move</i>
Differentiation	Members have different abilities, roles, or attributes from one another.	<i>Maybe the ones clustered have a similar pheromone (sic). Also the levels of what they give off could be different.</i>
Goal-oriented	Specifies a behavior being performed to fulfill a specific, stated purpose.	<i>He takes the path he does because he's searching for food.</i>
Lack of Central Control	Refers to lack of a group member determining, directing, or guiding the actions of other members.	<i>I think the ants are generally just concerned with getting some food, so following a leader was not the goal. They all followed very similar paths because they shared a common goal.</i>
Random Processes	Describes movement or other activity explicitly as "random." Does not include descriptors such as "haphazard" or "scattered," but only those which or seem to be referring to a reasonably accurate version of statistical randomness.	<i>I think this is a random pattern while they search for food. The first makes random search while the followers more directly follow.</i>

Our first step in analyzing the data was to calculate the means and standard errors for each domain on each of these 6 codes (see Table 2 for descriptive and inferential statistics). We took a "token-counting" approach, adding up the number of times a particular code was used a participant in a domain. This gives a sense of how strongly the participants relied on a particular conception in providing their explanations for the phenomena. Since a participant could have invoked a particular concept or principle in answering each question, the maximum token score for each code is seven.

Table 2. Descriptives For Each Domain, By Code (alpha corrected to account for experiment-wide error)

Code	Slime	Ants	Geese	F(2, 78)
Centralized Control	0.23 (.07)	3.35 (.27)	1.18 (.21)	64.22***
Cooperating Agents	1.08 (.17)	0.55 (.13)	1.50 (.27)	8.10**
Differentiated	1.05 (.22)	3.95 (.26)	1.85 (.28)	35.86**
Goal-Oriented	2.70 (.29)	3.77 (.25)	3.03 (.29)	5.34*
Lack Central Control	0.78 (.09)	0.32 (.17)	0.38 (.13)	3.40 ^m
Random Processes	0.70 (.22)	0.48 (.14)	0.38 (.13)	1.51 ^{ns}

We also calculated participants' use of these codes using a binary process; a score of "1" meant that the participant used the code at least once within that domain; "0" indicated they did not use the code at all in that domain. The results were quite similar; the same pattern of significant findings was found for all but two of the codes. In the case of "goal-oriented," the differences decreased, and the F-value fell to 2.69 (non-significant). In the case of "lack of centralized control," differences increased, and the F-value rose to 16.98 ($p < 0.01$). We believe these differences are due to the following: in the case of goal-orientation, almost every participant invoked it at least once in every domain, restricting the range when using binary scoring. The opposite is true in the case of a lack of centralized control; so few participants invoked this, a binary analysis was able to detect differences that were swamped by non-responses in the token analysis.

Other Points of Interest

As noted above, there were themes in the data that were not as central, but might shed some light on how participants conceptualized emergence. For example, in reviewing the protocols, we found that participants were expressing quite different ideas, even when using similar language. In one

case, we inquired as to whether the participants believed that the agents followed rules in carrying out their actions. The consensus seemed to favor that they did not follow rules (approximately 2/3 of the replies).

However, we also discovered that participants had different ideas about what constituted a “rule.” For some, following a rule meant making a conscious decision based on a learned rule—we learn to stop at red lights, for example, and we (usually) follow that rule. For others, rules could also be innate or instinctual. Some even went so far as to explicitly state “if you mean conscious rules, no, but if you mean instincts, then yes, they follow instincts.”

Because we could not go back and further probe to see what meaning of “rule” each participant used, we excluded it from further analysis, but we think this disagreement about what constitutes a rule is interesting, for reasons we will address in the discussion.

Discussion

As predicted, slime molds elicited fewer misconceptions overall than the other two entities, and produced the lowest level of misconception use in three of the four categories associated with misconceptions. Ants also elicited the predicted performance, with the highest use of misconceptions in three of the four categories. Trends in the two categories related to correct conceptions were unclear; reference to an explicit lack of centralized control was only significant in the binary coding of the data; this trend did favor our prediction, in that slime molds had the highest invocation of this correct concept. However, random processes produced no significant differences in either analysis.

The mathematical and scientific power of complexity theory and emergence comes from the ability of these theories to draw bridges between seemingly disparate disciplines. These isomorphisms, along with the tremendous overhead involved in modeling any phenomenon, have led educational researchers and cognitive scientists to focus on a small sub-set of emergent phenomena, reasonably inferring that the errors that crept up in one domain would appear in another, given the underlying similarities. Even if novices did not know the phenomena were isomorphs, the phenomena were governed by the same principles, manifest in similar ways, and created similar puzzles.

There was indeed some similarity in how the participants responded to phenomena; of the 13 themes we identified, every one was present at least once in each domain. That suggests a relatively high degree of consistency across domains in terms of how participants describe and explain phenomena.

However, we also believe that researchers have not been paying enough attention to the fact that each phenomenon is carried out by a different cast of characters—be it molecules, ants, geese, or air streams—and novices might rely on prior knowledge and beliefs in perceiving a phenomenon and devising an explanation for it. As a result, the likelihood of invoking a particular concept or

misconception is not just due to the phenomenon’s abstract characteristics, but also what the novice brings to the phenomenon, perhaps in the form of specific knowledge of the entities, or perhaps in the form of folk theories.

The problem of interpreting participants’ use of the word “rules” illustrates our account well. Differences in one’s beliefs about what constitutes a rule, and whether an entity is capable of acting on rules created differences in the way participants responded. Most participants seem to think of rules as learned guides to appropriate behavior to which one consciously refers. They were reluctant to ascribe that ability to the entities we used in this study. Those who believed that instincts could be thought of as rules were much more willing to think of agents as following rules.

Similarly, we believe that the differences between the three domains on the codes we examined are driven less by specific knowledge of emergence, and more by one’s beliefs about the entities’ capacity for thinking, consciousness, and deliberate decision making. They invoked misconceptions less for slime molds, unicellular microorganisms, than for geese and ants, and there is some evidence that they were more likely to invoke a correct explanation for the slime molds, based on a lack of centralized control and random processes.

Their accounts of ants consistently showed the greatest number of misconceptions; only for cooperation did geese outperform ants. Anecdotally, a fair number of participants spontaneously stated that they knew how ants worked because (a) they have had extensive experience with ants, usually trying to get them out of their houses, and (b) because they had seen the movie ‘Antz.’ They were also inclined to mention that ants were social creatures, and that ability suggested organization, and the mental capacities needed to create organization.

At very least, this should serve as a warning to those of us engaging in research about complexity and emergence. By relying on one or a few phenomena to characterize how people perceive, explain, and understand emergence more generally, we may be greatly over or underestimating the abilities depending on the domains and agents we choose. Testing a model on a variety of phenomena, with agents at different levels of familiarity and perceived cognitive capacity would be a good step to take before deciding that a particular pattern of results arises because of the character of emergent systems generally, and because of the specific properties of the agents and the activities they undertake.

We believe, however, that there is something more interesting going on here, and that a better understanding of how people experience emergence will require us to draw upon research into folk theories (Arico, Fiala, Goldberg & Nichols, 2011) developmental constraints (e.g., intentionality, teleology; Sinatra, Brem & Evans, 2008), anthropomorphism (Tamir & Zohar, 2006), and sociocultural accounts of the differences in ways that different groups of people characterize animals, people, and objects. We need a better sense of how people characterize agents and their abilities to exhibit volition, teleological

thinking, to communicate, and to control themselves, others, and their environment.

We hypothesize that the greater the perceived capabilities of an agent or group of agents, the more likely it is that people will reject explanations that invoke emergence in favor of accounts that give agents greater control over the events that occur. Alternatively, the differences between simulations were due to differences in the phenomena we chose. It may be, for example, that flocking seems to require greater mental skill than following a pheromone trail.

As a first step in addressing these hypotheses, we are currently running a study in which we present isomorphic phenomena across different levels of agents (physical, "lower animal," "higher animal," and human), and are also gathering data about the perceived capacities of each of these agent types. We believe that simulations depicting agents deemed more mentally capable will correlate with greater misconceptions, even when the underlying mechanisms are actually identical. However, if it is the type of phenomenon that drives the differences in our first study, this should surface in this study; responses should be more similar by phenomenon than by level of agent.

In either case, having a better understanding of how perceptions of phenomena and agents vary, this should improve our ability to understand how people look at emergent phenomena, and suggest ways to dispel misconceptions.

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References

- Arico, A., Fiala, B., Goldberg, R.F., Nichols, S. (2011). The folk psychology of consciousness. *Mind and Language*, 26, 327-352.
- Charles, E.S. & d'Apollonia, S.T. (2004). Developing a conceptual framework to explain emergent causality: Overcoming ontological beliefs to achieve conceptual change. *Proceedings of the 26th Annual Meeting of the Cognitive Science Society*. Mahwah, NJ: Erlbaum Associates.
- Chi, M.T.H. (2005). Common sense conceptions of emergent processes: Why some misconceptions are robust. *Journal of the Learning Sciences*, 14, 161-199.
- Chi, M.T.H., Roscoe, R., Slotta, J., Roy, M., & Chase, M. (in press). Misconceived causal explanations for "emergent" processes. *Cognitive Science*.
- Colella, V.S., Klopfer, D., Resnick, M. (2001). *Adventures in Modeling: Exploring Complex, Dynamic Systems with StarLog*. Willston, VT: Teachers College Press.
- Evans, E.M. (2001). Cognitive and Contextual Factors in the Emergence of Diverse Belief Systems: Creation versus Evolution. *Cognitive Psychology*, 42, 217-266.
- Hmelo-Silver, C.E. & Azevedo, R. (2006). Understanding Complex Systems: Some Core Challenges. *Journal of the Learning Sciences*, 15, 53-61.
- Hmelo-Silver, C.E. & Pfeffer, M.G. (2004). Comparing expert and novice understanding of a complex system from the perspective of structures, behaviors, and functions. *Cognitive Science*, 28, 127-138.
- Holland, J. H. (1999). *Emergence: From Chaos to Order*. New York: Basic Books.
- Jacobson, M.J. (2001). Problem solving, cognition, and complex systems: Differences between experts and novices. *Complexity*, 6, 41-49.
- Poling, D. A., & Evans, E. M. (2002). Why do birds of a feather flock together? Developmental change in the use of multiple explanations: Intention, teleology, essentialism. *British Journal of Developmental Psychology*, 20, 89-112.
- Rappoport, L.T. & Ashkenazi, G. (2008). Connecting Levels of Representation: Emergent versus subemergent perspective. *International Journal of Science Education*, 30, 1585-1603.
- Resnick, M. (1996). Beyond the centralized mindset. *Journal of the Learning Sciences*, 5, 1-22.
- Sinatra, G.M., Brem, S.K., & Evans, E.M. (2008). Changing minds? Implications of Conceptual Change for Teaching and Learning about Biological Evolution. *Evolution Education and Outreach*, 2, 189-195.
- Talanquer, V. (2008) Students' predictions about the sensory properties of chemical compounds: Additive versus emergent frameworks. *Science Education*, 92, 96-114.
- Tamir, P. & Zohar, A. (2006). Anthropomorphism and teleology in reasoning about biological phenomena. *Science Education*, 75, 57-67.
- Tisue, S. & Wilensky, U. (2004). NetLogo: A simple environment for modeling complexity. *International Conference on Complex Systems*. Boston.
- Wilensky, U. & Resnick, M. (1999). Thinking in Levels: A Dynamic Systems Approach to Making Sense of the World. *Journal of Science Education and Technology*, 8, 3-19.