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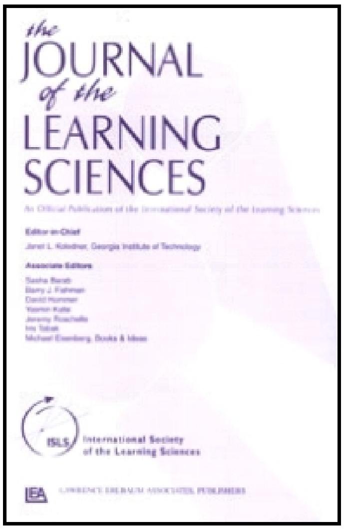

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Promoting Transfer by Grounding Complex Systems Principles

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Promoting Transfer by Grounding Complex Systems Principles

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Understanding scientific phenomena in terms of complex systems principles is both scientifically and pedagogically important. Situations from different disciplines of science are often governed by the same principle, and so promoting knowledge transfer across disciplines makes valuable cross-fertilization and scientific unification possible. Although evidence for this kind of transfer has historically been controversial, experiments and observations of students suggest pedagogical methods for promoting transfer of complex systems principles. One powerful strategy is for students to actively interpret the elements and interactions of perceptually grounded scenarios. Such interpretation can be facilitated through the presentation of a situation alongside a description of how the agents in the situation are behaving, and by students exploring and constructing computational models of the situation. The resulting knowledge can be both concretely grounded yet highly perspective dependent and generalizeable. We discuss methods for coordinating computational and mental models of complex systems, the roles of idealization and concreteness in fostering understanding and generalization, and other complementary theoretical approaches to achieving transfer.

When and how do students transfer what they have learned to new situations? This is one of the most important questions confronting education and cognitive science. Addressing it has crucial practical consequence while also touching on deep

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basic research issues related to learning, analogical reasoning, and conceptual representation. Considerable research has suggested that students do not spontaneously transfer what they have learned, at least not to superficially dissimilar domains (Detterman, 1993; Gick & Holyoak, 1980, 1983). This is disturbing, because teachers choose content with the hope that students will apply what they have learned to relevant new situations. We believe that students can transfer scientific principles across superficially dissimilar domains, and we are not alone in this belief (Bransford & Schwartz, 1999; Jacobson, 2001; Judd, 1908; Simon, 1980). To present our case, we describe kinds of transfer that are worth "fighting for." Identifying these turns out to be not only an educational question, but a scientific question as well. Accordingly, we describe an approach toward science that seeks to unite phenomena from disparate domains according to general principles that govern complex systems. This complex systems approach to science offers unique educational opportunities for imparting scientific understanding that is both concretely grounded yet widely applicable across many domains.

The notion of a grounded generalization may sound like an oxymoron, but it is key to our account of transfer. The time-honored method for conveying generalizations has been to use symbolic formalisms such as predicate logic or algebra. These formalisms can enable a student to transcend the specifics of a situation, but they also run the risk of disconnecting the resulting abstraction from an intuitive understanding of the situation. Instead, we propose learning and teaching methods that promote situation construals that are concrete insofar as they are perceptually, temporally, and spatially grounded. However, they are still idealizations in that many elements of a situation are ignored or highly simplified.[1] In this article, our argument for how to achieve grounded generalizations involves the following steps: (1) Describe the nature of complex systems accounts of science, (2) provide examples of general complex systems principles that appear in several case studies, (3) describe pedagogical benefits of teaching science through complex systems, (4) discuss the importance of transfer and generalization in relation to complex systems, (5) present a method for achieving generalization through perceptually grounded yet interpreted simulations, and (6) compare generalization from grounded simulations to formalism-centered strategies and other methods for achieving transfer. Our goal in integrating complex systems (Steps 1–3) with transfer (Steps 4–6) is that we believe that recent grounded modeling approaches to complex systems offer pedagogical innovations that promote transfer of scientific knowledge and that, reciprocally, the cognitive science of how people transfer what they have learned offers specific suggestions for teaching increasingly pertinent topics in complex systems.

[1]See also the notion of situated abstraction in the section "Comparison to Existing Approaches to Transfer."

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CONNECTING SCIENCE WITH COMPLEX SYSTEMS PRINCIPLES

One way to advance science is to progressively flesh out theories, adding experimental details and elaborating mechanistic accounts. By this account, "the devil is in the details," and the proper occupation of scientists is to pursue these details. This vision of science was most emphatically painted by John Horgan in his 1996 book *The End of Science*. He argued that the age of fundamental scientific theorizing and discoveries has passed, and that all that is left to be done is to refine the details of theories already laid down by the likes of Einstein, Darwin, and Newton. The rapid rate of scientific specialization seems to support Horgan's argument. We have gone from an era when the only major scientific journals were *Nature* and *Science* to an era with specialized journals such as the *Journal of Contaminant Hydrology* and the *Journal of Shoulder and Elbow Surgery*, each an umbrella outlet for several distinct subspecializations. Yet many scientists feel compelled to specialize to still further degrees because of the sheer volume of scholarly output that competes for their eyes and minds.

One group of scientists that has chosen to reverse the trend toward increasing specialization is complex systems researchers. With historical roots in cybernetics and general systems theory, the field of complex systems theory has been rapidly developing over the past few decades (Bar-Yam, 1997; Holland, 1995, 1998; Kauffman, 1993; Wolfram, 2002). Complex systems researchers study how relationships between elements within a system give rise to emergent properties of the system, and how the system interacts and forms relationships with its environment (Jacobson & Wilensky, 2006). The "systems-level" perspective emphasizes that understanding how a part of a system behaves depends upon understanding the system's other parts, and that the system as a whole has properties and organization that cannot be deduced from a consideration of the parts in isolation (Holland, 1998; Kauffman, 1993). Although the complex systems research community is diverse, some common assumptions are the following: (a) Many natural systems operate at multiple distinct levels of organization; (b) such systems involve nonlinear interactions among the system's elements including positive and negative feedback loops; (c) even when the only interactions that exist in a system are among its individual elements, important macroscopic descriptions can still be applied to the system as a whole and are critical for understanding its patterns; (d) system-level patterns can emerge without any force explicitly striving for the pattern, through the self-organized activity of many interacting elements; and (e) the same system pattern can often be found in diverse domains, and it is useful to describe systems in sufficiently general terms such that these commonalities can be revealed. Consistent with this fifth point, researchers have pursued principles that apply across many scientific domains, from physics to biology to social sciences. Their general claim is that the same complex systems principle can describe seemingly very different phenomena.

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One major thread of complex systems research has focused on formal equations that summarize the dynamics of a natural phenomenon. Examples of this approach include fitting power-law equations to earthquake magnitude and frequency data (Bak, 1996) or differential equations to the populations of predators and prey over time (Lotka, 1925). These equations turn out to have applicability that goes far beyond their original domains. Power laws have been implicated in the distribution of connections within actor, neural, power grid, and telephone networks (Barabási, 2002; Barabási & Albert, 1999). Differential equations describing predator–prey dynamics have been recruited to model chemical reactions and business cycles (Ball, 1999).

Within the complex systems community, there is another major thread that strives to build computational models that, when run, generate critical aspects of the behavior of natural systems. This approach is known as *agent-based modeling*, or ABM (Epstein, 2007; Epstein & Axtell, 1996; Goldstone & Janssen, 2005; Miller & Page, 2007; Railsback, Lytinen, & Jackson, 2006; Wilensky, 2001a; Wilensky & Rand, in press). These models contain numerous distinct elements (agents) that move and interact, resulting in a system globally changing over time (also known as an *emergent phenomenon*). Unlike the macroscopic-equation approach to complex systems, the goal is not simply to describe the high-level behavior of a system but to provide a model that *generates* the macroscopic behavior from the behavior and interactions of lower level agents. In this way, ABMs create an explicit causal link between the micro-level elements of a system and its macro-level global behavior, thus providing an explanation at a lower level for the global behavior. ABMs are typically implemented as computer programs. The programs create a population of agents and specify rules of behavior for each of the agents. These rules are typically very simple, such as "Look ahead, turn and move forward," but they can also be more elaborate and governed by mathematical equations. Crucially, program implementers do not explicitly program in the global behavior of the system as they would if they were creating a plot of a macroscopic equation. Instead they program the rules for the individual agents, and the high-level system behavior emerges from the unfolding agent actions and interactions. The aforementioned predator–prey dynamic provides an illustrative contrast between ABMs and equation-based complex systems approaches. The macroscopic-equation approach involves two coupled differential equations: one that describes the change in the population of predators, and the other the population of prey. Only overall populations, not individual predators and prey, are factors in the differential equations. The equations, when iterated, produce oscillating populations. In contrast, an ABM approach would create many separate animal agents—one for each predator and prey—and assign them locations in space. Rules describe how the animals move, eat one another, and reproduce; and each agent individually follows its rules. Macroscopic properties such as predator and prey population levels can be analyzed and plotted (see Figure 1a), but they do not explicitly

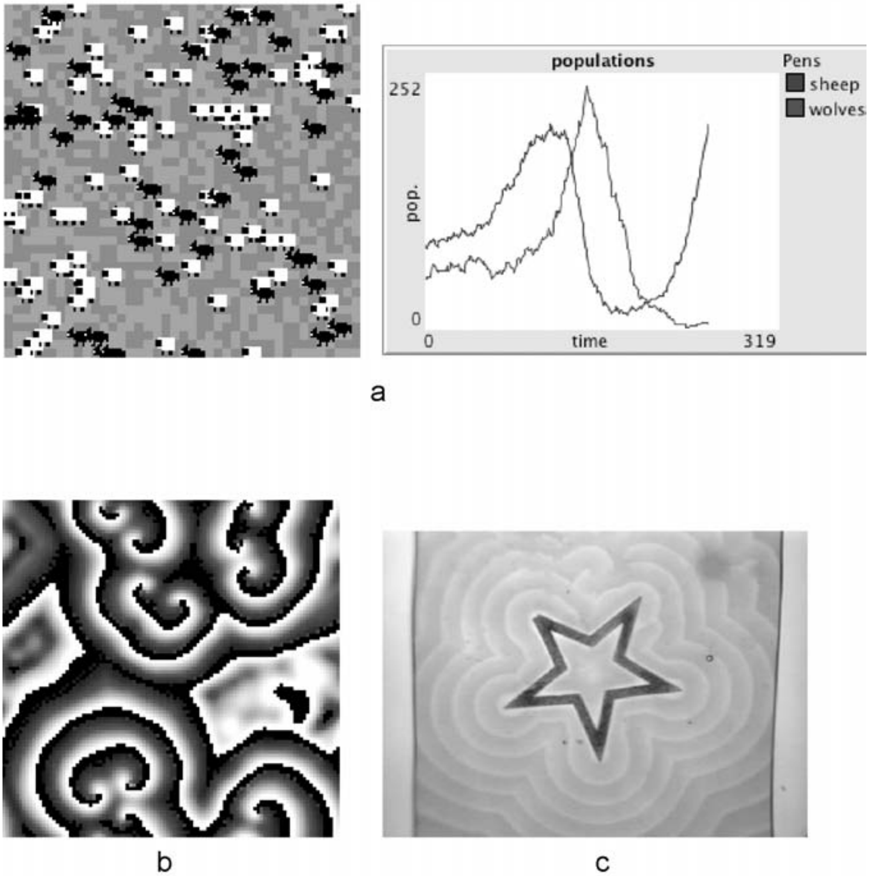

FIGURE 1 Two systems with oscillating behavior. These phenomena seem very different, but they can be viewed as two examples of a general complex systems principle. (a) An agent-based computer simulation of oscillating populations in wolf–sheep predation (from Wilensky, 1997b). The left panel shows a snapshot of wolves (black), sheep (white), and grass (green), and the right panel shows fluctuations in their populations over time. (b) An agent-based simulation of oscillating levels of chemicals in the Belousov–Zhabotinsky reaction (from Wilensky, 2003). (c) A photo of the physical Belousov–Zhabotinsky reaction taking place around a star-shaped stamp (photo courtesy of Kyle Bishop and Bartosz Grzybowski; see http://dysa.northwestern.edu/).

play a role in determining how the system will behave in the future given the present state (see Wilensky & Reisman, 2006, for a fuller account of this example).

In what follows, we are mostly concerned with the ABM approach to complex systems because we believe it offers a potentially promising method for fostering

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transferable understandings of complex systems. It is promising because it occupies a unique, bridging position between concrete and general accounts of phenomena. On the one hand, ABMs are concrete in that they posit objects that correspond to the individual elements within a system. On the other hand, they are general in that the models are often idealizations that strip away attributes of the elements that are extraneous for a particular purpose. The sheep and wolves in Figure 1a have neither wool nor fangs. They are represented in terms of their coordinates in a two-dimensional space and in the specific conditions for their participating in events such as reproducing, eating grass, or eating sheep. This idealized, stripped-away representation is helpful in promoting transfer to other domains that have the same relations among their elements. An important point implicit in this characterization of ABMs is that the pivotal difference between equations for macroscopic properties of complex systems and ABMs is not whether they are equation based. Both typically are formal. The pivotal difference is whether the equations, or rules, are describing the macro-level behavior of the entire system or the micro-level behavior of elements.[2]

We are not arguing that a cross-discipline, complex systems approach to science is superior to a specialist's focus on the details of a single domain. Both approaches are necessary for a complete science, and in fact it is only by understanding a system's details that researchers can determine the general principles by which it is governed. However, given the climate of progressive specialization in contemporary science, it is important to remember that many of the most noteworthy advances of science have involved finding deep principles shared by seemingly dissimilar phenomena.

Practicing what we preach, we present a couple of grounded examples of specific complex systems principles and how they might be instantiated by ABMs. A commonly found system architecture in nature is the following:

> *Pattern 1:* An entity causes more entities like itself to be produced. At the same time, it causes another kind of entity to be produced that eliminates the first entity.

The previously described example of this is when prey (e.g., sheep) produce more prey through reproduction and also increase the number of predators (e.g., wolves) by providing biomass energy while the predators cause prey to be eliminated through predation. A second instantiation of this pattern is the Belousov–Zhabotinsky chemical reaction (see Figures 1b and 1c), in which one chemical is involved in a reaction that produces more of itself and a second chemical while the second chemical removes the first chemical by reacting with it (Kapral & Showalter, 1995). Both systems can be de-

[2]Although we do not use this argument herein, elsewhere we have argued that rule sets are a superior form of representation to equations for exploring, understanding, and explaining the behavior of a complex system (Wilensky, 2006).

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scribed by very similar differential equations called *reaction–diffusion systems* (Ball, 1999) and show the same large-scale patterns over time. Both systems can also be described by an ABM (see Wilensky & Reisman, 1998, 2006; Wolfram, 2002). Macroscopically, both systems produce oscillating amounts of the two entities, and the pattern of distribution is often a dynamically moving spiral.

> *Pattern 2:* Many individual elements move randomly. If a moving element touches another element, it becomes attached. The emergent result is a fractally connected branching aggregate.

This process, called *diffusion-limited aggregation*, has been implicated in the growth of human lungs (Garcia-Ruiz, Louis, Meakin, & Sander, 1993), frost on glass (Bentley & Humphreys, 1962; Halsey, 2001), and cities (Batty & Longley, 1994). As with the reaction–diffusion systems, the individual elements of different diffusion-limited aggregation systems are highly dissimilar, but the interactions between the elements can be captured by very similar agent-based rule sets (Bar-Yam, 1997; Wilensky, 1997a). The resultant overall patterns of thin, fractally connected branches are remarkably similar and have almost identical statistical properties (Ball, 1999; see Figure 2 for an example).

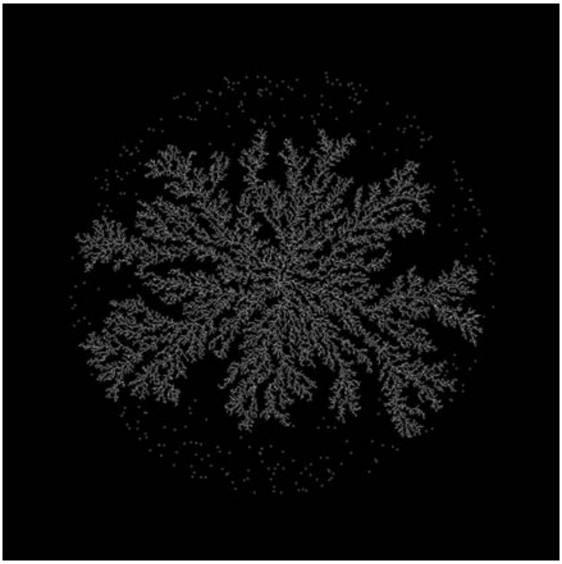

FIGURE 2 An agent-based computer simulation of diffusion-limited aggregation (see Wilensky, 1997a). Moving elements (shown as dots) are added to the system one at a time. When they come into contact with one of the static elements (shown as branches), they become attached to the static element.

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Apart from the cross-fertilizing scientific benefits accrued by applying principles from one domain to new domains, there are also pedagogical benefits for the cross-domain integrations provided by complex systems. Students are often heard to complain that their science classes are too particularistic (Wicklein & Schell, 1995). These students feel that they are asked to go from subject to subject but are not given tools for making connections between subjects and seeing the coherence among them. Theories from complex systems can provide these organizational frameworks. Blikstein and Wilensky (2005, 2006) have found, for example, that undergraduates studying crystal growth in a materials science class often "mix and match" different levels of explanation to solve crystal growth problems. Typically they use equations (such as the Laplace-Young or flux equations) and/or heuristics (such as "large grains grow, small grains shrink") to solve these problems. In a study of a group of undergraduates. Blikstein and Wilensky found that students had fragmented views of the process of crystal growth, seeing it as a set of related but distinct subprocesses. This lack of a coherent view was troubling for these students, and they recognized that they failed to see the different subprocesses as falling under a broad principle. In contrast, the students in the same class using the MaterialSim models (Blikstein & Wilensky, 2004a, 2004b) easily attained insight into the mechanism of crystal grain growth (Blikstein & Wilensky, 2005, 2006). Furthermore, they came to see many apparently different instances of crystal growth as instances of the general principle of energy minimization. We have often seen students, through coming to understand this powerful general principle and understanding how it works out in the micro-mechanisms of the relevant phenomena, apply the principle in other domains (Blikstein & Wilensky, 2006).

Another example: One of our students who learned about positive feedback systems from an example of a microphone feeding into, and placed near, a loudspeaker was spontaneously reminded of this example when she was discussing a scenario involving people purchasing products that other people had already purchased. The reminding was apt. Both situations are instantiations of positive feedback systems, where the presence of an attribute in a system variable leads to further increase of the same attribute. Furthermore, seeing the similarity in the two situations enabled an inference: When two products compete in the marketplace, if one gets a lead, for whatever reason, positive feedback will result in its increasing its lead regardless of the relative quality of the two products.[3] The principles of complex systems are naturally applicable in many, often seemingly unrelated, situations. This is because the principles are expressed in generic terms such as element, agent, resource, inhibition, excitation, interactions, connection, motion, force, neighbor, energy, and strength. Some examples of complex systems are presented in Table 1. There are other approaches that also advocate descriptions at a

[3]The case of VHS and Betamax video recorders is often described as a case in which the technically inferior product won out through positive feedback (Arthur, 1988, 1989).

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TABLE 1
Examples of Complex Systems Principles, With Specific Cases of Each

System	*Principle*	*Example*
Positive feedback	The presence of an attribute in a system leads to more of the same attribute.	Microphone placed near, and connected to, a speaker. Citations of an article lead to more citations of the article. Wealth begets more wealth.
Negative feedback	An increase in a system variable leads to a decrease in the same variable	Thermostat that triggers heat when temperature falls too low. Lack of food causes blood sugar to decrease, which causes hunger.
Competitive specialization	Elements collectively cover a resource effectively by iteratively adapting the closest element to a randomly selected resource patch and inhibiting other elements from rapid adaptation.	Different visual cortex neurons become specialized to lines with different orientations Different oil companies become specialized for different oil reserves.
Autocatalysis	A reaction product is itself the catalyst for that reaction, where a catalyst is a substance that accelerates the rate of a reaction without being consumed.	As soon as tin organ pipes start to decompose, the decomposition process speeds up, feeding on itself. The reaction of chlorine nitrate with ozone that leads to continued depletion of the ozone layer.
Stigmergic path formation	Elements affect their environment as they move, facilitating subsequent agents that follow the same path.	Human path formation on grassy fields. Ant trails during food foraging.
Lateral inhibition	Neighbors inhibit one another, with the result that one unit will become much more activated than the others.	When one is reading, the two meanings of a homograph (e.g., *bank*) inhibit one another. Edge enhancement: Light-detecting cells inhibit their neighbors, leading to light regions near dark regions to be more salient than light regions surrounded by other light regions.
Simulated annealing	To get a system to find a good solution, begin by adding a large amount of randomness to the search, and then gradually decrease the amount of randomness.	Balls find deepest valley if they move randomly at first but then gradually become more influenced by gravity. Agents form paths around obstacles if they first move randomly but then gradually move more toward one another.

generic level that are still grounded, such as pragmatic reasoning schemas (Cheng & Holyoak, 1985) and spatial diagrams (Novick, 2006), but the terms of complex systems tend to be more dynamic and tailored for representing physical situations.

The principles of complex systems can be expressed generically, but we do not advocate this as a stand-alone pedagogical procedure. The principles are typically very difficult to understand when presented only in a generic form but highly intuitive when instantiated in a case study. However, the existence of the generic description level does offer opportunities for transfer between dissimilar scenarios. When a case study of a complex systems principle is presented in a way that the generic principle to be understood, either implicitly or explicitly, then there is potential for transfer. This will most typically not be achieved by simply presenting a single case study (Detterman, 1993). It is more likely to be achieved by having people experience and compare multiple case studies of the same principle (Gentner, Loewenstein, & Thompson, 2003; Gick & Holyoak, 1980; Kurtz, Miao, & Gentner, 2001), explain the case studies to themselves (Ainsworth & Loizou, 2003; Graesser & Olde, 2003), or construct explicit (e.g., computational) models of the cases (Resnick, 1996; Wilensky, 1999a; Wilensky & Reisman, 1998, 2006).

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Benefits of a Complex Systems Perspective

As suggested by the above analysis, complex systems cases are pedagogically valuable because they give students fresh and fertile perspectives. In addition to this general benefit, there are a number of other benefits that we briefly describe here.

Inductively rich perspectives. Situations that are dissimilar according to most perspectives are seen as deeply related by a complex systems perspective. The student or scientist armed with a model of diffusion-limited aggregation (see Figure 2) may see striking similarities between lungs and window frost that are missed by most others—both consist of fractal arrangements of branches on branches. Although highly perspective dependent, complex systems concepts are inductively potent. Once frost is appreciated as an example of diffusion-limited aggregation, one can predict how it will change with time, how it will be affected by temperature, what shapes it can and cannot attain, and so on.

Bridging explanations. Learning complex systems cases (either through a specialized complex systems course or through the integration of complex systems materials in a subject area course) gives students experience with an under-represented but vitally important skill for science—explaining large-scale, macro-level phenomena in terms of local, micro-level events. The principles provide explanations of phenomena that bridge two levels, explaining, for example, how organized economies can emerge from businesses each acting in self-interest, how the spiral structure of pine cones emerges from inhibition between individual leaves as they grow, and how ordered thought emerges from neurons that simply pass electrical and chemical signals among themselves. The explanations are satisfying because they provide comprehensible mechanisms for otherwise mysterious objects and events, and because they explain the entities at a global level in terms of better understood elements that are less assumptive (Jacobson & Wilensky, 2006).

Researchers have noted that bridging between levels is difficult cognitive work. Chi (2005) argued that misconceptions of systems with emergent processes are particularly resistant to correction because students must typically make a conceptual shift across ontological kinds. Wilensky and Resnick (1999) and Penner (2000) specifically attributed the difficulty in understanding complex systems to the need to connect phenomena occurring at the microscopic level with those that occur at the macroscopic level. Wilensky and Resnick (1999) showed that people often use nonemergent constructs to bridge the levels, construing the relation between the macro and the micro in terms of the metaphors of hierarchy or containment. Wilensky and Resnick have also described a resistance to emergent explanations (Resnick, 1994, 1996; Resnick & Wilensky, 1993, 1998; Wilensky, 1999a, 2001a; Wilensky & Resnick, 1995, 1999). They have described two components of this resistance: (a) a tendency to understand complex phenomena as orchestrated by a leader or designed by a single entity and (b) a resistance to seeing randomness as constructive of order and pattern. Together they refer to these two components as the *deterministic-centralized mindset* (or DC mindset for short; Resnick & Wilensky, 1993; Wilensky & Resnick, 1995, 1999).

Unlike Chi, Wilensky and colleagues have not located the difficulties with reasoning about emergence in a need for an ontological shift. Rather, they have located the difficulties in cognitive load limitations of computing interactions of large numbers of objects, limitations in perception of objects at multiple scales and a lack of micro-level contextual clues (Sengupta & Wilensky, in press; Wilensky, 1993). When these obstacles are minimized, Levy and Wilensky (2008) have found that students can spontaneously bridge levels. Through interaction with ABM environments that reduce cognitive and perceptual limitations, students are able to use extant object-based resources to reason about emergence (Sengupta & Wilensky, 2006, in press). Wilensky, Hazzard, and Longenecker (2000) described stages in eighth graders' development of emergent reasoning. The students typically start in Stage 1 by paying attention to a single level. Then they move on to Stage 2, or being able to move between levels but still seeing the aggregate level as a simple collection of individuals, sometimes referring to the macroscopic level as an "illusion," claiming that only the individual level is real. In Stage 3 they see the emergent level as a new entity, its properties different from those of its constituents. Finally, in Stage 4 they come to see all stable entities as emergent and as processes in some kind of dynamic equilibrium.

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Researchers have also stressed another difficult aspect of bridging levels—the need to understand not only the lower level structures, but also their interactions (and mechanisms of interaction), functions, and behavior (Centola, Mckenzie, & Wilensky, 2000; Jacobson & Wilensky, 2006; Resnick & Wilensky, 1998; Wilensky & Reisman, 2006). Hmelo-Silver and Pfeffer (2004) found that the largest difference between expert and novice mental models of complex systems, such as aquarium ecosystems, is in terms of how the parts function and behave with respect to one another, not in terms of their intrinsic structures. It is understanding the interactions among parts that promotes expertise and true bridging explanations. For this purpose, ABM approaches to complex systems offer powerful advantages over equation-based descriptions for complex systems because ABMs inherently focus on the rules governing the agents' interactions, letting the higher level description fall out of the system rather than having an equation as an assumed starting point. By contrast, an equation-based approach that explicitly models macroscopic qualities such as population or temperature can encourage the false belief that these macroscopic properties follow their own independent laws rather than having bridges to elemental interactions (Chi, 2005).

Grounding for formalisms. Complex systems provide an appealing entryway to learning tools in mathematics and computation. A shared mathematical formulation applies to frost and lungs, and attaining fluency with the formulation is important for proving properties of the systems' behaviors and making quantitative predictions. However, without a bridge between the formalisms and the systems, the mathematics is frequently conceptually inert and opaque. A complex systems perspective provides a bridge because classes of system behaviors can be tied to classes of formalism.

Well-known equations describe the macroscopic behavior of the ABMs that we have described. For example, whenever a substance travels across a lattice of fixed agents and the total amount of substance is conserved, standard equations for diffusion are applicable. When substances are transmitted across the agents without conservation, equations for epidemic spread are applicable. People who bring to mind a schematic complex systems model when they are faced with its associated equation or rule set are much more likely to be able to reason flexibly about the behavior of the formalism. In this way, complex systems give students and researchers tools to connect formalisms to real-world phenomena. Formalisms can bring to mind characteristic situations, simultaneously grounding the formalism and adding a productive perspective to the situation.

Cross-fertilization between sciences. The central thesis of complex systems is that apparently unrelated systems often exhibit a common underlying principle. This thesis is a welcome antidote to the frequently myopic and alienating nature of scientific specialization. The aggregation of slime molds, the changing popularity of musical styles, and the development of regional centers of technology such as Silicon Valley can all be understood as positive feedback systems. Sand piles, earthquakes, and human memory for temporal intervals can all be understood as systems that naturally adapt to a point of self-organized criticality governed by a 1/f power spectrum (Bak, 1996; Gilden, Thornton, & Mallon, 1995). As noted by Bar-Yam (1997),

> The study of the dynamics of complex systems creates a host of new interdisciplinary fields. It not only breaks down the barriers between physics, chemistry and biology, but also between these disciplines and the so-called soft sciences of psychology, sociology, economics, and anthropology. (xii)

Taking this perspective, one can view science itself as a complex system—its component disciplines differentiate and aggregate, resulting in a dynamically transforming reorganization of the scientific world (Börner, Maru, & Goldstone, 2004).

This cross-domain applicability of complex systems principles is valuable for psychological investigations because it allows for a natural examination of the extent of transfer of a domain-general principle to different domains. Instead of creating word problems with different cover stories, or abstract schemas that can be instantiated with different insight problems, one can select diverse domains that naturally and intrinsically instantiate principles of complex adaptive systems. Systems are inherently rather than arbitrarily connected to their general principles (Bassok, 1996).

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STRATEGIES FOR PROMOTING TRANSPORTABLE UNDERSTANDINGS

Now that we have described the benefits of organizing science according to complex systems principles, our next agenda is to portray effective strategies for learning and teaching them. Generalizing beyond complex systems per se, we are interested in methods for promoting transportable knowledge. By *transportable knowledge*, we mean knowledge that is applied to domains significantly beyond those presented when the knowledge was initially acquired. We begin by contrasting a traditional strategy based on explicitly teaching formalisms with a method based on presenting general principles in concretely grounded contexts.

Generalization Through Summary Formalisms

As a tool, mathematics has historically been an unparalleled device for distilling situations to an essence. The formalizations provided by algebra, set theory, and logic are immensely powerful because they are domain general. An equation for

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combinatorics is equally applicable to the worlds of manufacturing, sports, science, and dining. Determining the number of handshakes if every person in a group shakes hands with every other person is the same problem as finding the number of possible chopstick pairs obtainable from a pile of chopsticks. Their common combinatorical equation is the palpable proof of this sameness. The domain independence of equations is the ultimate in the economy of scale to which mass production aspires. Once methods for processing formalisms are derived and validated, then they can be applied off the rack to an infinite number of situations. Customization is not only not required but forbidden within a consistent formal system. By eliminating the content of a scenario and reducing it to a purely formal equation, one is assured that the sanctioned transformations of the equation will be valid. This focus on content-irrelevant processing has led some to quip that formalists are not able to understand anything unless it is made meaningless (Smullyan, 1983), but the advantages of all-purpose formalisms are too compelling to let pass.

Given the attractiveness of formalisms, it is understandable that so many educators have been drawn to couch their explanations in terms of them. Mathematical and logical formalisms are the epitome of devices for eliminating misleading superficial features. Once equivalent manufacturing, sports, science, and dating situations have been couched in equations, it might be expected to be possible to freely transfer knowledge from one domain to another. This notion is endemic in high school mathematics curricula, which often feature abstract formalisms that, once presented, are subsequently fleshed out by examples. Systematic analyses of mathematics textbooks have shown that formalisms tend to be presented before worked-out examples and that this tendency increases with grade level (Nathan, Long, & Alibali, 2002). Word problems typically provide examples of the application of formalisms rather than justifications for why the formalism was initially developed. The justification for a formalism, if provided at all, is usually based on formal transformations of axioms.

Philosophers, mathematicians, and educators have noted the mismatch between how mathematics is publicly presented and how it is actually practiced (Lakatos, 1976; Papert, 1972; Schoenfeld, 1992; Thurston, 1994). In their own published research, mathematicians tend to provide formal proofs but not the visuospatial inspiration for the proofs. This has led mathematicians to complain that the true heart of the proof, the intuitive conceptualization, is ignored in the formal description of the proof steps themselves (Hadamard, 1949). The scholarly articles contain the step-by-step, formally sanctioned steps, but if one wishes to understand where the idea for these steps comes from, then one must attempt to generate the underlying idea oneself, without much insight from the published report. The exterior face of mathematics is presented without revealing the skeleton that is the source of the facial structures. This tendency to hide the conceptual structure has spread from the research to educational mathematical community. In mathematics textbooks, ei-

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ther formalisms are treated as givens or, when they are derived, they tend to be derived formally from other formalisms.

Mathematicians, mathematical historians, and mathematics educators have lamented the dissociation between explicit presentations of formalisms and the visual and bodily intuitions that drive the formalisms but are left out of the presentation (Lakatos, 1976; Mazur, 2003; Papert, 1980; Poincare, 1908; Wilensky, 1993). The cognitive scientists Lakoff and Nuñez (2000) argued that traditional mathematics education, with its emphasis on symbolic formalisms, bans exactly the kind of images, metaphorical thought, signs, and pictures that make mathematics one of the most imaginative activities of humankind. Their proposed solution is to teach mathematics by using the conceptual, embodied metaphors that were the original motivations for the formalisms. Arguing against claims that mathematics must be decontextualized to be transportable, these researchers showed that even mysterious quantities like i and mysterious equations like $eip = -1$ arose from the grounded experience of mathematicians at the time of discovery and can still now be made intuitive and grounded in experience.

The assumptions of the "formalism-first" approach to promoting generalization across domains are there: (a) If an equation is known, it should be able to be recognized and applied when it is relevant in a new situation; (b) generalizations are obtained by eliminating superficial features of a scenario, and this is achieved by distilling the scenario to its formalism; and (c) potential for generalization is maximized by creating the most formal, content-reduced representation.

We question these assumptions and the resulting conception of generalization via equations. We question the first assumption because the connection between equations and scenarios is typically indirect and difficult to see. Students often have difficulty finding the right equation to fit a scenario even when they know both the equation and the major elements of the scenario (Ross, 1987, 1989). We question the second assumption because elements that are construed as superficial often turn out to be critical for understanding a system. Bassok (1996; Bassok, Chase, & Martin, 1998) has found that people assume and create connections between semantic aspects of the elements in word problems and their roles in equations. For example, a problem requiring the number of apples to be divided by the number of baskets is easier to solve than one requiring baskets to be divided by apples. Students can use the semantic relation PLACE IN [apples, baskets] to infer the mathematical roles of apples and baskets in the DIVIDE [dividend, divisor] structure (Bassok, 2001). Formally equivalent word problems are not treated equivalently, and if natural parallels between semantic aspects and mathematical roles are honored, then understanding is promoted. We question the third assumption because, even though formalisms are maximally content independent, they run the risk of being cognitively inert. They offer little by way of scaffolding for understanding, and they may not generalize well because cues to resemblance between situations have been stripped. For example, there is experimental evidence that students who have taken an entire course in formal logic do not transfer what they have learned to reasoning problems outside of the class. By contrast, instruction in more grounded pragmatic reasoning schemas such as the permission schema "If the action is to be taken, then the precondition must be satisfied" produces better transfer despite the more specific nature of the schemas (Cheng, Holyoak, Nisbett, & Oliver, 1986).

Generalization Through the Interpretation of Grounded Situations

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We are in agreement with the formalism-first position that generalization is a valuable goal. Very often principles are taught in the hope that they will be applied whenever they are useful in the future. However, we offer an alternative method for promoting generalization that we believe is more likely to be successful. The motivation for this method stems from our observation of students learning principles of complex systems using computer simulations. We have observed that students often interact with the simulations by actively interpreting the elements and their interactions. Their interpretations are grounded in the particular simulation with which they are interacting. However, because the interpretations may be highly selective, perspectival, and idealized, the same interpretation can be given to two apparently dissimilar situations. The process of interpreting physical situations can thus provide understandings that are grounded yet transportable. We ground our notion of interpretive generalization with a "simulated annealing" principle example from our Complex Adaptive Systems courses (see http://cognitrn.psych.indiana.edu/rgoldsto/complex/p747description.htm and http://ccl.northwestern.edu/courses/complexity/). This scientific principle is elucidated using two computer simulations that can be downloaded from http://cognitrn.psych.indiana.edu/rgoldsto/complex.

Simulated annealing refers to a search technique that makes use of randomness in order to find optimal solutions to a problem (Kirkpatrick, Gelatt, & Vecchi, 1983). In actual annealing, ductile metal structures are formed by first heating then gradually cooling the metal. At high temperatures, the atoms of the metal have high mobility with respect to one another. If the metal is cooled slowly, thermal mobility is gradually lost. The atoms arrange themselves to form a pure crystal, thereby increasing the strength of the structure. Similarly, the notion of simulated annealing is to gradually reduce the randomness in a system. Early on, randomness helps the system sample different candidate solution spaces. Later on, stability helps the system settle down into a single strong solution. In order to find the best solution (the global minimum) rather than solutions that are merely better than their neighbors (local minima), it is often necessary to temporarily increase the randomness in the system.

Dropping Balls. A classic domain involving simulated annealing is balls dropping on a user-drawn landscape, as shown in Figures 3 and 4. Having students imagine a ball rolling with some randomness on a landscape is one of the most commonly used analogies for teaching simulated annealing. Small red balls fall according to three rules: (a) A ball will tend to fall downward because of gravity, (b) a ball also moves with a user-controlled degree of randomness (because of "chance winds"), and (c) if a ball's movement would place it on a user-drawn green patch (the landscape), then it does not move. Learners are given the general goal of developing an automatic strategy that will cause the balls to fall to the lowest region of the landscape they draw. The learner can control several aspects of the simulation by manipulating buttons, sliders, and the cursor. The learner can reset the balls' positions to the top of the screen, start and stop the balls' movements, clear the screen of all landscape, and enter in four different modes of interaction: draw landscape, erase landscape, place balls, and move balls. By manipulating sliders, learners can change five parameters of the simulation: the number of balls that are dropped, the amount of randomness in the balls' movements, the amount of movement at each time step, the size of the pen used for drawing, and the frequency of

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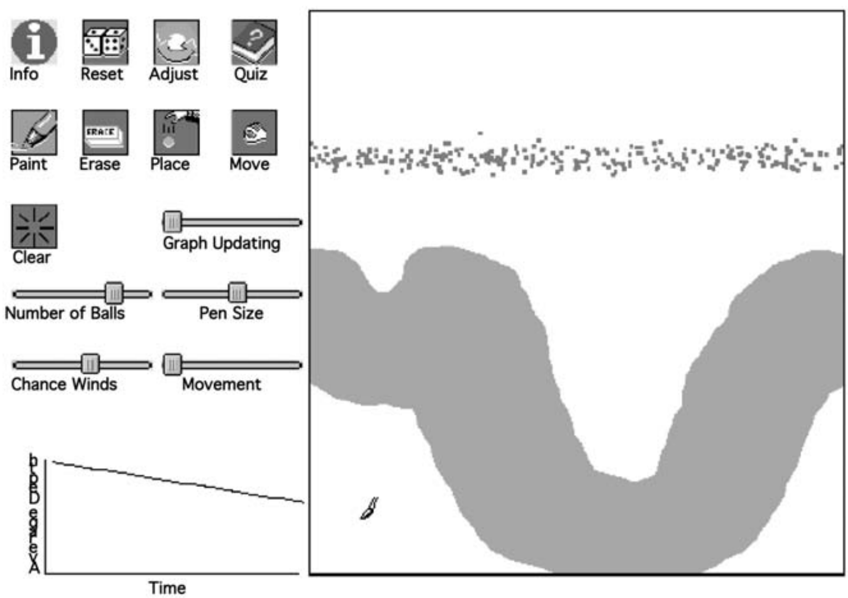

FIGURE 3 A screen-dump from the Dropping Balls simulation (Goldstone, 2005b) before the balls have completely dropped onto the landscape. User-controlled buttons and sliders, and the continuously updating graph, are shown on the left side. In the right window is a dynamically changing environment in which balls are dropping, landscapes are drawn and altered, and balls are selected and moved.

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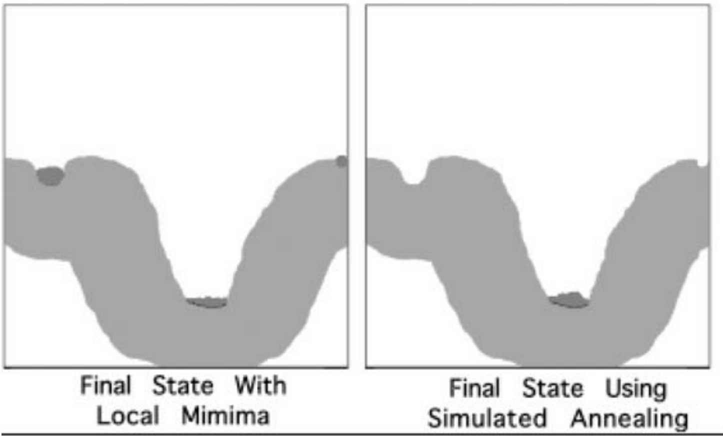

FIGURE 4 Two possible final configurations for the Dropping Balls simulation. If balls drop without much randomness added to their movements, then the final configuration of balls will typically show several local minima. A ball is in a local minimum if its location is lower than neighboring locations but is not the lowest location for the whole landscape. If the amount of randomness is gradually reduced as specified by a simulated annealing method, then all of the balls will occupy the lowest position on the landscape.

updating a running graph that shows the average depth of the balls over time. These parameters can be manipulated with immediate impact on the simulation. Starting with the configuration of balls and the user-drawn landscape in Figure 3, Figure 4 shows two possible end states. If the amount of randomness is never very large, or if the amount of randomness is reduced too quickly, then local minima are likely to arise. A local minimum occurs if a ball falls to rest in a valley that is not the deepest valley of the landscape. If randomness is gradually reduced and thus consistent with simulated annealing, then all of the balls will eventually come to rest at the lowest spot on the landscape.

Path Finder. The second example of simulated annealing involves finding a pathway to a specified location when there are obstacles in the way. The pathway ideally connects two fixed blue points at the top and bottom of the screen, avoids the green obstacles, and is as short as possible. In traditional artificial intelligence, the search for a pathway through a maze is typically viewed as a process of a single agent adding segments to its pathway and backtracking when dead ends are found. The alternative method pursued here is to have very simple agents locally influence one another's positions. Together, they globally form a path even though no agent by itself represents an entire solution. In the Path Finder simulation, the agents are represented as red balls. Each ball is assigned two "associate" balls, making a set of balls arranged from first to last. There are also two fixed blue points. One is assigned to be one of the two associates of the first ball. The other blue point is one of the associates of the last ball. The balls are then placed randomly on the screen, and green obstacles are painted on the screen. On each time step of the simulation, the red balls follow two rules: (a) Each ball moves toward each of its two associates and also moves with a certain amount of randomness controlled by a slider; and (b) if the location to which a ball would move is painted green, then the ball does not move. The buttons and sliders are similar to those used in Dropping Balls and are shown in Figure 5. Starting with the initially random configuration in Figure 5, Figure 6 shows two possible final configurations of the balls. In the configuration on the left, each of the balls is as close as it can get to its two associates without traveling through a green region. The configuration does not indicate a strong pathway between the fixed points and is typical of the kind of pattern that is found when the balls do not move with sufficient randomness or when the randomness is reduced too quickly. These "knots" cannot be avoided if the balls do not have some randomness that allows them to break out of arrangements that place them as close to their associates as possible given the constraints of the third rule, but they still are not globally good solutions. By contrast, the configuration on the right shows the kind of pattern reached by using simulated annealing.

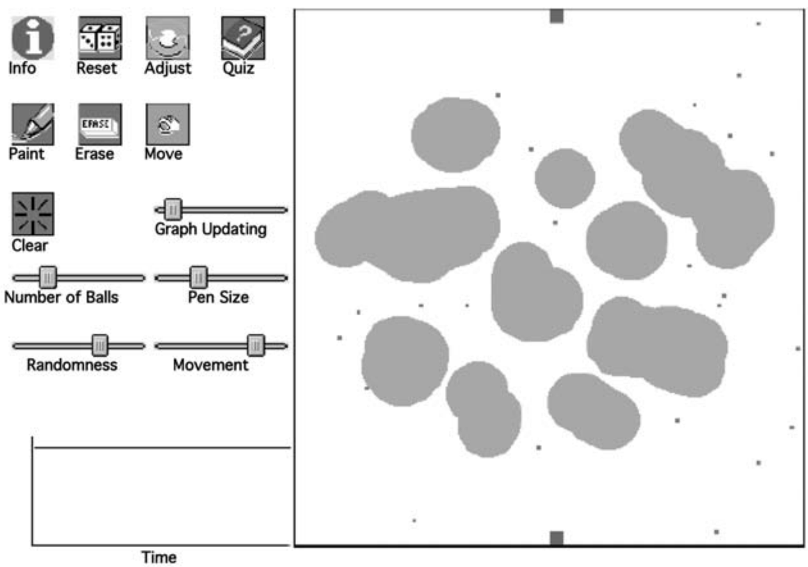

FIGURE 5 A screen-dump from the Path Finder simulation (Goldstone, 2005a). In this initial configuration, balls are randomly positioned on the screen. They move toward their prespecified two associates, unless the movement will place them on top of a patch.

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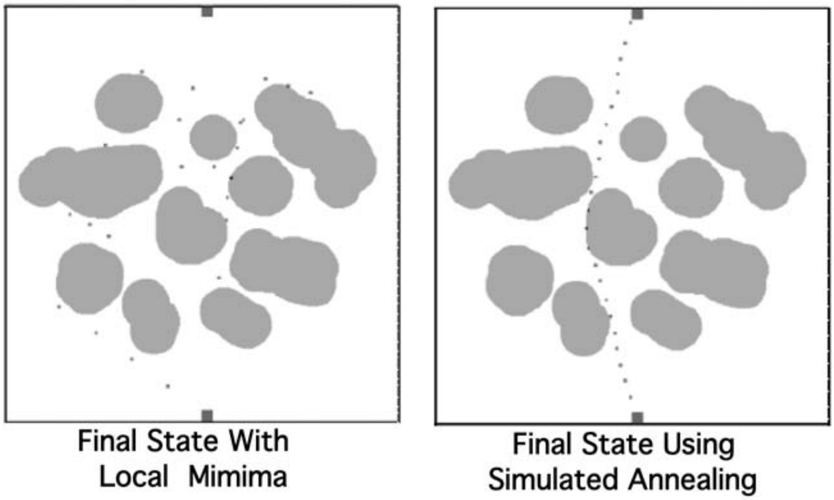

FIGURE 6 Two possible final configurations for the Path Finder simulation. If the balls move toward their neighbors without any randomness, then they will typically create "knots" that fail to form a single coherent pathway between the endpoints. If the amount of randomness is gradually reduced, then coherent pathways are formed. These two possibilities are analogous to the two possibilities shown in Figure 4.

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The situations in the left panels of Figures 4 and 6 are analogous (both showing systems that are stuck in local minima), as are the patterns on the right panels (both showing globally optimal solutions). Although these figures show some superficial similarities (red balls and green "blobs"), we continue to find transfer across these simulations when the color and parameter slider similarities are removed (Goldstone & Sakamoto, 2003). Furthermore, the superficial similarity between red balls is inviting, but this is not the correct analogical correspondence. A single red ball in Dropping Balls corresponds to the entire set of balls in Path Finder—each represents a single solution to their respective problems of finding the lowest valley and forming an efficient path, respectively.

Transporting simulated annealing. Our laboratory and classroom investigations with these two demonstrations of simulated annealing have shown that students can, under some circumstances, transfer what they learn from one simulation to another (Goldstone & Sakamoto, 2003; Goldstone & Son, 2005). In our experiments with college students who participate in 1-hr long sessions as part of their Introductory Psychology course requirement, we first give students a 20-min period of focused exploration with the Dropping Balls simulation because it embodies simulated annealing in a canonical physical example. They are then given a

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quiz of their knowledge of the simulation, and then we let students explore the Path Finder simulation. We probe their understanding of the latter simulation through (a) multiple choice questions designed to measure their appreciation of the principle of simulated annealing in the path-finding context and (b) open-ended questions in a structured interview about their conceptualization of the path-finding scenario and its connection to the dropping balls scenario.

By using this method, we have found that students show better understanding of the Path Finder simulation when it has been preceded by Dropping Balls than by a simulation governed by a different principle. Better understanding was shown both on explicit multiple choice quiz items as well as implicit action-based measures of students' interactions with the simulations. Student interviews revealed that a large part of the positive transfer was due to training perceptual interpretations of grounded situations. That is, experiencing Dropping Balls caused students to see events in the Path Finder simulation in new ways. In a small way, our students experienced what Thomas Kuhn described as the perceptual transformation of the world because of knowledge. Kuhn (1962) described how scientists, when exposed to a particular theoretical paradigm, see physical phenomena in new ways: "Though the world does not change with a change of paradigm, the scientist afterward works in a different world" (p. 121), and "during [scientific] revolutions, scientists see new and different things when looking with familiar instruments in places they have looked before" (p. 111).

Examples of transformed perceptual interpretations can be understood in connection with Figure 6. Without experience with Dropping Balls, students looking at the left panel of this figure typically described the final configuration in terms of balls simply not finding good paths. When the students were pressed on why good paths were not found, a typical response was, "The balls are attracted to each other in small clumps, but there's no reason that these small clumps should unite." By contrast, experience with Dropping Balls gave students an understanding of the left panel as a local minimum. Students now saw attractive forces between nonadjacent balls. In one student's words, "The ball here would like to move over there to be close to that ball, but it can't because of the green blob, and so it stays stuck." Another student saw the left panel as a suboptimal situation in which "the balls can't get together because they are always trying to go straight for their neighbors, but obstacles are in the way." This interpretation, in turn, frequently gave the students the insight necessary to create the coherent, globally optimal path. One student reasoned as follows:

> With no random movements, the balls will stay stuck forever. These balls are forever trying to get together, but the obstacles won't let them. So, we need to add some randomness to the balls so they don't always try the same thing. If one of these balls happens to move above this obstacle, then it can successfully move to its partner, and bring all of the rest of the balls under it along for the ride.

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Another student was even more explicit about the pertinence of local minima for Path Finder:

> Sometimes the balls get stuck in a bad configuration. The only way to get them unstuck is to add randomness to their movements. The randomness jostles them out of their bad solution and gives them the chance to find a real path.[4]

Although students rarely mentioned the connection between two simulations, it is clear that their interpretations of the second simulation were affected by their experiences with the first. What is most striking about the students' descriptions of Path Finder is the extent of knowledge-driven perceptual interpretation. Their online interpretations of the behaviors of the balls are affected by their prior exposure to a canonical simulated annealing situation. These interpretations are not simply formalisms grafted onto situations. Rather, the interpretations affect the perception of the simulation elements. The prepared students see attractive forces that create clusters of balls, stuck configurations, and obstacles that could be skirted with the injection of sufficient randomness. To the experienced eye, analogous perceptual configurations are visible in both the Dropping Balls and Path Finder simulations. Having a ball trapped in a shallow valley in Dropping Balls does not generally look like a scrambled knot of balls in Path Finder. However, if one has understood the principle of simulated annealing as applied to Dropping Balls, then one can form an interpretation that makes the two situations perceptually similar. In both cases, there is a less-than-ideal configuration that is stable. Randomness dislodges the configuration, and when randomness is gradually reduced, a more ideal configuration results. The elements of this interpretation are not purely formal elements like mathematical or logical symbols. Randomness, stability, and dislodgment all have perceptual signatures, and when these elements are selectively attended, the scenarios come to be seen as more similar than they originally were.

For this "grounded interpretation" account of generalization, transportable understandings come from the interaction between the physical elements of simulations and the interpretations of those elements. Simply giving the interpretation is not adequate. Like equations, stand-alone descriptions are unlikely to foster transfer because of their lack of contact to applicable situations. When we simply give students the rules for ball movements in Path Finder, students are seldom reminded of Dropping Balls. Physically grounding a description is one of the most effective ways of ensuring that it is conceptually meaningful. Conversely, giving the grounded situation but no interpretation is also inadequate. When the rules of either Dropping Balls or Path Finder are withheld from students, there is a general

[4]Education researchers have reported that access to controllable random events on a computer has led many students to discover the value of randomness as a tool for getting unstuck (see, e.g., Papert, 1996, 2000).

failure to transfer knowledge from one to the other. The insufficiency of the physical situation itself to provide a basis for reminding is consistent with evidence that spontaneous remindings tend to be superficial (Gentner, Rattermann, & Forbus, 1993; Keane, 1988; Ross, 1987, 1989). A single ball finding a deep valley in Dropping Balls does not bear much overall resemblance to a set of balls forming a coherent and short path in Path Finder. It is only when the interpretation is added to the presentation of the situations that the resemblance becomes apparent.

It could be plausibly argued that the situations shown in Figures 3 and 5 actually are fairly similar to each other because they involve red balls and green blobs. However, we have found other examples of transfer from scenarios that have less conspicuous similarity. Neural networks and foraging ants have been unified by the principle of competitive specialization (Goldstone & Son, 2005), which states that agents can often produce near-optimal coverage of a set of resources by repeatedly executing the steps of (a) randomly selecting a resource patch, (b) finding the agent closest to this patch and moving it quickly toward the patch, and (c) moving all of the other agents more slowly toward the patch. Participants presented with the ants and food scenario (left side of Figure 7) show transfer of this principle to the neural detector scenario (right side of Figure 7). Their original lack of subjective similarity gives way to people seeing similarities such as single agents trying to cover too many resources (if only the closest agent moves), all agents becoming too similar (if all agents move equally quickly), and spontaneous differentiation of agents so that each covers one patch (if the competitive specialization principle is followed). As another example of spontaneous transfer based on complex systems principles, we have found that foraging for spatially located re-

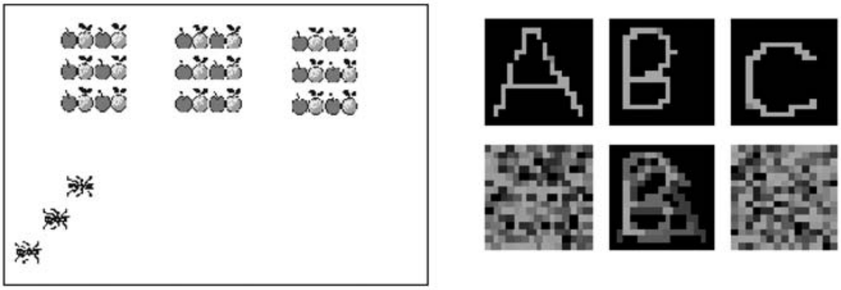

FIGURE 7 Another example of transfer between complex systems simulations (adapted from Goldstone & Sakamoto, 2003; Goldstone & Son, 2005). In this example, ants foraging for food resources are analogous to neural detectors (bottom row on right) adapting toward input patterns (top row on right). The complex systems principle instantiated by both simulations is that an effective way of having agents cover a set of resources is to have the closest agent move toward a randomly selected resource quickly while all other agents move toward the resource more slowly.

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sources in a virtual world can be unified with searching for solutions to anagram problems through the principle of exploration/exploitation trade-offs (Hills, Todd, & Goldstone, 2008). Participants who are encouraged to explore their foraging environments tend to spontaneously sample anagrams widely, and participants who are encouraged to exploit already found foraging patches tend subsequently to persevere on anagram problems. Similarly, Jacobson (2001) found transfer of broad complex systems concepts such as emergence and multiple scales of analysis to new problems. In honesty, failures to transfer principles such as these are as common as successes. Generalizing over many cases of each, our best hypothesis is that successful transfer is found when the principle to be transferred is conveyed in a visuospatial and dynamic manner and triggers core elements of a cognitive model. Some of these core elements include forces, local interactions, attraction and repulsion, movement, and state changes.

When both an interpretation and a relevant physical situation are simultaneously present, then there is an opportunity for the distant transfer of principles. Grounded situations with spatial and temporal dynamics serve as strong cues for reminding. The capacity of the interpretation to shift a learner's perspective allows only some of the physical properties to be functionally important for the reminding. A pedagogical implication is that case studies and interpretations should be intermingled rather than separated. Education researchers have long debated whether rules should be given before or after case studies. On the one hand, the vast majority of textbooks proceed from rules to examples (Bagchi & Wells, 1998; Nathan et al., 2002). The argument is frequently made that examples prior to definitions or rules are ineffective because it is not clear how the example is an example of the rule until the rule is given. This is a classic deductive argument, going from general claims to specific instantiations. On the other hand, other researchers have noted that there is a striking dissociation between teaching methods and learning preferences. Felder and Silverman (1988) noted that almost all engineering professors claim to use deductive instruction methods when teaching others, even though they themselves use inductive learning methods as much as deductive ones. Inductive methods proceed from particulars to generalities and are often useful when the generalization is difficult to comprehend. In contrast to most textbooks, some researchers have advised that "as a rule, one should start with the presentation of one or more modeling examples and then explicitly present the problem-solving phases and rules of thumb that are illustrated by those examples" (van Merriënboer, Clark, & de Croock, 2002, p. 50).

In contrast to either a "rules first" or an "examples first" strategy, our simulations use either concurrent or alternating presentations of rules and case studies. The argument that rules should be given before examples because otherwise examples are not clear neglects the fact that rules are often equally hard to fathom despite their apparent precision. In our simulations, we have often found that examples clarify rules as much as vice versa. For example, one student exploring

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Dropping Balls observed, "I read the rule that balls would move with randomness, but I didn't really understand what this meant until I saw them jiggling around." By presenting case studies and rules simultaneously, one grounds the rules and makes the case study meaningful. The power of mutually supportive rules and examples is most apparent when our students are interacting with simulations and interpreting those elements. When a student looks at the stable but stuck configuration in Figure 6 and realizes, "These balls can't break out of their pattern unless randomness is added," the student has learned something about both the principle of simulated annealing and the Path Finder simulation. The specific case study helps the students to decipher the meaning of the simulation rules, remember and spontaneously use the rules, and, most important, understand why the rules have been so devised.[5] In turn, the rules enable the students to understand the otherwise baffling motion of the balls. In a nutshell, when the simulations are effective, students are not just seeing events, they are seeing events as instantiating principles. This act of interpretation, an act of "seeing something as X" rather than simply seeing it (Wittgenstein, 1953), is the key to cultivating transportable knowledge.

Generalization Through the Constructive Modeling of Grounded Situations

ABM is a powerful technology for analyzing and depicting complex systems. ABMs are increasingly used to bring complex systems perspectives to a wide variety of fields including the natural sciences, social sciences, and engineering (e.g., Amaral & Ottino, 2004; Epstein & Axtell, 1996; Langton & Burkhardt, 1997; Ottino, 2004). Several efforts are ongoing to bring agent-based methods to educational contexts (e.g., Abrahamson & Wilensky, 2004; Ionnidou, Repenning, Lewis, Cherry, & Radner, 2003; Klopfer, 2003; Wilensky, 2003). Wilensky has focused his development effort on integrated environments that are both "low threshold" (novices can start right in on exploring and constructing models) and "high ceiling" (scientists are able to construct useful and accurate models for their research; Tisue & Wilensky, 2004). Using the multi-agent environment NetLogo[6] (Wilensky, 1999b), Wilensky and colleagues have worked with students at a variety of educational levels to explore, modify, and construct ABMs of complex systems situations (Abrahamson, Janusz, & Wilensky, 2006; Blikstein & Wilensky, 2004a; Centola et al., 2000; Levy & Wilensky, 2006; Sengupta & Wilensky, 2005a,

[5]Wilensky (1993) found that when competent students followed mathematical rules without understanding the rationale for those rules or the space of possible rules from which these rules were drawn, they experienced "epistemological anxiety" stemming from their uncertainty about the epistemological status of the rules—for example, are the rules arbitrarily or conventionally selected, or are they necessary truths?

[6]And earlier versions of it, such as StarLogoT (Wilensky, 1997c). In these languages, agents are referred to as "turtles."

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2005b; Stieff & Wilensky, 2003; Wilensky, 1999a). In one such project (Wilensky et al., 2000), they devised a secondary curriculum that explicitly asks students to practice seeing a diverse range of phenomena as "emergent." Students switch between an agent-level view and a bird's-eye view of different phenomena such as population ecologies (Wilensky et al., 2000), traffic patterns (Wilensky & Stroup, 1999), and probability distributions (Abrahamson & Wilensky, 2004). In an eighth-grade implementation of this curriculum, students learned to spontaneously switch perceptual focus in a variety of cases in which both an agent-level and an aggregate-level perspective were possible. In a science classroom, students were asked to give simple rules to agents and then describe the result "in terms of the agent's point of view and also in terms of the overall pattern." The default initialization of the agents had all of the agents at a single location but with different headings. A typical simple rule the students tried was to tell the agents to move forward 10 units. Initially, the students' two descriptions were very similar: The agent view was described as "the turtle moved 10 units," and the overall pattern was described as "all the turtles moved 10 units." After being challenged to describe the overall pattern, the students came to describe the overall pattern as "a circle of radius 10." This very simple example of an "emergent entity" served as a touchstone case. After many such (what the teacher called) "emergent exercises," students came to see the overall pattern resulting from their increasingly complex rules not as a pattern of many individuals, but instead as a description of a new emergent entity, a "population" or "aggregation" of agents. Being able to shift between these two levels of description enabled them to understand a basic complex systems principle: that properties of the individual elements of a system are not necessarily properties of the aggregate system as a whole and vice versa. A rudimentary example of students coming to understand this principle is seen through the students giving the agents a rule to move around the perimeter of the circle. Even though, from the agent's point of view, it is moving, the aggregate entity of which it is a part, the circle, stays still.

Later in the year, the class was reading an article titled "The Graying of America," describing how the U.S. population was aging. In discussing this article, the students discussed the baby boom and how the aging of that large cohort was a major factor in explaining the graying. In the class discussion, students thought about what would happen when that cohort passed on. One student said that there would be a "younging of America." The discussion proceeded to this question: "How could America be getting younger when each individual is getting older?" The students were not troubled by this apparent paradox; they explained it by referring to cases such as the agents circling where the agents' movements were strikingly different than the motion of the aggregate (Wilensky et al., 2000).

In the approach embodied in this curriculum, students are not presented with a simulation, but rather the pedagogical strategy is to present a theme that allows students to select their own situation. Students typically begin by selecting an existing simulation to explore, proceed to modify the simulation, then progress to creating a simple simulation. Creating a simulation or model of a situation forces the creator to ground his or her interpretation of the elements. Creating a simulation is a powerful strategy for extracting a general principle from the situation (see Papert, 1980). In order for the simulation to work, the student must model the mechanisms through which systems elements interact. When they encounter a new situation with similar system element interactions, students are primed to see those mechanisms at work. They can thus come to see patterns of mechanisms as in our Patterns 1 and 2.

By carefully selecting the themes and starting cases, students can be led to discover proto-versions of general complex systems principles. In the class described above, one theme was for students to create models of population-level change by devising rules of birth and death for agents and observing the resulting population levels. Typically, students started with a population of agents (each with a randomly selected color) and gave them simple birth and death rules. In one class discussion, students noticed that even though their birth and death rules did not favor one color over another, after some time, the population would end up being composed entirely of agents of the same color. Students came to understand that if one color, by chance, came to have larger numbers, then it would tend to increase its advantage. Through this case they came to an understanding of a proto-version of the principle of positive feedback (Wilensky, 2001b).[7] Papert (2000) described students trying to program a virtual creature to reach a designated target. When they tried to guide the creature directly to the target, it would get stuck if there was an intervening obstacle. However, they discovered that if they added a little random "wiggle" to the creature's movement toward the target, it would get unstuck and reach the target. In this way they discovered *a proto-version version of the principle of simulated annealing*.

THE COGNITIVE SCIENCE OF TRANSFERRING COMPLEX SYSTEMS PRINCIPLES

Thus far, we have presented an initial case for students learning complex systems principles by interacting with or constructing a simulation that embodies a general principle. Crucially, the aim is for students to actively interpret the elements of the simulation according to theoretical elements underlying the principle to be taught. Students learn how to see events as manifesting principles, and this learning prepares them for seeing future events in terms of the same principles (Bransford &

[7]And also the principle of genetic drift, under which a trait can spread through a population even though it has no selective advantage.

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Schwartz, 1999). It is difficult for anybody to spontaneously see events as manifesting mathematical formalisms, which is why transfer based upon shared formalism alone is so rare. It is far more plausible for transfer to proceed by someone applying previously learned methods of interpreting events. For example, practice interpreting the balls in Figure 4 as being stuck without randomness facilitates interpreting the paths in Figure 6 similarly (Goldstone & Sakamoto, 2003). In this section, we provide additional empirical support for transfer based on interpreting grounded situations and flesh out aspects of the proposal.

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The Flexible Perception of Similarity

> "You see," Mrs. Whatsit said, "if a very small insect were to move from the section of skirt in Mrs. Who's right hand to that in her left, it would be quite a long walk for him if he had to walk straight across." Swiftly Mrs. Who brought her hands, still holding the skirt, together. "Now, you see," Mrs. Whatsit said, "he would be there, without that long trip. That is how we travel." (L'Engle, 1962)

An important plank of our proposal is that the similarity between situations governed by the same complex systems principle can be used to promote transfer even if the situations are dissimilar to the untutored eye, and even if the similarity is not explicitly noticed. This claim apparently contradicts the empirical evidence for very limited transfer between remote situations (Detterman, 1993; Reed, Ernst, & Banerji, 1974; but see also Barnett & Ceci, 2002, for a balanced evaluation of the evidence). In fact, our claim is that the perceived similarity of situations is malleable, not fixed by objective properties of the situations themselves. It may well be that remotely related situations rarely facilitate one another. However, well-designed activities can alter the perceived similarity of situations, and what were once dissimilar situations can become similar to one another with learning. Much of the apparent inconsistency in the empirical evidence for and against remote transfer is eliminated if one considers whether the learner possesses an understanding that can relate originally unrelated situations (A. L. Brown, 1989). For example, students can transfer the survival strategy of mimicry from one animal to another if they are taught the causal principles underlying the defense mechanism (A. L. Brown & Kane, 1988). Our hope, then, is not to have students transfer by connecting remotely related situations, but rather to have students warp their psychological spaces so that formerly remote situations are similar.

There is strong evidence that this kind of warping spontaneously occurs. Objects that share membership in important categories become increasingly similar. In one study, Goldstone (1994) first trained participants on one of several categorization conditions in which one physical dimension was relevant and another was irrelevant. Participants were then transferred to same/different judgments ("Are

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these two squares physically identical or not?"). Ability to discriminate between squares in the same/different judgment task, measured by signal detection theory's d´), was greater when the squares varied along dimensions that were relevant during categorization training. The warping of similarities according to experience has been found in other laboratory experiments as well (Goldstone, Lippa, & Shiffrin, 2001; Livingston, Andrews, & Harnad, 1998; Özgen, 2004). It has also been found in cross-cultural studies on color perception (Roberson, Davies, & Davidoff, 2000), where color discriminations are affected by the color categories of one's native language. The weight of this evidence indicates that even perceptual similarities are affected by categories learned over one's lifetime as well as those learned in restricted laboratory contexts.

One might argue that these studies show relatively modest changes in similarities, but not the kind of shift that would make the ozone layer perceptually similar to organ pipes (see Table 1). However, research also indicates more radical shifts in similarities with experience. Whorf (1941/1956) argued for similarities that depend on cultural context. For Shawnee Native Americans, the sentences "I pull the branch aside" and "I have an extra toe on my foot" reflect similar situations. Roughly speaking, the first sentence would be represented as "I pull it (something like the branch of a tree) more open or apart where it forks," and the second sentence would be represented as "I have an extra toe forking out like a branch from a normal toe." Controlled laboratory studies have similarly shown that language has a large impact on conceptualization of time (Boroditsky, 2001) and that learning relational language can lead children to see abstract commonalities between situations that they would have otherwise missed (Gentner, 2003). Computer modeling languages for describing ABMs are literally languages and accordingly offer new cognitive tools for describing the phenomena of one's world. With respect to educational situations per se, case-based reasoning researchers have stressed the feasibility and importance of flexibly assessing the similarity between scenarios (Kolodner, 1997). Researchers have found that experts shift their basis for judging the similarity of problems from superficial to structural aspects (Chi, Feltovich, & Glaser, 1981; Schoenfeld & Herrmann, 1982) and that this influences their spontaneous remindings (Novick, 1988).

A sense of similarity, it seems, is highly educable. However, the real power of adaptive similarity is that it can be implicitly trained and automatically deployed (Landy & Goldstone, 2007). People seem predisposed to interpret ambiguous situations in a way that makes them similar to previously presented situations. For example, in the situation depicted in Figure 8, participants are asked to assess the similarity of either the pairs A and B or B and C (Medin, Goldstone, & Gentner, 1993). The center objects B are ambiguous and have mutually exclusive interpretations that are consistent with A or C. When participants are asked to describe how the objects A and B in the top row are similar, they frequently respond with some variant of "They both have three prongs." However, when presented with B and C,

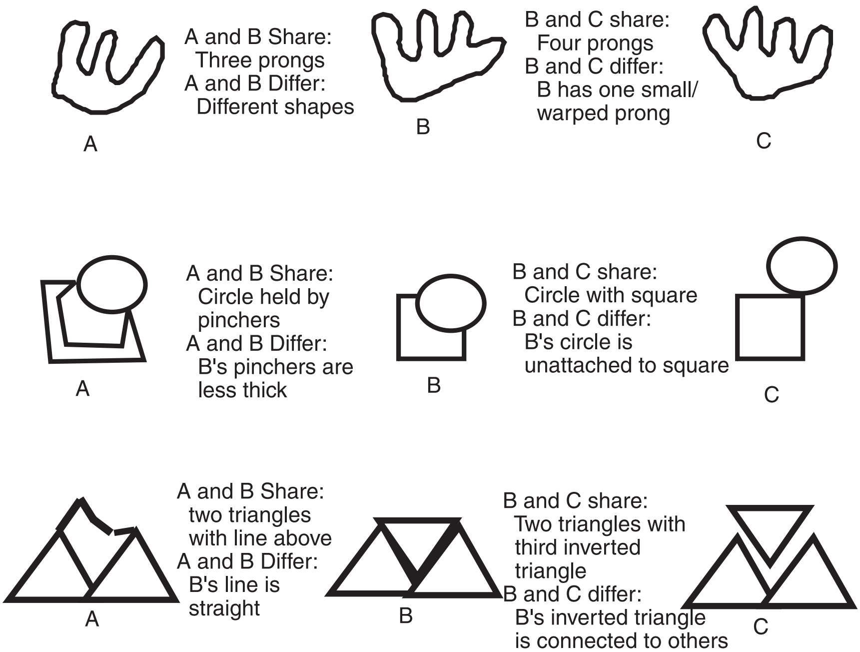

FIGURE 8 Examples of stimuli from Medin et al. (1993). Participants were asked to describe features that were shared and different between pairs of objects. The middle objects labeled B are ambiguous and tend to be interpreted in a manner that is consistent with the objects (A or C) with which they are paired. When determining both common and distinctive features, people apparently first interpret objects so as to make them more comparable.

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participants tend to respond with "They both have four prongs." Clearly, participants' representation of B is not fixed but rather is constructed as B is compared to A and C (see also Hofstadter, 1997). Objects are often interpreted in a manner consistent with previously presented objects (Bugelski & Alampay, 1961; Leeper, 1935), even when people are unaware of this influence.

With respect to teaching complex systems, the implication is that giving people experience with one system embodying a principle can prime their ability to see another system as embodying the same principle. This should be particularly true if the priming is visual, rather than strictly intellectual. Priming is particularly potent if perceptual routines are configured that can apply in new situations (Kolers & Roediger, 1984). One reason why skeptics doubt remote transfer is because of a focus on analytic and explicit transfer. It may be difficult to get people to analytically bring to mind previously learned schemas (Gick & Holyoak, 1983). Instead, we propose to teach people ways of looking at situations that become natural perceptual habits. When we say *looking*, we mean perception, but we also mean using

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representations to encode situations—just as telescopes and microscopes extend perception, so cognitive technologies can extend perception by giving people representations that extend their abilities to encode situations. diSessa and Sherin (1998) also emphasized the importance of perceptual shifts for achieving conceptual change and argued that these shifts may be both perceptual and interpretational: “In many instances this seeing is a substantial accomplishment of learning and will depend only very partially on basic perceptual capabilities” (p. 1172). In this extended sense of perceptual learning, acquiring diagramming techniques such as Euler Circles for logic, Cayley diagrams for group theory, and Feynman diagrams for quantum field theory are all methods for changing perception so that it becomes sensitive to otherwise obscure and esoteric properties of a situation. The impact of diagramming techniques like these also refutes the notion that perception is merely a passive pick-up of information present in a scenario. Diagrams, computational modeling, and the transformation of physical symbols are all active ways of actively constructing representations that change how the world appears.

Idealized but Grounded Models

Although we have been advocating grounded knowledge for scientists and students alike, we need to clarify what is and is not entailed by grounding. In particular, grounding is compatible with idealization. In fact, we consider here evidence hat models ought to be at least partially idealized if the goal is to promote trans - portable understandings.

By *grounded knowledge*, we mean knowledge that is conveyed by perceptual simulations. The simulations are perceptual in that they incorporate spatial and temporal information and do so by using brain regions that are dedicated to perceptual processing. Arnheim (1970), Barsalou (1999; Goldstone & Barsalou, 1998), and others have argued that individuals’ concepts are not amodal and abstract symbolic representations but rather are grounded in the external world via their perceptual systems. According to Barsalou’s perceptual symbols theory, conceptual knowledge involves activating brain areas dedicated for perceptual processing. When a concept is brought to mind, sensorimotor areas are reactivated to implement perceptual symbols. Even apparently abstract concepts, such as truth and negation, are grounded in complex perceptual simulations of combined physical and introspective events. Several lines of empirical evidence are consistent with a perceptually grounded conceptual system. Detailed perceptual information is represented in concepts, and this information is used when reasoning about those concepts (Barsalou, Simmons, Barbey, & Wilson, 2003). Concepts that are similar to one another give rise to similar patterns of brain activity, and a considerable amount of this activity is found in regions associated with perceptual processing (Simmons & Barsalou, 2003).

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The essence of a grounded representation is that dimensions in the model naturally correspond to dimensions of the modeled world. However, this does not require that the modeling world superficially resemble the modeled world or preserve all of the raw, detailed information of that world (Barsalou, 1999; Shepard, 1984). Researchers have found that idealized graphics can lead to better mathematical understanding than richer animations (Scheiter, Gerjets, & Catrambone, 2006). Mathematical systems are more readily transferred when they are conveyed with generic symbolic forms rather than more concrete graphical representations, even when the latter have features that intrinsically conform to the underlying formalism (Kaminski, Sloutsky, & Heckler, 2008). Similarly, our experience with students' understanding of complex systems computer simulations indicates that simulations lead to the best transfer when they are relatively idealized. Goldstone and Sakamoto (2003) gave students experience with two simulations exemplifying the principle of competitive specialization. The first simulation involved ants foraging for food, whereas the second involved categories adapting to pictures. The first simulation, that of foraging ants, was presented using either line drawings of ants and food or simplified geometric forms. Overall, students showed greater transfer to the second scenario when the elements were graphically idealized rather than realistic (see also Smith, 2003, and Son, Smith, & Goldstone, in press, for consistent results with rich vs. simple geometric objects). It is interesting that the benefit of idealized graphical elements was largest for students who had relatively poor understanding of the initial simulation. It might be thought that strong contextualization and realism would be of benefit to those students with weak comprehension of the abstract principle. Instead, it seems that poor comprehenders are particularly at risk for interpreting situations at a superficial level, and using realistic elements encourages this tendency.

Other researchers have found that idealization is often effective for promoting symbolic understanding. In a standard paradigm employed by Judy DeLoache (1991, 1995; DeLoache & Burns, 1994; DeLoache & Marzolf, 1992), a child around the age of 2.5 years is shown a model of a room, the child watches as a miniature toy is hidden behind or under a miniature item of furniture in the model, and the child is told that a larger version of the toy is hidden at the corresponding piece of furniture in the room. Children were better able to use the model to find the toy in the actual room when the model was a two-dimensional picture rather than a three-dimensional scale model (DeLoache, 1991; DeLoache & Marzolf, 1992). Decreasing children's access to a model of a room by placing it behind a window allowed children to more effectively use it as a model (DeLoache, 2000). DeLoache and her colleagues (DeLoache, 1995; Uttal, Liu, & DeLoache, 1999; Uttal, Scudder, & DeLoache, 1997) explained these results in terms of the difficulty in understanding an object as both a concrete, physical thing and as a symbol standing for something else. Word problems in mathematics presents another example in which the ability of an object to serve as a symbol decreases as its physical properties become more salient (Bassok & Holyoak, 1989).

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A natural question to ask is "How can we tell whether a particular perceptual detail will be beneficial because it provides grounding or detrimental because it distracts students from appreciating the underlying principle?" This question is not unique to complex systems principles but is crucial for the perceptually grounded ABM approaches to complex systems that we have been advocating. The answer depends on the nature of both complex systems principles and mental simulations. Complex systems models are typically characterized by simple, similarly configured elements that each follow the same rules of interaction. For this reason, idiosyncratic element details can often be eliminated, and information about any element only need be included to the extent that it affects its interactions with other elements. Mental simulations are efficient at representing spatial and temporal information but are highly capacity limited (Hegarty, 1992, 2004b). Under the assumption that a student's mental model will be shaped by the computational model that informs it, we suggest the following prescriptions for building computer simulations of complex systems: (a) Eliminate irrelevant variation in elements' appearances, (b) incorporate spatial–temporal properties, (c) do not incorporate realism just because it is technologically possible, (d) strive to make the element interactions visually salient, and (e) be sensitive to peoples' capacity limits in tracking several rich, multifaceted objects.[8] Another empirically supported suggestion for compromising between grounded and idealized presentations is to begin with relatively rich, detailed representations and gradually idealize them over time (Goldstone & Son, 2005; see also Medin & Ross, 1989, for their discussion of "Conservative Generalization"). This regime of "concreteness fading" was proposed as a promising pedagogical method because it allows simulation elements to be both intuitively connected to their intended interpretations but also eventually freed from their initial contexts in a manner that promotes transfer.

The above prescriptions for the design of simulations imply corresponding prescriptions for the design of computer modeling environments. To facilitate the construction of simulations compatible with students' mental models, such environments must provide interface elements and language constructs that facilitate the construction of simulations that satisfy these criteria. Tisue and Wilensky (2004) described how these design principles continue to guide the development of NetLogo.

Developmental Considerations for Teaching and Learning About Complex Systems

For there to be positive change in science classrooms, arguments for the utility of complex systems concepts must mesh with what is known about children's capacities for understanding these concepts. If the necessary concepts are fundamentally

[8]See Kornhauser, Rand, and Wilensky (2007) for design principles for taking into account human capacity limits.

too advanced for children to acquire, then even if the concepts are fertile and offer the promise of generalizeable knowledge, it may be irresponsible to organize a scientific curriculum around them. Some research suggests that there are reasons to believe that caution is necessary. Penner (2000) found that middle-schoolers have difficulties connecting changes at the micro-level to patterns at the global level, understanding that a system may not be governed by a single causal force, and appreciating that even a small micro-level change can have a large macro-level impact. In a partially overlapping description, Chi (2000; Chi, Slotta, & De Leeuw, 1994) has identified difficulties that novices have with understanding nonlinear influences of causal events, considering critical interactions between agents at the micro-level, and grasping emergent processes as the result of interactions between a collective and an environment. Children frequently harbor misconceptions, classifying heat or electricity as material substances rather than emergent processes, for example (Chi, 2005). Consistent with this tendency for children to see their world in terms of substances rather than processes, Hmelo-Silver and Pfeffer (2004) found that children (and novice adults) explaining the operation of aquarium ecosystems focused on structures and provided few functional or behavioral descriptions, whereas experts were more likely to employ all three components in their explanations.

The account of children's difficulties as based on the dichotomy between substance- and process-based classifications remains controversial. Considering Chi's domain of electricity, Sengupta and Wilensky (2006, in press) have argued that misconceptions about electricity result when otherwise productive knowledge elements are activated because of predominantly macro-level contextual cues. They argued that the same knowledge structures that Chi and her colleagues have identified as "materialistic" or "object-based" (Chi et al., 1994) can be bootstrapped to engender a correct understanding when the same phenomenon (e.g., electric current in a circuit) is computationally represented in an *emergent* fashion in terms of the atoms, ions, and electrons in the various circuit elements and their interactions. In other words, the same object-based knowledge elements, when activated because of both aggregate-level and micro-level contextual cues embodied in the NetLogo-based emergent representations of electric current in a circuit, can generate a productive sense-of-mechanism of the represented phenomena in the learners' minds (Sengupta & Wilensky, in press). All of these studies, however, were conducted with complex phenomena that were not very familiar to the children. Levy and Wilensky (2008) studied children's reasoning about more familiar emergent phenomena such as social emergent systems. Sixth-grade students were interviewed regarding social emergent systems that they experience in everyday life, such as moving at the start of a physical education class in order to do their exercises. Levy and Wilensky found that the interviewees were able to effectively reason about such systems. The students did so by resegmenting the system to include a midlevel grouping to support a mental simulation at two description levels. In

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short, there is evidence that children, and perhaps everybody (Resnick, 1994; Resnick & Wilensky, 1993; Wilensky & Resnick, 1999), have biases against the correct interpretation of many complex systems and also that these biases can be overcome in familiar or well-designed contexts.

What are the implications for instructional design given the developmental discussion above? These cognitive challenges can be addressed by appropriate pedagogical designs and learning environments. Several suggestions exist for doing precisely this. First, Papert (1991) found that children are particularly prone to building new knowledge when they are actively engaged in constructing external artifacts upon which they can reflect. Second, these artifacts can be virtual rather than corporeal. Students building NetLogo models develop special awareness of the constituent objects and their interactions that embody processes that give rise to eventual constructions (Wilensky, 2001a; Wilensky & Reisman, 2006). A computer program is nothing more than a process for creating patterns, and learning complex systems through programming is a promising way to have students develop process-based perspectives.

Third, pertaining to their view of children's ontological misclassifications of phenomena as responsible for the children's difficulty understanding complex systems, Slotta and Chi (2006) developed "ontology training" materials explicitly designed to prevent misclassifications and buttress the category of emergent processes. This training has succeeded in preventing students' misconceptions (e.g., claims that "bulbs closer to the battery come on before bulbs farther away, and burn brighter," which suggests that electricity is a substance) and in facilitating correct systems-level understandings.

Fourth, well-designed technology can help students make the crucial bridge between agent-based and aggregate forms of reasoning. Children may often lack practice in the metacognitive facility to strategically shift between seeing the trees and the forest. In these cases, simulations and experiences can be crafted to facilitate the switch. For example, NetLogo-based curricula (e.g., Blikstein & Wilensky, 2004b; Sengupta & Wilensky, 2005a, 2005b) are designed to facilitate the switch through bootstrapping students' object-based knowledge at multiple levels—agent, aggregate, and midlevel. Furthermore, participatory simulations can be designed in which each student in a classroom plays the role of an agent within the system (Colella, 2000; Goldstone, Roberts, & Gureckis, 2008; Wilensky & Stroup, 1999). Given that the student viscerally appreciates his or her own agent's perspective, if the classroom's overall behavioral pattern is sufficiently salient, the student can relatively easily shift his or her attention between levels. Other design solutions for facilitating cross-level attention include (a) highlighting the activity of one agent by giving it a distinctive mark or tracking it, (b) allowing user-controlled speed control so that students can slow down a simulation to see individual interactions and then speed it up to see the global pattern, and (c) providing students with a method for dynamically controlling their level of spatial resolution by zooming in and out of the world.

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In sum, there is evidence both that complex systems can be difficult for children to understand, but also that interventions, technology, and appropriate learning environments have proven effective in meeting the challenges inherent in these topics. These topics are too important to wait for adulthood. In the American Association for the Advancement of Science's (1993) benchmarks for scientific literacy, four themes were seen as running through all of science: (a) models, (b) scale, (c) constancy and change, and (d) systems. A complex systems perspective is pivotal to each of these themes.

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COMPARISON TO EXISTING APPROACHES TO TRANSFER

An appreciation of the power of complex systems principles, and how they are effectively taught, adds a useful perspective to the large and growing literature on transfer (reviewed by National Research Council, 1999). Transfer is a multifaceted topic that has been tackled from many perspectives (Carraher & Schliemann, 2002). What is meant by *transfer*, and whether transfer is found, is defined by task, content, and context. Complex systems are a natural domain for exploring transfer because superficially dissimilar systems are inherently connected to one another by these principles. The most meaningful evidence that learners have appreciated these connections is that they can better understand one system after having experienced another system governed by the same principle.

The Role of Formalisms in Transfer

In an earlier section we distinguished the approach we advocated (i.e., of getting students to interpret grounded situations) from a formalism-first approach in which transfer occurs primarily by learning formalisms that connect superficially unrelated situations. Learners are most likely to transfer what they have learned when they have developed a causal mental model (Gentner & Schumacher, 1986). The problem with formalisms is that, even when they have been acquired, it is difficult to recognize when the formalism is applicable to a situation, and so spontaneous transfer is unlikely.

Naturally, pedagogy matters, and it is possible to tie formalisms to situations during teaching. In fact, we see ABMs as playing exactly such a linking function by being physically instantiated on the one hand, but also amenable to formal analysis on the other hand. Another reason why ABMs are well poised for connecting formalisms to the world is that they provide a motivation for developing a formalism in the first place. In the same way that exploring a dynamic geometry environment (Goldenberg & Cuoco, 1998) can motivate students to develop a formal proof for events that they observe ("Hmm, when I draw the angle bisectors for each

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of the angles of this triangle, they meet at a single point. Hey, they always do no matter how I change the triangle! Why is this so?"), exploring ABMs gives students a wealth of observations that are candidates for formalisms or at least formal thought. As students observe a chemical diffusing in a space, they may observe that, macroscopically speaking, the chemical always spreads from regions of higher concentration to lower concentration even though, microscopically, each molecule of the chemical is moving randomly. Observing this apparent cross-level discrepancy between high-level regularity and low-level randomness can usefully problematize the situation for students in a way that can lead them to make sense of or develop formalisms for Brownian motion and perhaps even Einstein's general expression for diffusion. Moreover, even if students never achieve these formalisms, by thinking carefully about the ABM they can still make substantial progress in predicting distributions over time of different chemicals in different spaces.

If ABMs play a valuable role in attaching formalisms to situations, one pedagogically useful enterprise would be to develop a table of ABM principles and their associated formalisms and to teach students these connections. As an example, consider random walk processes that are implicated in the Brownian motion of molecules, the search paths of foraging animals, fluctuating stock prices, and the dynamics of human decision making. In the one-dimensional version of all of these situations, the expected distance of a randomly moving agent from its starting point after N unit-length steps is $\sqrt{\frac{2N}{\pi}}$. The connection between this equation and the actual random walk process is clarified substantially by creating a simple simulation of an agent making random left–right movements iteratively.[9] It becomes clear that the agent's distance from the starting point increases with the number of steps it has taken, but it increases less quickly than linearly because many movements will cancel one another out. The ABM is useful for justifying and grounding some of the aspects of the equation, and the equation itself is useful for connecting random walk processes to the central limit theorem, pi, and other mathematical relations.

Although we are not sanguine about the prospects of formalism-first approaches to transfer, we also do not advocate a "formalism-never" approach. Once a grounded mental model has been built for a complex system, it can provide a scaffold for constructing mathematical and logical formalisms. The advantage of eventually generating formalisms is that, like simulations, they provide new ways of interpreting complex situations. Perhaps even more so than simulations, mathematical formalisms (either in the traditional form of equations or in the newer form of computational rule sets) are able to connect superficially dissimilar situations.

[9]See, for example, Wilensky (1998).

For example, once one has learned a reaction–diffusion equation, relevant situations are likely to be naturally decomposed into activators and inhibitors. The formal distinction between these elements helps propel the conceptual distinction. The very fact that equations and their elements are labeled provides useful tags for accessing them. Simply knowing that a formalism is called the Lotka–Volterra equation is not likely to help somebody identify instances of it. However, if one understands the critical elements of the equation (e.g., the birth rate of prey, the efficiency with which prey are turned into predators, and the death rate of predators), then one will tend to see future situations in terms of these elements. If one of these variables is hidden within a system, knowledge of the equation can give one the impetus to uncover it. In addition, when one hears that Lotka–Volterra equations are relevant to a situation, a constellation of expectations and causal models are brought to mind. Formalisms provide important "handles" for rich relational structures. Like the handle of a mug, when the formalism is manipulated, the structure that it is connected to is also apprehended, and it has the potential advantage of being easier to grasp.

The above discussion groups formalisms together as if they were all equivalent. However, not all formalisms are created equal—formalisms differ in the degree to which they admit grounding and more naturally fit with perceptual and motor schemes. Wilensky and Papert (Wilensky, 2006) have presented a framework for assessing representations as they relate to content. They use the word *structuration* to describe the encoding of some domain of content using a particular representational infrastructure. A *restructuration*, then, is a reencoding of the content using an alternative representation. Using this framework, we can examine properties of structurations, including their ability to transfer, and compare them across dimensions. Wilensky and Papert have argued that agent-based formalisms are a more natural fit with perceptual and motor schemes that aggregate equations as they describe properties of individuals. Agent actions such as move forward, turn, eat can easily be understood in terms of human actions. This is similar for agent perceptions. Furthermore, because agent-based representations are so easy to modify in an environment like NetLogo, "what if" experiments can easily be conducted and the modified representations immediately linked to visualized behavior.

Grounded but Transportable Knowledge

Several other researchers have proposed ideas similar to our notion of transfer of interpretations of grounded situations. Our notion blends the concreteness of actual situations, as filtered through mental and computer models, with the perspective-dependence and idealization of interpretations. Other researchers have described the concept of situated abstraction (Hoyles & Noss, 1992, 1994; Noss & Hoyles, 1996) or situated generalization (Carraher, Nemirovsky, & Schliemann,

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1995) to highlight the interpenetration and inseparability of concrete (specific and contextual) and abstract (general) learning. Wilensky (1991) described the process of concretion (as opposed to abstraction) to highlight the groundedness of non-superficial understanding. Hoyles and Noss discussed situated abstractions as emerging from a wealth of previous learning experiences. This work, like our own, provides an account of how early experience can inform later experience without abandoning concrete spatial–temporal aspects of the original experience. Noss and Hoyles noted that new technologies, often computational, offer effective alternatives to the use of abstractions. They noted, "This we suggest is not an accident: the constraints and boundedness of static media are often invisible due to their ubiquity so that their role in 'non-transfer' is not recognized" (Hoyles & Noss, 2004, p. 382). The science of complex systems, deeply embedded as it is in computational media, is thus a natural candidate for offering improvements to the frequent lack of transfer afforded by static media.

Our empirical research has led us to propose computer simulations that are perceptually grounded yet also idealized in many respects. This proposal runs counter to much of the work in virtual reality that has as an explicit goal the realistic mimicking of real-world phenomena (Grady, 1998; Heim, 2000). To be fair, there is definite virtue to virtual reality, particularly when the performance one wishes to learn is specific to a particular situation, such as driving a race car or flying a Cessna Skyhawk. However, if one is a science or mathematics teacher predominantly interested in having students apply their learned knowledge and skills to new and markedly different situations than those initially trained, then there is evident power to visualizations that abstract from, or distort, reality (Hegarty, 2004a; Schwan & Riempp, 2004). Similar to our findings with poor comprehenders being distracted and overly constrained by realistic details, Lowe (2003, 2004) found that novices are often distracted by perceptually salient aspects of a realistic and dynamic display rather than deeper, and more important, relational aspects. Lowe (2004) concluded that learners will often require specific guidance regarding search strategies so that they will not be distracted by salient visual elements. This is consistent with our efforts to provide learners with not just interactive simulations but also the apparatus needed to guide their interpretations of these simulations. When combined with rules that guide interpretation, idealized computer simulations can be appropriated into productive and generative mental models (Rieber, 1992). Rieber, Tzeng, and Tribble (2004) found that learning with graphical simulations was more successful when it was supplemented with written and graphical explanations. It is possible to have knowledge that is both grounded and airborne. A contribution of a complex systems perspective beyond this previous work has been to provide guidelines on which aspects of a real-world system should be perceptually instantiated and that should be idealized.

Our emphasis on educating students to interpret concrete situations according to models straddles a commonly made division between low-road and high-road transfer (Salomon & Perkins, 1989). *Low-road transfer* results from extensive, varied practice and the automatic triggering of routinized, stimulus-controlled behavior in new situations. *High-road transfer* involves the deliberate generalization of principles that apply across contexts and is exemplified by the explicit application of previously learned mathematical formalisms. The perceptually mediated nature of our transfer is consistent with the nonstrategic nature of low-road transfer as well as with Bransford and Schwartz's (1999) observation that using old materials to facilitate learning of new material frequently occurs in the absence of conscious remindings even though the old materials have successfully led to preparation for future learning. The perceptually grounded nature of transfer is also consistent with results showing that people employ mental models that are analog in the sense that they intrinsically embody constraints similar to those found in physical situations, such as the necessity to rotate through intermediate angles when reorienting an object (Schwartz & Black, 1996a, 1996b). Our students seem to develop new ways of looking at situations that depend upon their previous learning, but they are not typically intellectually aware of this debt. However, because the learned mental models are idealized, they do naturally apply across contexts, and they also support the development of mathematical formalisms. This "middle-road" transfer is both perspectival and automatic and is consistent with Mayer's (2004) call for specific transfer based on general knowledge.

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Situated Learning

A major theoretical position related to transfer was developed in the 1980s and 1990s and called *situated learning*. This community argued that learning takes place in specific contexts, and these contexts are essential to what is learned (Lave, 1988; Lave & Wenger, 1991). Traditional models of transfer were criticized as treating knowledge as a static property of an individual rather than as contextualized or situated, both in a real-world environment and a social community. According to situated learning theorists, one problem of traditional theorizing is that knowledge is viewed as tools for thinking that can be transported from one situation to another because they are independent of the situation in which they are used. In fact, a person's performance on school tasks is often worse than his or her performance on a street task even though by some analyses, the same abstract tools are required (Nunes, 1999).

Our approach has a number of similarities and differences in relation to the situated learning perspective. One of the primary similarities is that we view the similarity of tasks or situations as the result of activity by both the problem solver and the community. We are dubious of attempts to find an objective metric for measuring the distance between situations. The educability of similarity is pivotal for us. Accordingly, we have talked about learning as changing the perceived similarities between scenarios rather than learning as allowing people to relate dissimilar scenarios (see also Greeno, 2006). A second similarity is that we both emphasize grounded knowledge. For us, knowledge is not simply in the extracted verbal description of a situation but rather in the interpretation of a concrete scenario. Learning consists of developing methods for processing concrete situations, methods that may be widely applicable.

One of the most obvious differences is that we continue to frame learning in terms of transfer, a suspect notion for some situated learning theorists (J. S. Brown, Collins, & Duguid, 1989; Lave & Wenger, 1991). Brazilian children who sell candy may be quite competent at using currency even though they have considerable difficulty solving word problems requiring calculations similar to the ones they use on the street (Nunes, 1999). This case study has become a paradigmatic example of the contextualized nature of knowledge according to situated learning theorists, and it is very different from the kind of cross-domain transfer we have tried to teach and champion. We have championed this cross-domain transfer because, as described in the first section, we believe that complex systems principles are valuable additions to the science curriculum and to science more generally and that the same complex systems principle arises in numerous domains. Given these beliefs, we have been compelled to try to distill natural situations to idealized mental models, agent rule sets, and/or mathematical formalisms.

These similarities and differences highlight two different senses of knowledge decontextualization. We are not advocating decontextualized knowledge in the sense of formalism-based transfer. Formalisms per se rarely provide the basis for deep remindings (Ross, 1989). Instead, knowledge should be couched in terms of learned processes for interpreting concrete scenarios. However, there is another sense of decontextualization that we do support. We believe in the importance of complex systems principles, and that the same principle applies in multiple situations. Accordingly, we support learners acquiring principles of complex systems in a way that enables the principles to be recognized in the myriad of concrete forms that they can take. For example, we are interested in people recognizing both microphones attached to speakers and fashion-buying habits as positive feedback systems. This is achieved by people creating mental models of the situations that feature a variable whose presence causes more of the variable to be produced. We seek learning and teaching methods that enable people to develop mental models that implement general complex systems principles while at the same time pushing for spatial–temporal grounding for those models.

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Integration With Other Approaches to Transfer

We have proposed transferring complex systems knowledge by having students rig up their perceptual systems to perceive situations in a manner informed by a provided or constructed rule set and then simply "leave this rigging in place" when presented with new situations (see also Goldstone, Landy, & Son, in press). Although we have been impressed with the effectiveness of this perceptual–interpretive transfer, we certainly do not mean our advocacy to imply the inadequacy of other methods. Other promising methods include (a) giving students multiple examples of the same principle (Gick & Holyoak, 1980, 1983), (b) encouraging students to explicitly compare (Gentner, 2005) and contrast (Schwartz, Bransford, & Sears, 2005; Schwartz, Sears, & Chang, in press) deeply related examples to better appreciate their unique properties (Marton, 2006), and (c) helping students to connect their contextualized knowledge to other efforts in their communities and to other contexts (Engle, 2006). In fact, our methods can be effectively combined with these others. Connecting with the second method, students who manipulate parameters of our ABMs using interactive controls benefit from comparing and contrasting the results of the minimally different simulation runs. Students who construct simulations go even further by comparing and contrasting variations in the underlying model. Connecting to the third method, students who discuss their predictions for simulation outcomes in a class come to be able to adopt multiple perspectives on a phenomenon, a particularly useful enterprise when thinking about ABMs because of their inherent multilevel nature.

Our use of ABMs to teach complex systems topics fits under the wide umbrella of embodied cognition (Barab & Roth, 2006; Clark, 1998) but also helps to disentangle various claims that are made by this community. Our observations have supported visuospatial grounding and the importance of educating perceptual–motor skills, not simply abstract reasoning. We also support a conception of minds as extended to include the simulations (and other people) with which students interact to form predictions and understandings. Finally, our simulations are instance grounded in the sense of instantiating individual agents and their interrelations rather than modeling summary properties of whole systems. However, given our, and other researchers', success with strategic idealizations, we see dangers in situational grounding when it treats narratively rich, situation-specific details as necessarily beneficial. Important work must still be done in isolating the separate consequences of the 5 E's of "wide" cognitive science (embodied, embedded, extended, enactive, and ecological cognition). Our current wager is that the kind of situational information that ought to be preserved when learning complex systems is that which captures spatially grounded and individual-level interactions.

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SUMMARY

Our line of argumentation makes several interrelated claims. (a) We argue that understanding complex systems principles is important scientifically and pedagogically. Seemingly unrelated systems are often deeply isomorphic, and the mind that is prepared to use this isomorphism can borrow from all of science in understanding a concrete scenario. (b) Complex systems principles are unique because they

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lead to the construction of categories that are both perspective dependent and inductively powerful. Because they are perspectival, these categories are not likely to be discovered without guidance. Teaching these categories is worthwhile because of their inductive potential. (c) If one is committed to fostering the productive understanding of complex systems, then one must be interested in promoting knowledge that can be transported across disciplinary boundaries. (d) Our observation of students interacting with complex systems simulations indicates that one of the most powerful educational strategies is to have students actively interpret situations. A situation's events inform and correct interpretations, and the interpretations give meaning to the events. (e) One effective way for students to make these interpretations is for them to construct models of the situations. This is particularly easy to do using ABMs, for which the modeling is done at the level of the individual. Modeling requires students to explicitly make interpretive choices. (f) Perspective-dependent interpretations can promote transfer where formalism-centered strategies fail, by educating people's flexible perception of similarity. Transfer, by this approach, occurs not by applying a rule from one domain to a new domain but rather by allowing two scenarios to be seen as embodying the same principle. Complex systems theory opens up new ways of organizing science according to underlying principles, not according to established disciplines such as biology, physics, chemistry, and psychology. (g) To realize this promise, we recommend that computer simulations be designed or student-constructable so as to mesh well with idealized mental models. For transportable knowledge, realism is sometimes disadvantageous. Computer models, like their corresponding mental models, should be spatially–temporally grounded to take advantage of individuals' highly evolved perceptual capabilities but idealized in other respects to reduce cognitive load and increase generality.

As is clear from the preceding paragraph, the steps in this argument depend upon and extend one another. To the reader's exasperated question "Is your foremost agenda to argue for benefits of thinking in terms of complex systems principles, or to describe ways of achieving scientific transfer?" our reply is an emphatic "Yes!" We have fused these two agendas because the cognitive science of transfer explains why complex systems principles are cognitively beneficial, and the existence of cross-discipline connections between the sciences motivates the effort to learn how to achieve transportable knowledge. The transfer of knowledge across disciplinary lines is cognitively possible because it scientifically exists (see Table 1), and it is scientifically possible because it cognitively exists.

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REFERENCES

Abrahamson, D., Janusz, R. M., & Wilensky, U. (2006). There once was a 9-block … —A middle-school design for probability and statistics. *Journal of Statistics Education, 8*(1). Retrieved September 13, 2008 from http://www.amstat.org/publications/jse/v14n1/abrahamson.html.

Abrahamson, D., & Wilensky, U. (2004, July). S.A.M.P.L.E.R.: Collaborative interactive computer-based statistics learning environment. *Proceedings of the 10th International Congress on Mathematical Education.* Retrieved September 13, 2008 from http://www.icmeorganisers.dk/+sg11/Papers/Abrahamson%20&%20Wilensky.doc

Ainsworth, S., & Loizou, A. T. (2003). The effects of self-explaining when learning with text or diagrams. *Cognitive Science, 27,* 669–681.

Amaral, L. A. N., & Ottino, J. M. (2004). Complex networks: Augmenting the framework for the study of complex systems. *European Physical Journal B, 38,* 147–162.

American Association for the Advancement of Science. (1993). *Benchmarks for science literacy.* New York: Oxford University Press.

Arnheim, R. (1970). *Visual thinking.* London: Faber & Faber.

Arthur, W. B. (1988). Competing technologies: An overview. In G. Dosi, C. Freeman, R. Nelson, G. Silverberg, & L. Soete (Eds.), *Technical change and economic theory.* London: Pinter, 114–135.

Arthur, W. B. (1989). Competing technologies, increasing returns and lock-in by historical events. *Economic Journal, 99,* 116–131.

Bagchi, A., & Wells, C. (1998). Varieties of mathematical prose. *Primus, 8,* 116–136.

Bak, P. (1996). *How nature works: The science of self-organized criticality.* New York: Springer-Verlag.

Ball, P. (1999). *The self-made tapestry.* Oxford, England: Oxford University Press.

Barab, S. A., & Roth, W. (2006). Curriculum-based ecosystems: Supporting knowing from an ecological perspective. *Educational Researcher, 35*(5), 3–13.

Barabási, A. (2002). *Linked: The new science of networks.* Cambridge, MA: Perseus.

Barabási, A., & Albert, R. (1999, October 15). Emergence of scaling in random networks. *Science, 286,* 509–512

Barnett, S. M., & Ceci, S. J. (2002). When and where do we apply what we learn? A taxonomy for far transfer. *Journal of Experimental Psychology: General, 128,* 612–637.

Barsalou, L. W. (1999). Perceptual symbol systems. *Behavioral and Brain Sciences, 22,* 577–660.

Barsalou, L. W., Simmons, W. K., Barbey, A. K., & Wilson, C. D. (2003). Grounding conceptual knowledge in modality-specific systems. *Trends in Cognitive Sciences, 7,* 84–91.

Bar-Yam, Y. (1997). *Dynamics of complex systems.* Reading, MA: Addison-Wesley.

Bassok, M. (1996). Using content to interpret structure: Effects on analogical transfer. *Current Directions in Psychological Science, 5,* 54–58.

Bassok, M. (2001). Semantic alignments in mathematical word problems. In D. Gentner, K. J. Holyoak, & B. N. Kokinov (Eds.), *The analogical mind* (pp. 401–433). Cambridge, MA: MIT Press.

Bassok, M., Chase, V. M., & Martin, S. A. (1998). Adding apples and oranges: Alignment of semantic and formal knowledge. *Cognitive Psychology, 35,* 99–134.

Bassok, M., & Holyoak, K. J. (1989). Interdomain transfer between isomorphic topics in algebra and physics. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 15,* 153–166.

Batty, M., & Longley, P. A. (1994). *Fractal cities: A geometry of form and function.* New York: Academic Press.

Bentley, W. A., & Humphreys, W. J. (1962). *Snow crystals.* New York: Dover.

Blikstein, P., & Wilensky, U. (2004a). MaterialSim: An agent-based simulation toolkit for materials science learning. *Proceedings of the International Conference on Engineering Education.* Retrieved September 13, 2008 from http:/www.succeed.ufl.edu/icee/Papers/402_BliksteinICEEFinalPaper_(3).pdf.

Blikstein, P., & Wilensky, U. (2004b). *MaterialSim model-based curriculum.* Evanston, IL: Northwestern University, Center for Connected Learning and Computer Based Modeling. Available at http://ccl.northwestern.edu/curriculum/materialsim

Blikstein, P., & Wilensky, U. (2005). *Less is more: Agent-based simulation as a powerful learning tool in materials science.* Paper presented at the Agent-Based Systems for Human Learning Workshop, 4th International Joint Conference on Autonomous Agents and Multiagent Systems, Utrecht, Holland.

Blikstein, P., & Wilensky, U. (2006). A case study of multi-agent-based simulation in undergraduate materials science education. *Proceedings of the Annual Conference of the American Society for Engineering Education.* Retrieved September 13, 2008 from http://www.asee.org/acPapers/code/getPaper.cfm?paperID=10906&pdf=2006Full2496.pdf.

Börner, K., Maru, J. T., & Goldstone, R. L. (2004). The simultaneous evolution of article and author networks in PNAS. *Proceedings of the National Academy of Science, USA, 101,* 5266–5273.

Boroditsky, L. (2001). Does language shape thought? English and Mandarin speakers' conceptions of time. *Cognitive Psychology, 43,* 1–22.

Bransford, J. D., & Schwartz, D. L. (1999). Rethinking transfer: A simple proposal with multiple implications. *Review of Research in Education, 24,* 61–101.

Brown, A. L. (1989). Analogical learning and transfer: What develops? In S. Vosniadou & A. Ortony (Eds.), *Similarity and analogical reasoning* (pp. 369–412). New York: Cambridge University Press.

Brown, A. L., & Kane, M. J. (1988). Preschool children can learn to transfer: Learning to learn and learning from example. *Cognitive Psychology, 20,* 493–523.

Brown, J. S., Collins, A., & Duguid, P. (1989). Situated cognition and the culture of learning. *Educational Researcher, 8*(1), 32–42.

Bugelski, B. R., & Alampay, D. A. (1961). The role of frequency in developing perceptual sets. *Canadian Journal of Psychology, 15,* 201–211.

Carraher, D. W., Nemirovsky, R., & Schliemann, A. D. (1995). Situated generalization. *Proceedings of the 19th Annual Meeting of the International Group for the Psychology of Mathematics Education, 1,* 234.

Carraher, D., & Schliemann, A. D. (2002). The transfer dilemma. *Journal of the Learning Sciences, 11,* 1–24.

Centola, D., McKenzie, E., & Wilensky, U. (2000). Survival of the groupiest: Facilitating students' understanding of the multiple levels of fitness through multi-agent modeling—The EACH Project. *Proceedings of the Fourth International Conference on Complex Systems.*

Cheng, P. W., & Holyoak, K. J. (1985). Pragmatic reasoning schemas. *Cognitive Psychology, 17,* 391–416.

Cheng, P. W., Holyoak, K. J., Nisbett, R. E., & Oliver, L. M. (1986). Pragmatic versus syntactic approaches to training deductive reasoning. *Cognitive Psychology, 18,* 293–328.

Chi, M. T. H. (2000). Self-explaining expository texts: The dual processes of generating inferences and repairing mental models. In R. Glaser (Ed.), *Advances in Instructional Psychology,* Hillsdale, NJ: Lawrence Erlbaum Associates, 161–238.

Chi, M. T. H. (2005). Commonsense conceptions of emergent processes: Why some misconceptions are robust. *Journal of Learning Sciences, 14,* 161–199.

Chi, M. T. H., Feltovich, P., & Glaser, R. (1981). Categorization and representation of physics problems by experts and novices. *Cognitive Science, 5,* 121–152.

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Chi, M. T. H., Slotta, J. D., & De Leeuw, N. (1994). From things to processes: A theory of conceptual change for learning science concepts. *Learning and Instruction, 4,* 27–43.

Clark, A. (1998). Embodied, situated, and distributed cognition. In W. Bechtel & G. Graham (Eds.), *A companion to cognitive sciences* (pp. 506–517). Malden, MA: Blackwell.

Colella, V. (2000). Participatory simulations: Building collaborative understanding through immersive dynamic modeling. *Journal of the Learning Sciences, 9,* 471–500.

DeLoache, J. S. (1991). Symbolic functioning in very young children: Understanding of pictures and models. *Child Development, 62,* 736–752.

DeLoache, J. S. (1995). Early understanding and use of symbols: The model model. *Current Directions in Psychological Science, 4,* 109–113.

DeLoache, J. S. (2000). Dual representation and young children's use of scale models. *Child Development, 71,* 329–338.

DeLoache, J. S., & Burns, N. M. (1994). Symbolic functioning in preschool children. *Journal of Applied Developmental Psychology, 15,* 513–527.

DeLoache, J. S., & Marzolf, D. P. (1992). When a picture is not worth a thousand words: Young children's understanding of pictures and models. *Cognitive Development, 7,* 317–329.

Detterman, D. R. (1993). The case for prosecution: Transfer as an epiphenomenon. In D. K. Detterman & R. J. Sternberg (Eds.), *Transfer on trial: Intelligence,* Norwood, NJ: Ablex, 1–24.

diSessa, A. A., & Sherin, B. (1998). What changes in conceptual change? *International Journal of Science Education, 20,* 1155–1191.

Engle, R. (2006). Framing interactions to foster generative learning: A situative explanation of transfer in a community of learners classroom. *Journal of the Learning Sciences, 15,* 451–498.

Epstein, J. M. (2007). *Generative social science: Studies in agent-based computational modeling.* Princeton, NJ: Princeton University Press.

Epstein, J. M., & Axtell, R. (1996). *Growing artificial societies: Social science from the bottom up.* Washington, DC: Brookings Institution Press.

Felder, R. M., & Silverman, L. K. (1988). Learning and teaching styles in engineering education. *Engineering Education, 78,* 674–681.

Garcia-Ruiz, J. M., Louis, E., Meakin, P. M., & Sander, L. M. (1993). *Growth patterns in physical sciences and biology.* New York: Plenum Press.

Gentner, D. (2003). Why we're so smart. In D. Gentner & S. Goldin-Meadow (Eds.), *Language in mind: Advances in the study of language and thought* (pp. 195–236). Cambridge, MA: MIT Press.

Gentner, D. (2005). The development of relational category knowledge. In L. Gershkoff-Stowe & D. H. Rakison (Eds.), *Building object categories in developmental time* (pp. 245–275). Hillsdale, NJ: Erlbaum.

Gentner, D., Loewenstein, J., & Thompson, L. (2003). Learning and transfer: A general role for analogical encoding. *Journal of Educational Psychology, 95,* 393–405.

Gentner, D., Rattermann, M. J., & Forbus, K. D. (1993). The roles of similarity in transfer: Separating retrievability and inferential soundness. *Cognitive Psychology, 25,* 524–575.

Gentner, D., & Schumacher, R. M. (1986). Use of structure-mapping theory for complex systems. *Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics, 8,* 252–260.

Gick, M. L., & Holyoak, K. J. (1980). Analogical problem solving. *Cognitive Psychology, 12,* 306–355.

Gick, M. L., & Holyoak, K. J. (1983). Schema induction and analogical transfer. *Cognitive Psychology, 15,* 1–39.

Gilden, D. L., Thornton, T., & Mallon, M. W. (1995, March 24). 1/f noise in human cognition. *Science, 267,* 1837–1839.

Goldenberg, P., & Cuoco, A. (1998). What is dynamic geometry? In R. Lehrer & D. Chazan (Eds.), *Designing learning environments for developing understanding of geometry and space* (pp. 351–367). Hillsdale, NJ: Erlbaum.

Downloaded By: [Indiana University Libraries] At: 04:56 12 November 2008

Goldstone, R. L. (1994). Influences of categorization on perceptual discrimination. *Journal of Experimental Psychology: General, 123,* 178–200.

Goldstone, R. L. (2005). *Dropping balls simulation.* Bloomington, IN: Percepts and Concepts Laboratory. Available at http://cognitrn.psych.indiana.edu/rgoldsto/complex/

Goldstone, R. L., & Barsalou, L. (1998). Reuniting perception and conception. *Cognition, 65,* 231–262.

Goldstone, R. L., & Janssen, M. A. (2005). Computational models of collective behavior. *Trends in Cognitive Sciences, 9,* 424–430.

Goldstone, R. L., Landy, D., & Son, J. Y. (in press). A well grounded education: The role of perception in science and mathematics. In M. de Vega, A. Glenberg, & A. Graesser (Eds.), *Symbols, embodiment, and meaning.* Oxford, England: Oxford University Press.

Goldstone, R. L., Lippa, Y., & Shiffrin, R. M. (2001). Altering object representations through category learning. *Cognition, 78,* 27–43.

Goldstone, R. L., Roberts, M. E., & Gureckis, T. M. (2008). Emergent processes in group behavior. *Current Directions in Psychological Science, 17,* 10–15.

Goldstone, R. L., & Sakamoto, Y. (2003). The transfer of abstract principles governing complex adaptive systems. *Cognitive Psychology, 46,* 414–466.

Goldstone, R. L., & Son, J. Y. (2005). The transfer of scientific principles using concrete and idealized simulations. *Journal of the Learning Sciences, 14,* 69–110.

Grady, S. M. (1998). *Virtual reality: Computers mimic the physical world.* New York: Facts on File.

Graesser, A. C., & Olde, B. A. (2003). How does one know whether a person understands a device? The quality of the questions the person asks when the device breaks down. *Journal of Educational Psychology, 95,* 524–536.

Greeno, J. C. (2006). Authoritative, accountable positioning and connected, general knowing: Progressive themes in understanding transfer. *Journal of the Learning Sciences, 15,* 537–547.

Hadamard, J. (1949). *The psychology of invention in the mathematical field.* Princeton, NJ: Princeton University Press.

Halsey, T. (2001). Diffusion-limited aggregation: A model for pattern formation. *Physics Today Online.* Retrieved September 1, 2008 from http://web.archive.org/web/20070405094836/http://aip.org/pt/vol-53/iss-11/p36.html

Hegarty, M. (1992). Mental animation: Inferring motion from static diagrams of mechanical systems. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 18,* 1084–1102.

Hegarty, M. (2004a). Dynamic visualizations and learning: Getting to the difficult questions. *Learning and Instruction, 14,* 343–351.

Hegarty, M. (2004b). Mechanical reasoning by mental simulation. *Trends in Cognitive Sciences, 8,* 280–285.

Heim, M. (2000). *Virtual realism.* Oxford, England: Oxford University Press.

Hills, T., Todd, P., & Goldstone, R. L. (2008). Search in external and internal spaces: Evidence for generalized cognitive search processes. *Psychological Science, 19,* 676–682.

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.

Hofstadter, D. (1997). *Fluid concepts and creative analogies: Computer models of the fundamental mechanisms of thought.* New York: Basic Books.

Holland, J. (1995). *Hidden order: How adaptation builds complexity.* Reading, MA: Helix Books/Addison-Wesley.

Holland, J. (1998). *Emergence from chaos to order.* Oxford, England: Oxford University Press.

Horgan, J. (1996). *The end of science: Facing the limits of knowledge in twilight of the scientific age.* Reading, MA: Addison-Wesley.

Hoyles, C., & Noss, R. (Eds.). (1992). *Learning mathematics and logo.* Cambridge, MA: MIT Press.

Downloaded By: [Indiana University Libraries] At: 04:56 12 November 2008

Hoyles, C., & Noss, R. (2004). Situated abstraction: Mathematical understandings at the boundary. *Proceedings of Study Group 22 of ICME-10, 7,* 212–224.

Ioannidou, A., Repenning, A., Lewis, C., Cherry, G., & Rader, C. (2003). Clayton. Making constructionism work in the classroom. *International Journal of Computers for Mathematical Learning, 8,* 63–108.

Jacobson, M. J. (2001). Problem solving, cognition, and complex systems: Differences between experts and novices. *Complexity, 6,* 41–49.

Jacobson, M. J., & Wilensky, U. (2006). Complex systems in education: Scientific and educational importance and research challenges for the learning sciences. *Journal of Learning Sciences, 15,* 11–34.

Judd, C. H. (1908). The relation of special training to general intelligence. *Educational Review, 36,* 28–42.

Kaminski, J. A., Sloutsky, V. M., & Heckler, A. F. (2008, April 25). The advantage of abstract examples in learning math. *Science, 320,* 454–455.

Kapral, R., & Showalter, K. (1995). *Chemical waves and patterns.* Dordrecht, The Netherlands: Kluwer Academic.

Kauffman, S. (1993). *The origins of order: Self-organization and selection in evolution.* New York: Oxford University Press.

Keane, M. T. (1988). *Analogical problem solving.* New York: Halsted Press.

Kirkpatrick, S., Gelatt, C. D., & Vecchi, M. P. (1983, May 13). Optimization by simulated annealing. *Science, 220,* 671–680.

Klopfer, E. (2003). Technologies to support the creation of complex systems models—Using StarLogo software with students. *Biosystems, 71,* 111–123.

Kolers, P. A., & Roediger, H. L. (1984). Procedures of mind. *Journal of Verbal Learning & Verbal Behavior, 23,* 425–449.

Kolodner, J. L. (1997). Educational implications of analogy: A view from case-based reasoning. *American Psychologist, 52,* 57–66.

Kornhauser, D., Rand, W., & Wilensky, U. (2007, November). Visualization tools for agent-based modeling in NetLogo. Paper presented at Agent2007, Chicago, November 15–17.

Kuhn, T. S. (1962). *The structure of scientific revolutions.* Chicago: University of Chicago Press.

Kurtz, K. J., Miao, C., & Gentner, D. (2001). Learning by analogical bootstrapping. *Journal of the Learning Sciences, 10,* 417–446.

Lakatos, I. (1976). *Proofs and refutations.* Cambridge, England: Cambridge University Press.

Lakoff, G., & Nuñez, R. E. (2000). *Where mathematics comes from.* New York: Basic Books.

Landy, D., & Goldstone, R. L. (2007). How abstract is symbolic thought? *Journal of Experimental Psychology: Learning, Memory, & Cognition, 33,* 720–733.

Langton, C., & Burkhardt, G. (1997). *Swarm.* Retrieved September 1, 2008 from www.swarm.org/release.html.

Lave, J. (1988). *Cognition in practice: Mind, mathematics, and culture in everyday life.* New York: Cambridge University Press.

Lave, J., & Wenger, E. (1991). *Situated learning: Legitimate peripheral participation.* New York: Cambridge University Press.

Leeper, R. (1935). A study of a neglected portion of the field of learning: The development of sensory organization. *Journal of Genetic Psychology, 46,* 41–75.

L'Engle, M. (1962). *A wrinkle in time.* New York: Farrar, Straus & Giroux.

Levy, S. T., & Wilensky, U. (2006, April). *Emerging knowledge through an emergent perspective: High-school students' inquiry, exploration and learning in the Connected Chemistry curriculum.* Paper presented at the annual meeting of the American Educational Research Association, San Francisco, CA.

Levy, S. T., & Wilensky, U. (2008). Inventing a "mid-level" to make ends meet: Reasoning through the levels of complexity. *Cognition and Instruction, 26,* 1–47.

Downloaded By: [Indiana University Libraries] At: 04:56 12 November 2008

Livingston, K. R., Andrews, J. K., & Harnad, S. (1998). Categorical perception effects induced by category learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 24,* 732–753.

Lotka, A. J. (1925). *Elements of physical biology.* Baltimore: Williams & Wilkins.

Lowe, R. (2003). Animation and learning: Selective processing information in dynamic graphics. *Learning and Instruction, 13,* 157–176.

Lowe, R. (2004). Interrogation of a dynamic visualization during learning. *Learning and Instruction, 14,* 257–274.

Marton, F. (2006). Sameness and difference in transfer. *Journal of the Learning Sciences, 15,* 499–535.

Mayer, R. E. (2004). Teaching of subject matter. *Annual Review of Psychology, 55,* 715–744.

Mazur, B. (2003). *Imagining numbers.* New York: Farrar, Straus & Giroux.

Medin, D. L., Goldstone, R. L., & Gentner, D. (1993). Respects for similarity. *Psychological Review, 100,* 254–278.

Medin, D. L., & Ross, B. H. (1989). The specific character of abstract thought: Categorization, problem solving, and induction. In R. Sternberg (Ed.), *Advances in the psychology of human intelligence* (Vol. 5, pp. 120–154). Hillsdale, NJ: Erlbaum.

Miller, J. H., & Page, S. E. (2007). *Complex adaptive systems: An introduction to computational models of social life.* Princeton, NJ: Princeton University Press.

Nathan, M. J., Long, S. D., & Alibali, M. W. (2002). The symbol precedence view of mathematical development: A corpus analysis of the rhetorical structure of textbooks. *Discourse Processes, 33,* 1–21.

National Research Council. (1999). *How people learn: Brain, mind, experience, and school.* Washington, DC: National Academy Press.

Noss, R., & Hoyles, C. (1996). *Windows on mathematical meanings: Learning cultures and computers.* Dordrecht, The Netherlands: Kluwer.

Novick, L. R. (1988). Analogical transfer, problem similarity, and expertise. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 14,* 510–520.

Novick, L. R. (2006). Understanding spatial diagram structure: An analysis of hierarchies, matrices, and networks. *Quarterly Journal of Experimental Psychology, 59,* 1826–1856.

Nunes, T. (1999). Mathematics learning as the socialization of the mind. *Mind, Culture, and Activity, 6,* 33–52.

Ottino, J. M. (2004, January 29). Engineering complex systems. *Nature, 427,* 399.

Özgen, E. (2004). Language, learning, and color perception. *Current Directions in Psychological Science, 13,* 95–98.

Papert, S. (1972). Teaching children to be mathematicians vs. teaching about mathematics. *International Journal of Mathematics Education in Science and Technology, 3,* 249–262.

Papert, S. (1980). *Mindstorms.* New York: Basic Books.

Papert, S. (1991). Situating constructionism. In I. Harel & S. Papert (Eds.), *Constructionism* (pp. 1–11). Norwood, NJ: Ablex.

Papert, S. (1996). An exploration in the space of mathematics educations. *International Journal of Computers for Mathematical Learning, 1*(1), 138–142.

Papert, S. (2000). What's the big idea? Towards a pedagogy of idea power. *IBM Systems Journal, 39*(3/4), 21–48.

Penner, D. E. (2000). Explaining processes: Investigating middle school students' understanding of emergent phenomena. *Journal of Research in Science Teaching, 37,* 784–806.

Poincare, H. (1908). *The foundations of science.* New York: Science Press.

Railsback, S., Lytinen, S., & Jackson, S. (2006). Agent-based simulation platforms: Review and development recommendations. *SIMULATION, 82,* 609–623.

Reed, S. K., Ernst, G. W., & Banerji, R. (1974). The role of analogy in transfer between similar problem states. *Cognitive Psychology, 6,* 436–450.

Resnick, M. (1994). *Turtles, termites, and traffic jams.* Cambridge, MA: MIT Press.

Downloaded By: [Indiana University Libraries] At: 04:56 12 November 2008

Resnick, M. (1996). Beyond the centralized mindset. *Journal of the Learning Sciences, 5,* 1–22.

Resnick, M., & Wilensky, U. (1993, April). *Beyond the deterministic, centralized mindsets: New thinking for new sciences.* Presentation at the annual meeting of the American Educational Research Association, Atlanta, GA.

Resnick, M., & Wilensky, U. (1998). Diving into complexity: Developing probabilistic decentralized thinking through role-playing activities. *Journal of Learning Sciences, 7,* 153–172.

Rieber, L. P. (1992). Computer-based microworlds: A bridge between constructivism and direct instruction. *Educational Technology Research & Development, 40,* 93–106.

Rieber, L. P., Tzeng, S.-C., & Tribble, K. (2004). Discovery learning, representation, and explanation within a computer-based simulation: Finding the right mix. *Learning and Instruction, 14,* 307–323.

Roberson, D., Davies, I., & Davidoff, J. (2000). Color categories are not universal: Replications and new evidence in favor of linguistic relativity. *Journal of Experimental Psychology: General, 129,* 369–398.

Ross, B. H. (1987). This is like that: The use of earlier problems and the separation of similarity effects. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 13,* 629–639.

Ross, B. H. (1989). Distinguishing types of superficial similarities: Different effects on the access and use of earlier problems. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 15,* 456–468.

Salomon, G., & Perkins, D. N. (1989). Rocky roads to transfer: Rethinking mechanisms of a neglected phenomenon. *Educational Psychologist, 24,* 113–142.

Scheiter, K., Gerjets, P., & Catrambone, R. (2006). Making the abstract concrete: Visualizing mathematical solution procedures. *Computers in Human Behavior, 22,* 9–25.

Schoenfeld, A. H. (1992). Learning to think mathematically: Problem solving, metacognition, and sense-making in mathematics. In D. Grouws (Ed.), *Handbook for research on mathematics teaching and learning* (pp. 334–370). New York: Macmillan.

Schoenfeld, A. H., & Herrmann, D. J. (1982). Problem perception and knowledge structure in expert and novice mathematical problem solvers. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 8,* 484–494.

Schwan, S., & Riempp, R. (2004). The cognitive benefits of interactive videos: Learning to tie nautical knots. *Learning and Instruction, 14,* 293–305.

Schwartz, D. L., & Black, J. B. (1996a). Analog imagery in mental model reasoning: Depictive models. *Cognitive Psychology, 30,* 154–219.

Schwartz, D. L., & Black, J. B. (1996b). Shuttling between depictive models and abstract rules: Induction and fallback. *Cognitive Science, 20,* 457–497.

Schwartz, D. L., Bransford, J. D., & Sears, D. (2005). Efficiency and innovation in transfer. In J. Mestre (Ed.), *Transfer of learning from a modern multidisciplinary perspective* (pp. 1–51). Greenwich, CT: Information Age.

Schwartz, D. L., Sears, D., & Chang, J. (in press). Reconsidering prior knowledge. In M. Lovett & P. Shah (Eds.), *Thinking with data.* Mahwah, NJ: Erlbaum.

Sengupta, P., & Wilensky, U. (2006, April). *NIELS: An agent-based modeling environment for learning electromagnetism.* Paper presented at the annual meeting of the American Educational Research Association, San Francisco, CA.

Sengupta, P., & Wilensky, U. (2008). On the learnability of electricity as a complex system. In G. Kanselaar, J. van Merri’nboer, P. Kirschner, & T. de Jong (Eds.), *Proceedings of the International Conference of the Learning Sciences (ICLS)* Vol. 3, pp.122–124. Utrecht, The Netherlands: ICLS.

Shepard, R. N. (1984). Ecological constraints on internal representations: Resonant kinematics of perceiving, imagining, thinking, and dreaming. *Psychological Review, 91,* 417–447.

Simmons, K., & Barsalou, L. W. (2003). The similarity-in-topography principle: Reconciling theories of conceptual deficits. *Cognitive Neuropsychology, 20,* 451–486.

Downloaded By: [Indiana University Libraries] At: 04:56 12 November 2008

Downloaded By: [Indiana University Libraries] At: 04:56 12 November 2008

Simon, H. A. (1980). Problem solving and education. In D. T. Tuma & R. Reif (Eds.), *Problem solving and education: Issues in teaching and research*. Hillsdale, NJ: Erlbaum, 81–96.

Slotta, J. D., & Chi, M. T. H. (2006). Helping students understand challenging topics in science through ontology training. *Cognition and Instruction, 24,* 261–289.

Smith, L. B. (2003). Learning to recognize objects. *Psychological Science, 14,* 244–250.

Smullyan, R. (1983). *5000 B.C. and other philosophical fantasies.* New York: St. Martin's Press.

Son, J. Y., Smith, L. B., & Goldstone, R. L. (2008). Simplicity and generalization: Short-cutting abstraction in children's object categorizations. *Cognition, 108,* 626–638.

Stieff, M., & Wilensky, U. (2003). Connected Chemistry—Incorporating interactive simulations into the chemistry classroom. *Journal of Science Education and Technology, 12,* 285–302.

Thurston, W. (1994). On proof and progress in mathematics. *Bulletin of the American Mathematical Society, 30*(2), 161–177.

Tisue, S., & Wilensky, U. (2004, May). *NetLogo: A simple environment for modeling complexity.* Paper presented at the International Conference on Complex Systems, Boston, MA.

Uttal, D. H., Liu, L. L., & DeLoache, J. S. (1999). Taking a hard look at concreteness: Do concrete objects help young children learn symbolic relations? In C. S. Tamis-LeMonda (Ed.), *Child psychology: A handbook of contemporary issues* (pp. 177–192). Philadelphia: Psychology Press.

Uttal, D. H., Scudder, K. V., & DeLoache, J. S. (1997). Manipulatives as symbols: A new perspective on the use of concrete objects to teach mathematics. *Journal of Applied Developmental Psychology, 18,* 37–54.

van Merriënboer, J. J. G., Clark, R. E., & de Croock, M. B. M. (2002). Blueprints for complex learning: The 4C/ID-Model. *Education Technology Research & Development, 50,* 39–64.

Whorf, B. L. (1956). Languages and logic. In J. B. Carroll (Ed.), *Language, thought, and reality: Selected papers of Benjamin Lee Whorf* (pp. 233–245). Cambridge, MA: MIT Press. (Original work published 1941)

Wicklein, R. C., & Schell, J. W. (1995). Case studies of multidisciplinary approaches to integrating mathematics, science, and technology education. *Journal of Technology Education, 6,* 59–76.

Wilensky, U. (1991). Abstract meditations on the concrete and concrete implications for mathematics education. In I. Harel & S. Papert (Eds.), *Constructionism* (pp. 193–203). Westport, CT: Ablex.

Wilensky, U. (1993). *Connected mathematics: Building concrete relationships with mathematical knowledge.* Doctoral dissertation, Massachusetts Institute of Technology, Cambridge, MA.

Wilensky, U. (1997a). *NetLogo DLA model.* Evanston, IL: Northwestern University, Center for Connected Learning and Computer-Based Modeling. Available at http://ccl.northwestern.edu/netlogo/models/DLA

Wilensky, U. (1997b). *NetLogo wolf sheep predation model.* Evanston, IL: Northwestern University, Center for Connected Learning and Computer-Based Modeling. Available at http://ccl.northwestern.edu/netlogo/models/WolfSheepPredation

Wilensky, U. (1997c). *StarLogoT.* Evanston, IL: Northwestern University, Center for Connected Learning and Computer-Based Modeling. Available at http://ccl.northwestern.edu/cm/StarLogoT/

Wilensky, U. (1998). *NetLogo random walk left right model.* Evanston, IL: Northwestern University, Center for Connected Learning and Computer-Based Modeling. Available at http://ccl.northwestern.edu/netlogo/models/RandomWalkLeftRight

Wilensky, U. (1999a). GasLab: An extensible modeling toolkit for exploring micro-and-macro-views of gases. In N. Roberts, W. Feurzeig, & B. Hunter (Eds.), *Computer modeling and simulation in science education (*pp. 151–178). Berlin: Springer Verlag.

Wilensky, U. (1999b). *NetLogo.* Evanston, IL: Northwestern University, Center for Connected Learning and Computer Based Modeling. Available at http://ccl.northwestern.edu/netlogo

Wilensky, U. (2001a). Modeling nature's emergent patterns with multi-agent languages. *Proceedings of EuroLogo 2001.*

Wilensky, U. (2001b, April). *Emergent entities and emergent processes: Constructing emergence through multi-agent programming.* Paper presented at the annual meeting of the American Educational Research Association, Seattle, WA.

Wilensky, U. (2003). *NetLogo B-Z reaction model.* Evanston, IL: Northwestern University, Center for Connected Learning and Computer-Based Modeling. Available at http://ccl.northwestern.edu/netlogo/models/BZReaction

Wilensky, U. (2006, April). *Complex systems and restructuration of scientific disciplines: Implications for learning, analysis of social systems, and educational policy.* Paper presented at the annual meeting of the American Educational Research Association, San Francisco, CA.

Wilensky, U., Hazzard, E., & Longenecker, S. (2000). *A bale of turtles: A case study of a middle school science class studying complexity using multi-agent modeling.* Paper presented at the annual meeting of the Spencer Foundation, New York, NY, October 11–13, 2000.

Wilensky, U., & Rand, W. (in press). *An introduction to agent-based modeling: Modeling natural, social and engineered complex systems using NetLogo.* Cambridge, MA: MIT Press.

Wilensky, U., & Reisman, K. (1998). ConnectedScience: Learning biology through constructing and testing computational theories—An embodied modeling approach. *InterJournal of Complex Systems, 234,* 1–12.

Wilensky, U., & Reisman, K. (2006). Thinking like a wolf, a sheep or a firefly: Learning biology through constructing and testing computational theories—An embodied modeling approach. *Cognition and Instruction, 24,* 171–209.

Wilensky, U., & Resnick, M. (1995, April). *New thinking for new sciences: Constructionist approaches for exploring complexity.* Paper presented at the annual meeting of the American Educational Research Association, San Francisco, CA, April 18–22.

Wilensky, U., & Resnick, M. (1999). Thinking in levels: A dynamic systems perspective to making sense of the world. *Journal of Science Education and Technology, 8,* 3–18.

Wilensky, U., & Stroup, W. (1999). Learning through participatory simulations: Network-based design for systems learning in classrooms. *Proceedings of the Computer Supported Collaborative Learning Conference.* Article no. 80. International Society of the Learning Sciences. Retrieved September 13, 2008 from http://portal.acm.org/citation.cfm?id=1150240.115320&coli=GUIDE&dl=ACM&type=series&idx=SERIES11363&part=series&WantType=Proceedings&title=CSCL.

Wittgenstein, L. (1953). *Philosophical investigations* (G. E. M. Anscombe, Trans.). New York: Macmillan.

Wolfram, S. (2002). *A new kind of science.* Champaign, IL: Wolfram Media.

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