The Complex Systems See-Change in Education

Robert L. Goldstone

Indiana University

Running head: Understanding Complex Systems

Correspondence Address:

Robert Goldstone

Department of Psychology

Indiana University

Bloomington, IN. 47405

Other Correspondences: rgoldsto@indiana.edu (812) 855-4853

Running Head: THE COMPLEX SYSTEMS SEE-CHANGE

One of the most exciting promises of a complex systems perspective for learning and education, well captured in Jacobson and Wilensky's target article, is to provide a unifying force to bring together increasingly fragmented scientific communities. The day when scientists have time to read broadly across chemistry, biology, physics and social sciences is long gone. Journals, conferences, and academic departmental structures are becoming increasingly specialized and myopic. As Peter Csermely (1999), one of the organizers of the International Forum of Young Scientists expresses it, "There is only a limited effort to achieve the appropriate balance between the discovery of new facts and finding their appropriate place and importance in the framework of science. Science is not self-integrating, and there are fewer and fewer people taking responsibility for 'net-making" (p. 1621). One possible response to this fragmentation of science is to simply view it as inevitable. Horgan (1996) argues that the age of fundamental scientific theorizing and discoveries has passed, and that all that is left to be done is refining the details of theories already laid down by the likes of Einstein, Darwin, and Newton.

Complex systems researchers, and learning scientists more generally, offer an alternative perspective, choosing to reverse the trend toward increasing specialization. They have instead pursued principles that apply to many scientific domains, from physics to biology to social sciences. This movement, in which Jacobson and Wilensky are deeply enmeshed (I would have written that they are centrally located, but they have convinced me of the importance of decentralized networks) seeks common computational and mathematical descriptions for apparently unrelated phenomena. Reaction-diffusion equations that explain how cheetahs develop spots can be used to account for geospatial patterns of Democrats and Republicans in America. The same abstract schema underlies both phenomena – two kinds of elements (e.g. two skin cell colors, or two political parties) both diffuse outwards to neighboring regions but also inhibit one another. As a second example, identical equations underlie predator-prey dynamics and the B-Z chemical reaction, and it thus comes as no surprise that both systems show the same functional behavior -- oscillating amounts of two entities with distributions patterned as moving spirals over time (Ball, 1999). Recently, there has been considerable interest in "small-world networks" that are characterized by short path lengths between network elements but also highly clustered elements. Highly similar small-world profiles are found for networks of actor collaborations, neurons in nematodes, and the power grid (Watts & Strogatz, 1998). Similarly, the general process that already connected network elements will attract still further connections with newly recruited elements (called “preferential attachment”) has played a powerful explanatory role in explaining these same networks (Barabasi & Albert, 1999).

In all of these examples, apparently disparate phenomena, sometimes spanning orders of magnitude, are united under a single complex systems principle. These examples show why complex systems principles are an exciting development in the learning sciences (see also Jacobsen, 2001). If students can learn to learn these principles and recognize when they are applicable, then they not only develop an appreciation of the integrated web of science, but they also can transfer what they have learned to widely dissimilar domains, one of the greatest unsolved challenges for education (Bransford & Schwartz, 1999; National Research Council, 1999).

Seeing the World in New Ways

A complex systems perspective can lead to apparently contradictory conclusions about the encapsulation of knowledge. By one account, an appreciation of the larger system that surrounds and determines the behavior of elements should lead one to a <u>contextualized</u> account of knowledge. Barab et al. (1999) present a good example of this perspective, in which learners and environments are viewed not as separate entities, but rather part of a single entity. They argue that how an element behaves depends intrinsically upon the larger system in which it is contained. This insight is consistent with complex systems theorizing. One of its central tenets is that macroscopic behavior of elements cannot be deduced from the elements considered independently. Rather, interactions among the elements give rise to non-linear dynamics and emergent behaviors that would never arise if elements were independent.

As an example of the importance of acknowledging the broad system rather than just the elements, consider Schelling’s (1971) classic model of segregation. In this model, a group of individuals belonging to different classes (e.g. races) follow a simple rule like “If fewer than 30% of my neighbors belong to my class, then I will move." Surprisingly, after several iterations of this rule, widespread segregation is found in which the world is divided into large, class-homogeneous groups, even though no individual is motivated to live in such a segregated world. The discrepancy between the individuals' motivations and the collective organization underscores the notion that in complex systems the elements are all affecting one another. The proper perspective to take on the Schelling's model is that the elements must be contextualized within a larger system. If one is in the habit of drawing circles around critical conceptual elements, then one should draw a circle around the entire population, not individuals.

In contrast to this vision of contextualization, it is possible to draw exactly the opposite moral from complex systems. As described earlier, the same complex system principle can be applied to a wide variety of case studies from apparently unrelated domains. Complex systems can be viewed as strong cases for the utility of <u>decontextualized</u> knowledge. If knowledge of reaction-diffusion systems is too strongly tied to the specific learned case of spot patterns on cheetahs, then it will not be successfully applied to spatial patterns of political belief. Complex system principles unify domains that deal in very different kinds of content, so realizing the potential of these principles will be facilitated by processes that isolate the essential wheat from the domain-specific chaff (Gick & Holyoak, 1983; Goldstone & Sakamoto, 2003). This is not to advocate ungrounded or uninstantiated knowledge. Even when a principle or pattern is isolated from its "cover story," it is still perceptually instantiated, which is why teaching the principles using perceptually grounded simulations like NetLogo is so effective. Nonetheless, extracting the perceptually grounded principles from their specific scenario will often allow the principle to be better appreciated and transferred.

Although apparently diametrically opposed, these contextualized and decontextualized perspectives can be reconciled, and, in fact, seen as two aspects of a common process of conceptual reorganization. Complex systems are powerful mental tools because they allow widespread prediction and induction. For example, knowing that a system is a small-world network allows one to predict how quickly information will spread between nodes, how much diversity of opinion there will be at different times, and how influential neighborhoods will be in determining cliques. <u>Teaching</u> complex systems is important because their predictions and inductions would not normally occur to people who are not exposed to them. Principles like positive feedback systems, small-world networks, preferential attachment, and reaction-diffusion systems are not alone in admitting widespread inductions. So do concepts like **Dog**, **Money, Gold**, **Chair**, **Dolls**, and **Microphones**. The difference is that these latter concepts do not need to be taught; children naturally acquire them on their own. To the child, the world seems composed of things like dolls and microphones. However, when exposed to the notion of a positive feedback system, these categories can become reorganized. For example, one of my students who learned about positive feedback systems from an example of a microphone feeding into, and placed near, a loudspeaker was reminded of this example when she was discussing a scenario involving children wanting to buy a doll that many other children already possessed, leading to the still greater popularity of an otherwise unexceptional plaything. The reminding was apt. These scenarios do have important properties in common: an increase in a system variable leads to still greater increase to the same variable, accelerated growth to a variable, and eventual limits to the value that a variable can take that is independent of the positive feedback dynamic. Learning about complex systems allows one to perceive the world according to new categories.

Perceptual restructuring in inductively rich ways may require either contextualization, decontextualization, or both, depending upon one's initial categories. The benefit of greater contextualization occurs because people often initially conceptualize a system in terms of its physically separable elements, when, in fact, these elements often interact strongly enough that the system is more felicitously viewed from a broader, more macroscopic perspective. It is easy to isolate single birds from a flock, but it is more useful and predictive to ask where the <u>flock</u> is going, not where the birds individually considered are going. This flock-level perspective, of course, acknowledges that the flock is nothing more than individual birds and their interactions. The benefit of greater decontextualization occurs because people often initially fail to distinguish between functionally relevant and irrelevant properties of a situation. Often, a function can be realized by multiple physical instantiations. A biological heart can be replaced by an artificial heart, both of which can fulfill the functional role of pump. In these cases, isolating the functional properties and interactions from their physical substrata facilitates identifying them again later when they are differently embodied.

Both contextualization and decontextualization are perspectival shifts, and their relative utilities will depend upon the complete network of relations with a system, as well as a thinker's needs. The general prescription will be to create conceptual units so that connectivity among the elements within a unit is relatively dense while connectivity among elements across different units is sparse. Following this prescription, our constructed knowledge units will be both internally coherent and relatively compartmentalized packages that can be transported to new domains. So, with the above example of doll sales begetting doll sales, individuals purchasers are too restrictive a perspective because of the strong dependencies between purchasers' choice of dolls. This broader contextualization is accompanied by a decontextualization that extracts out the positive feedback system from extraneous details about dolls such as the particular kind, manufacturer, or period of the doll. Together, this <u>recontextualization</u> acts as a new kind of category for making predictions and inferences. Or, as one of my college students puts it: "Positive feedback systems can be made up of any kind of stuff – dolls, sounds, or bibliographies[1]. It's weird to think of these things as belonging together, but they do, and realizing this is actually useful for thinking about them."

Promoting Transfer with Complex Systems

Complex systems are exciting developments in the learning sciences because they are not standard ways of approaching the world, but once understood can become a conceptual tool with the potential to dramatically transform one's perception of this world. How can the pedagogical promise of complex systems best be realized? One key element is suggested by taking literally that notion that learning involves <u>perceiving</u> the world in new ways. Thomas Kuhn (1962) described how scientists, when exposed to a new 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]

[1] One of the examples that students in our Complex Adaptive Systems course had previously discussed was the case of authors citing papers that appear in other papers' bibliographies, thus creating a "rich getter richer" dynamic for paper citations (Borner, Maru, & Goldstone, 2004).

revolutions, scientists see new and different things when looking with familiar instruments in places they have looked before" (p. 111). We believe this kind of perceptual shift is not restricted to professional scientists, but can also be found when providing new conceptual tools such as complex systems.

The promise of complex systems is that the same principle rears its head in many different domains. The reality is that far-transfer is often difficult to attain (Detterman, 1993; Gick & Holyoak, 1980; National Research Council, 1999). Jacobson and Wilensky's exhilarating suggestion is that the gulf between promise and reality can be bridged by stressing new ways of perceiving, not just conceptualizing. Critically, the NetLogo computer environment immerses students in interactive and dynamic visual worlds. Students see complex systems principles instantiated in concrete case studies, and visually experience positive feedback systems, reaction-diffusion systems, and small-world networks in action. While students might understand the concept with respect to NetLogo, the goal of school and the power of the notion of complex systems is that we want students to adopt the more general conceptual tool in a manner that allows them to perceive relations in other systems beyond the NetLogo context.

It might have been thought that the best way to promote transferable complex systems principles is not by concrete visualizations, but through mathematics. Mathematics is without parallel as a device for stripping situations to an essence. Mathematical and logical formalisms are the epitome of devices for eliminating misleading superficial features. Once doll purchases, microphone, and imitative citation practices have been distilled to the same equation, it might be thought simple to freely transfer knowledge from one domain to another. This assumption is commonplace in high school mathematics curricula. Abstract formalisms are first presented, and then are subsequently fleshed out by examples. The premises of this formalism-based approach to transfer are that if an equation is known, it can be recognized and applied when it is relevant in a new situation, and that generalization potential is maximized by extracting the most formal, content-reduced representation.

There is reason to doubt these two premises. Contrary to the first premise, it is difficult to spontaneously notice that a learned equation can be applied in a new situation. 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). Contrary to the second premise, mathematical formalisms run the risk of being cognitively inert. They offer little scaffolding for understanding, and do not generalize well because cues to resemblance between situations have been stripped away. Even though formalisms are maximally general in the sense of eliminating all content-specific elements, this does not mean that they are maximally useful for generalization. To generalize across originally dissimilar domains, one needs training that allows the domains to be spontaneously seen as reflecting the same principle. Mathematicians and physicists may be able to spontaneously see equations when contemplating natural phenomena, but equations are too far removed from conceptually-driven interpretation processes for most people to alter their perception.

The use of NetLogo (Wilensky, 1999; Wilensky & Reisman, 1999) and other computer simulations (Goldstone & Son, 2005; Resnick, 1994) to teach complex systems offers a markedly different alternative for promoting generalization. Principles are not couched in equations, but rather in dynamic interactions among elements. Students who interact with the simulations actively interpret the resulting patterns, particularly if guided by goals abetted by knowledge of the principle. Their interpretations are grounded in the particular simulation, but once a student has practiced building an interpretation, it is more likely used for future situations. In contrast to explicit equation-based transfer, perceptually-based priming is automatic. For example, an ambiguous man/rat drawing is automatically interpreted as a man when preceded by a man and as a rat when preceded by a rat (Leeper, 1935). This phenomenon, replicated in countless subsequent experiments on priming (see Goldstone, 2003 for a theoretical integration), is not ordinarily thought of as transfer, but it is an example of a powerful influence on perception due to prior experiences. This kind of automatic shift of perceptual interpretation accompanies engaged interaction with complex system simulations. After experiencing simulations of growth featuring Fibonacci-sequence spirals (http://cognitrn.psych.indiana.edu/rgoldsto/complex/), one of my students reported, "After playing with the simulation, I found myself studying every pine cone I saw on the ground, and sure enough, they had Fibonacci spirals that I had never noticed before." Generalization arises here not from the explicit and effortful application of abstract formalisms, but from the simple act of "rigging up" a perceptual system to interpret a situation according to a principle, and leaving this rigging in place for subsequently encountered situations.

The skeptic might ask, "What is so special about computational models of complex systems? Why should they facilitate transfer and generalization any better than equations?" My proposed answer is that these models mesh well with people's own mental models. Computer simulations, such as Netlogo models, enact the same kind of simulation of elements and interactions that effective mental models do (Gentner & Stevens, 1983). Grounded and contextualized models naturally correspond to dimensions of the modeled world. For both human and computer models, running the model can produce genuinely novel knowledge. Computational models, then, are frequently more powerful agents of cognitive change than equations because they are expressed in terms (e.g. agents, space, forces, growth, inhibition, attraction, and causation) that are close to natural psychological structures and processes.

Conclusion

Considerable psychological evidence indicates that far transfer of learned principles is often difficult and may only reliably occur when people are explicitly reminded of the relevance of their early experience when confronted with a subsequent related situation (Gick & Holyoak, 1980; 1983). This body of evidence stands in stark contrast to other evidence suggesting that people automatically and unconsciously interpret their world in a manner that is consistent with their earlier experiences (Roediger & McDermott, 1993). These statements are reconcilable. A lasting influence of early experiences on later experiences occurs when perceptual and conceptual systems have been transformed. The later experience will be inevitably processed by the systems that have been transformed by the initial experience, and priming naturally occurs. When a principle is simply grafted onto an early experience but does not change how the experience is processed, there is little chance that the principle will come to mind when it arises again in a new guise. The moral is clear: to reliably make an interpretation come to mind, one needs to affect how a situation is interpreted as it is "fed forward" through the nervous system rather than tacking on the interpretation at the end of processing.

This moral fits well with an approach to learning science that focuses on educating perception, rather than formal symbol manipulation. Complex system simulations play an important role in this effort because they show the perceptual consequences of element interactions. An apt computational model can lead people to interpret their world differently because people are already predisposed to understand their world by making models of it. By tweaking students' natural models, rather than trying to introduce an entirely new mathematical language, we can change how students see their world. Students who learn models from their experience of the world will then, in turn, experience their world in terms of the models they have learned.

References

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

Barab, S., A., Cherkes-Julkowski, M., Swenson, R., Garrett, S., Shaw, R. E., & Young, M. (1999). Principles of self-organization: Learning as participation in autokatakinetic systems. The Journal of the Learning Sciences, 8, 349-390.

Barabasi, A., Albert, R. (1999). Emergence of scaling in random networks. Science, 286, 509-512.

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

Bransford, J. D., & Schwartz, D. L. (1999). Rethinking transfer: A simple proposal with multiple implications. In A. Iran-Nejad & P. D. Pearson (Eds.), Review of Research in Education , 24, 61-101.

Csermely, P. (1999). Limits of scientific growth. Science, 5420, 1621.

Detterman, D. R. (1993). The case for prosecution: Transfer as an epiphenomenon. In: Detterman D K, Sternberg R J (eds.) Transfer on Trial: Intelligence, Transfer on trial: Intelligence, cognition, and instruction. Norwood, NJ: Ablex

Gentner D, Stevens A L (eds.) (1983) *Mental Models*. Erlbaum, Hillsdale, NJ.

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.

Goldstone, R. L. (2003). Learning to perceive while perceiving to learn. In R. Kimchi, M. Behrmann, & C. Olson (Eds.) Perceptual organization in vision: Behavioral and neural perspectives. (pp. 233-278). New Jersey: Lawrence Erlbaum Associates.

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. The Journal of the Learning Sciences, 14, 69-110.

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

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

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

Resnick, M. R. (1994). Turtles, Termites, and Traffic Jams. Cambridge, MA: MIT Press.

Roediger, H. L., & McDermott, K. B. (1993). Implicit memory in normal subjects. In H. Spinnler & Boller (Eds.), *Handbook of Neuropsychology*. Amsterdam: Elsevier.

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.

Schelling, T. C. (1971). Dynamic models of segregation. Journal of Mathematical Sociology, 1, 143-186.

Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of ‘small-world’ networks, 393, 440-442.

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

Wilensky, U. & Reisman, K. (1999). ConnectedScience: Learning biology through constructing and testing computational theories -- An embodied modeling approach. InterJournal of Complex Systems, 234, 1-12.

Author Notes

Useful comments and suggestions were provided by David Landy, Michael Roberts, Ji Son, and particularly Sasha Barab. This research was funded by Department of Education, Institute of Education Sciences grant R305H050116. Correspondence concerning this article should be addressed to rgoldsto@indiana.edu or Robert Goldstone, Psychology Department, Indiana University, Bloomington, Indiana 47405. Further information about the laboratory can be found at http://cognitrn.psych.indiana.edu/.