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Fostering general transfer with specific simulations*

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Science education faces the difficult task of helping students understand and appropriately generalize scientific principles across a variety of superficially dissimilar specific phenomena. Can cognitive technologies be adapted to benefit both learning specific domains and generalizable transfer? This issue is examined by teaching students complex adaptive systems with computer-based simulations. With a particular emphasis on fostering understanding that transfers to dissimilar phenomena, the studies reported here examine the influence of different descriptions and perceptual instantiations of the scientific principle of competitive specialization. Experiment 1 examines the role of intuitive descriptions to concrete ones, finding that intuitive descriptions leads to enhanced domain-specific learning *but* also deters transfer. Experiment 2 successfully alleviated these difficulties by combining intuitive descriptions with idealized graphical elements. Experiment 3 demonstrates that idealized graphics are more effective than concrete graphics even when unintuitive descriptions are applied to them. When graphics are concrete, learning and transfer largely depend on the particular description. However, when graphics are idealized, a wider variety of descriptions results in levels of learning and transfer similar to the best combination involving concrete graphics. Although computer-based simulations can be effective for learning that transfers, designing effective simulations requires an understanding of concreteness and idealization in both the graphical interface and its description.

Keywords: abstraction, analogy, complex systems, concreteness, generalization, grounded learning, learning, science education, simulation, transfer

1.   Introduction

A central purpose of science is to produce models that provide unifying explanations of diverse phenomena and to generalize these models appropriately. Following the axiom of preaching what we practice, a corresponding goal of scientific education should be to teach students to appreciate and use these overarching models, not just particular instances. Models in physics seek to explain all types of masses under a variety of circumstances, not just a particular cube on an incline plane. Chemistry seeks to explain many types of reactions across different environmental conditions, not just the result of exposing magnesium oxide to water. Biological models that provide explanations that apply across organisms and psychological explanations that cut across particular situations move these fields forward. Because scientific models typically capture deep principles that govern concretely dissimilar phenomena, they are largely sparse descriptions of structure. But novices in a domain are often more likely to attend to rich concrete information than relational structure (Chi, Feltovich, and Glaser 1981; Rattermann and Gentner 1998; Markman and Gentner 1993), so although fostering an understanding of deep structure is the very purpose of science, this is also what makes science education challenging. How can sparse relational structure be highlighted in the midst of the rich salient details of the particular phenomena? Indeed this has been a source of much dissatisfaction with students' (and teachers') conceptions of science (Duschl 1990; Lederman 1992).

In the research presented here, the focus is on two, sometimes divergent, goals of scientific education: (1) the understanding of general models and (2) transferring that general structure across specific phenomena. Technological innovations such as computer simulations play an increasingly important role in science education by helping students build working models. However, to develop effective simulations we need to know how students understand and interact with simulations. Our research is an attempt to maximize the pedagogical impact of simulations to foster both learning of particular phenomena but also to promote appropriate transfer. To such an end, we will provide a review of complex systems, an example of a scientific approach that necessitates an understanding of general models. Then we will review previous research that shows the impact of simulations in learning. Finally, we will present theoretical and empirical motivations for strategically choosing a level of concreteness in simulations (perceptually and contextually) that effectively fosters transfer.

2.   Complex systems for science education

Complex adaptive systems (CAS) provide a particularly striking example of a situation where there is common structure shared among dissimilar concrete phenomena. CAS models phenomena use the simple interactions of individual units (or agents) to explain complex behavior at the macroscopic level. The key idea of these models is that even without a leader or centralized process, sophisticated high-level organization can emerge from low-level interactions (Bar-Yam 1997; Resnick 1994; Resnick and Wilensky 1993). Many real-world phenomena, from biology to social sciences, can be modeled with the formalisms of CAS. These principles often provide useful unifying descriptions across traditional scientific boundaries (Casti 1994; Flake 1998). For example, the growth of human lungs (Garcia-Ruiz et al. 1993), snowflakes (Bentley and Humphreys 1962), and cities (Batty 2005) can all be modeled by Diffusion-Limited Aggregation, where individual units enter a system randomly and if a moving unit touches another one, they become attached. The same pattern of fractally connected branches emerges across all these systems. Although lungs, snowflakes, and cities seem to belong in different domains of inquiry due to salient differences among these phenomena, the structural regularities highlighted by this CAS construal (Ball 1999) are highly useful for prediction and quantification. A CAS perspective can provide a unifying explanation for the development of spots on mammalian skin as well as the distribution of religious communities over a country (Turing 1952); oscillations in chemical reactions as well as predator-prey populations (Ball 1999); the specialization of ants over food resources as well as neurons over perceptual stimuli (O'Reilly 2001).

There are also some specifically pedagogical reasons to bring CAS principles to the science classroom. First, since transfer of structural principles unifying superficially dissimilar domains is particularly problematic for students, CAS theories provide many examples of models that do just that. This has the potential to overcome students' resistance to science classes that they frequently view as overly particularistic. CAS principles are mechanistic descriptions of phenomena and offer compelling accounts of the similarity between otherwise dissimilar phenomena. Also, since CAS models are of authentic scientific interest, this can foster productive cross-fertilization across fields. The bridging is not only across phenomena, but also within phenomena since CAS principles offer bridging causal explanations among microscopic elements in a system and observed macroscopic emergent behavior. Building these links across and within scientific domains demonstrates different levels of description and offers students new ways of parsing phenomena. Finally, these systems provide situations where analogical reasoning and transfer naturally emerge as cognitively crucial ingredients. This last reason is of particular importance to educators and students who hope that their efforts and

study will transfer between the classroom and the real world as well as between domains (Anderson, Greeno, Reder, and Simon 2000).

However, the very characteristics that make CAS principles such good science and potentially good for research in science education also make them particularly difficult to understand. First, because CAS modeling requires multiple levels of understanding, emergent and local interactions (Wilensky and Resnick 1999), students often only learn one-level of analysis and typically it is the overall structure that is most difficult to grasp. Second, past research has shown many failures of the spontaneous transfer of principles between superficially dissimilar contexts (e.g., Gick and Holyoak 1980; Reed, Ernst, and Banerji 1974). Third, relatively little research has been done to inform the design of CAS curricula, hands-on experiences, exercises, and laboratories to promote deep understanding of complex systems. Educational technology that is optimized for maximizing performance on a system will often not be the technology that is optimal for transferring knowledge and skills from one domain to another. For example, for training people to drive a car, developing a driving simulation that is as realistic as possible is sensible. However, it does not follow that realism and incorporating details faithful to a domain are beneficial if we are principally interested in transfer understandings to new domains with different details.

We propose to use recent developments in technology to address educational challenges. Technological advances have given rise to new tools for studying complex systems. Because effective real-life observation of whole system, such as an entire population of neurons or a predator-prey ecosystem, is often difficult, too complex, or too cumbersome, computer-based simulations provide a powerful new tool for scientific inquiry (Casti 1997) as well as education. Simulations offer promise in meeting the challenges of learning complex systems. We will discuss the broad advantages of using simulated environments to (1) effectively allow interactive control coupled with (2) perceptually grounding of higher order principles.

2.1   Advantages of simulations

Dynamic simulations instantiate scientific principles with simplified perceptual models, representing only the main elements and their interactions. These computer simulations have been called "artificial worlds", providing a functional laboratory for testing hypotheses (Casti 1997). Traditional laboratories are ideally controlled environments and computer simulations similarly constrain the potential influences on the environment via the availability of parameters. Students can explore these models by changing key parameters and examining the subsequent effects on the system (Miller, Lehman, and Koedinger 1999; Resnick 1994; Schank and Farrel 1988).

Such an interaction between a student and a simulation is particularly powerful because actions in this environment are coupled with ordered consequences. Often this coupling is designed to show students immediate visual consequences that correspond to changes in particular parameters (e.g., Jackson, Stratford, Krajcik, and Soloway 1996; Resnick 1994; Wilensky 1999). The organization of what gets learned is often directly connected to actions in the world (Scribner 1985), and so there has been an increasing interest in understanding cognition as the product of interactions with the environment. Embodied accounts of learning suggest that such coupling between activity and the environment is what leads to flexible and useful knowledge (Winn 1995; Smith and Gasser 2005). Even simple learning mechanisms can be flexibly 'intelligent' when they are sensitive to these couplings (Brooks 1991). Giving students feedback in these simulated environments gives them information about the system in a less direct, but potentially more effective, way than traditional textbook exposition. Particularly because CAS principles are often instantiated at the agent-level, it is difficult for students to connect changes at the micro-level to patterns at the global-level (Penner 2001). Simulations couple their micro-level changes to global consequences.

More specifically to scientific inquiry, simulations also provide economical opportunities for practicing skills. Because the environment is conducive to predictive problem-solving, students can test their theories and examine the consequences (White 1993; White and Fredericksen 1998). Resetting a computer simulation is easy to do, allowing students to start over and try out several tests in succession, something that might be costly or difficult in the real world or even a real laboratory. Additionally, as much as science is interested in predicting reality, the real world is unpredictable. Simulations are highly regular worlds that are created as perfect instantiations of scientific models. This allows a students' experimentation to be highly predictable, if they have a good understanding of the model. In the real world, a predictive failure is possible because either one's model is wrong or one does not understand the implications of one's model. By allowing students to explore simulations governed by exact and simple rules, the former possibility is eliminated and students can concentrate on understanding why a set of rules gives rise to the behavior describable at several levels.

Dede and colleagues (1997) have used simulated environments in ScienceSpace to help students realize when they do not have adequate models of the physical universe by allowing them to remove friction or gravity from the simulation. These impossible and extreme ways of controlling simulations are particularly needed to illustrate CAS principles. Emergent explanations are often overlooked for centralized ones (Resnick and Wilensky 1998; Jacobson 2001) and students are likely to seek a centralized authority or plan (i.e., one of the agents being a special leader), so being able to truly make every agent behave identically is important.

This control allows students to see that the emergent structures they see are not caused by seeded differences among the elements, but come about because of their interactions. Also, because these interactive systems are made up of independent agents, they can seem perceptually noisy. Simulated environments allow students to have control over "the noise" in regular ways.

These visual interactive simulations are perfect models and, perhaps equally importantly, are also tools for constructing mental models. Although mental models have been implicated in effective scientific understanding (Gentner and Stevens 1983), actually being able to model simultaneous agents and interactions poses high demands on working memory and other cognitive processes (Narayanan and Hegarty 1998). CAS principles may be particularly difficult to instantiate mentally because the behavior of the components may be very different from the global patterns that arise. Students are surprised when they find that a traffic system composed of cars moving forward creates traffic jams that move backwards along the highway (Wilensky 1997; Wilensky and Resnick 1999). They only realize that this is a consequence of the system by observing it in the simulation.

These are a few of the potential benefits to complex systems education that visual simulations might provide. Undoubtedly this potential has been recognized given the recent proliferation of simulations used in educational settings. A noteworthy example is the StarLogo/NetLogo environment developed by Resnick and Wilensky (Resnick 1994; Resnick and Wilensky 1998; Wilensky 1999, 2001). StarLogo/NetLogo provides a platform for creating virtual environments made up of fixed patches and moving agents that can interact with patches and each other. Students can control various parameters to change the nature of those interactions. Simulations such as NetLogo systems often foster intuitions for complex systems such as slime-mold aggregation and predator-prey oscillations better than abstract equations and noninteractive animations (Resnick and Wilensky 1998; Wilensky and Resnick 1999).

However, not all simulations are created equal and there have been relatively few attempts to test the effectiveness of particular design choices (for notable exceptions, see Jackson, Stratford, Krajcik, and Soloway 1996; Klahr and Carver 1988; Miller et al. 1999). Although simulations on the whole might offer potential advantages over more traditional tools, systematic differences between simulations might also influence their actual effectiveness, particularly for transfer. Simulations should not be seen as panaceas to science education, just as concrete manipulatives or other learning tools should not be seen as generic solutions to the aims of education (see Uttal, Scudder, and DeLoache 1997 for a defense of this claim). Cognitive studies of learning and transfer offer valuable direction for designing simulations that are optimal teaching tools for the aims of science education: Unifying structural construals and generalizable skills.

3.   Fostering transfer

Complex systems principles are cognitively influential because they lead to situations being construed in new and productive ways. The student or scientist armed with a model of Diffusion Limited Aggregation sees striking similarities between lungs and snowflakes that are missed by most others. Complex systems concepts are thus inductively productive; however, they are highly perspective-dependent. When corrosion on tin organ pipes speeds up the spread of further corrosion, it is exactly an autocatalytic process, with the rich mathematically governed behaviors that characterize all autocatalytic processes. However, the organ pipes not only instantiate an autocatalytic process, but also a resonating chamber and a harmonic series generator. An effective science education arms students with new perspectives to apply to the world.

The problem with these scientific construals is that they reflect a particular perspective out of a number of reasonable descriptions. Because of human processing limitations, differing construals compete against each other. However, appropriate generalization and transfer may require understanding multiple construals at once. At one level, participants do need to understand specific phenomena and how they instantiate certain principles. However, they also need to understand that these individual phenomena are in equivalence classes organized according to abstract principles. The specific and the general, the individual and the aggregate, the superficial and structural construals — all compete against each other, and every learning situation is wrought with these possible perspectives.

In the domain of science education, there is a wide variety of what could be considered critical transfer, from broadly generalizable skills, such as the ability to ask testable questions, to more specific instances of transfer, such as recognizing the link between a particular equation and a linguistic description of phenomena (for more detailed analysis of the types of transfer, see Barnett and Ceci 2002). Choosing the right perspective to apply to a situation may be important in many types of transfer but because we are limited in our ability to explore these in a series of short experiments, our empirical investigations will be restricted to transfer as solving problems similarly across deeply related phenomena, despite superficial differences. Thus, our aim is to design simulations that help students recognize structural similarities between two dissimilar contexts. Teaching or exposing students to a perspective that emphasizes deep structure may be critical for this type of transfer.

What can we do to emphasize structural information? One answer comes from evidence that deep processing can be facilitated with concrete representations (Barsalou 1999; Cheng 2002; Goldstone 1994a, 1994b; Goldstone and Barsalou 1999). When concrete details support relational reasoning, learners benefit from this redundancy (Gentner and Toupin 1986; Gentner and Rattermann 1991;

DeLoache et al. 1991). There are many ongoing attempts to make simulations more similar to their real world referents (DiFonzo, Hantula, and Bordia 1998; Grady 1998; Heim 2000).

As vivid and interesting as these representations may be, it remains to be seen whether concreteness leads to better learning. Particularly if we are interested in learning that transfers, a detailed and concrete construal may not be desirable. For instance, in the case of math manipulatives, detailed interesting objects may distract children from actual principles of mathematics (Uttal, Liu, and DeLoache 1999). These details are particularly critical when they detract from relational construals (Goldstone, Medin, and Gentner 1993).

However, even in situations where the details are not irrelevant but in fact relevant to structure, there is evidence to show that idealizations are better for generalization. Bassok and Holyoak (1989) examined transfer from algebra-to-physics versus physics-to-algebra. Even though physics is a fairly abstract domain, doing physics problems did not transfer to algebra as much as algebra to physics. Algebra captures the pure structural commonality shared by the two situations and this isolation of critical information may promote transfer. A particularly striking instance of relevant concreteness' detrimental effect on transfer comes from Kaminski, Sloutsky, and Heckler (2005, 2006). They taught students a version of modular arithmetic either through arbitrary abstract symbols or meaningful concrete representations of cups (see Figure 1). They taught students a system of relations structured according to addition modulo 3, a math system where there are only three numbers. Under modulo 3, $1+1=2$, $2+2=1$, and $1+2=0$. When students were taught this system with arbitrary symbols in place of numbers, learning was more difficult than learning with cups iconically filled 1/3 or 2/3 of the way. However, transfer to another modulo 3 system was better for the arbitrary condition than the iconic condition. They attributed this advantage of simple symbols to be by virtue of their similarity to other abstractly related systems. Another aspect of the transfer disadvantage of relevant concreteness is that these vivid details are conflated with relational structure. These findings demonstrate how even concreteness perfectly correlated with abstract structure can result in an overly
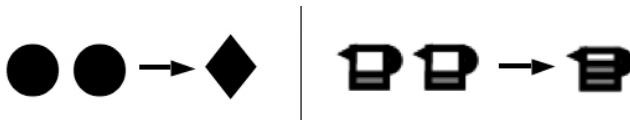

Figure 1. Training stimuli used in Kaminski, Sloutsky, and Heckler (2005, 2006) to teach students modular arithmetic. Although the modular arithmetic system is naturally instantiated by the cups scenario, instruction using the cups led students to generalize their knowledge less effectively than training with the more simplified geometric shapes.

concrete construal, because learners do not have to rely on abstract structure to comprehend the situation.

Because the benefits of concrete understanding and abstract transfer seem to map well to the concrete/idealized perceptual dimension, we want to examine their role in designing effective simulations. There are two ways of understanding concreteness that may be important to simulation design. One is in terms of situational concreteness with a high degree of similarity between the model and the real world situation that it represents (model-to-modeled-world relation). A second way of being concrete is to be perceptually-based. This way of being "concrete" is closer to Barsalou's Perceptual Symbols Theory (1999) which proposes a central role of perceptual processes in comprehending even abstract concepts such as logical relations. Simulations may include aspects of both situational and perceptual concreteness but we believe that these are separable. Presenting a general Diffusion Limited Aggregation system using the domain of water spreading into viscous oil, but with simple blue patches representing water and black patches representing oil, would count as situationally concrete but perceptually idealized. Presenting the same system in terms of two unidentified fluids but with slickly rendered, three dimensionally shaded graphics, would count as situationally idealized but perceptually rich.

Based on evidence that suggests that perceptual processes may ground conceptual ones (see Goldstone and Barsalou 1994 for a review), all of this research here on simulation design has been based on perceptual simulations. The magnitudes of situational and perceptual concreteness were adjusted to examine the resulting effects on learning and transfer. Our research group has conducted several studies aimed at informing the design of effective interactive simulations. The aim is to foster a flexible understanding of structural principles, the kind that transfers across dissimilar phenomena. To do this, these studies use simulations of two dissimilar phenomena, both governed by the CAS principle of "Competitive Specialization," to examine the effects of concreteness/idealization on transferable learning. First, here is a review of competitive specialization and an introduction to the simulations. Then we will summarize experiments that examined several aspects of the simulations' design.

4.   Case study: Competitive specialization

One advantage of teaching complex systems to study transfer is that these principles are of authentic scientific interest and the phenomena described by these systems are the result of real applications of these principles. We have focused here on one of the principles taught in our undergraduate CAS course at our university,

"competitive specialization." This principle describes situations where units start off homogenous and undifferentiated but by uniformly obeying simple rules, become specialized and individualized. A well-worked out example of Competitive Specialization is the development of neurons in the primary visual cortex that start off homogenous and become specialized to respond to visually presented lines with specific spatial orientations (von der Malsburg 1973). Another example regards the optimal allocation of agents that specialize to different spatial regions of territory. In such situations, specialization is required for optimal covering of all regions, so that every region has a reasonably close agent. For example, if oil drills are to optimally cover a territory or waitstaff are to optimally cover a party, they will each need to cover different regions. Inefficient covering means that there are some regions redundantly covered by multiple oil drills or waitstaff, while some regions are not covered at all. The same structure can be seen in neuron specialization if the range of visual stimuli is construed as a space where distance represents similarity: Efficient covering is achieved when each stimulus region has a neuron or neural assembly responsible for it.

A centralized solution might involve some sort of algorithm, plan, or leader to instruct these individual agents (e.g., oil drills, waitstaff, or neurons) to distribute over a territory (e.g., Texas, a party, or a range of stimuli). However, competitive specialization offers a *de*centralized solution to achieving optimal covering, by executing three simple steps repeatedly. In order to get agents to specialize over a territory: (1) randomly select one region from the entire territory to be covered, (2) determine the agent closest to the selected region, (3) adapt the closest agent towards the region with a relatively fast rate while adapting all other agents toward that region with a slower rate. These steps iterated repeatedly will result in agents specializing towards regions they are already close to. Agents that are not close to selected regions move slowly towards them so that they are free to cover other regions that may be selected later. The two critical parameters of competitive specialization are the adaptation rate of the closest agent and the rate of the other agents. Although there are other parameters that can be changed such as the number of agents or regions of space, the rates of adaptation are critical to achieving optimal specialization. Combinations of these critical parameters will be demonstrated in the next section.

Laboratory and classroom investigations have shown that simulations can foster transferable learning between instances of competitive specialization (Goldstone and Sakamoto 2003; Goldstone and Son 2005; Goldstone, Landy, and Son 2008). In these experiments, students are directed in a period of focused exploration with a relatively literal spatial instance of agents covering a territory. Then, students are probed with another simulation that instantiates the principles of competitive specialization in a metaphorical space — in particular, a similarity space. Their understanding of each simulation is measured with multiple-choice

quiz questions in all experiments. Some of the studies also examine how quickly students apply learned solutions as well as the quality of written out observations. An example simulation of agents covering a literal space (ants covering food patches) and another with agents covering metaphorical space (neuron sensors covering similarity space) will be shown in further detail. All simulations have been developed in NetLogo (Wilensky 1999).

4.1 Specialization in literal space

These simulations of competitive specialization involved agents spreading evenly over territory drawn by users. One example involves ants foraging food resources. At each time step, the ants-system iterates the rules described generally above and specifically here: A piece of food is randomly selected, the closest ant moves towards it with one rate while all other ants move toward it with a different rate. When a piece of food was selected, it was highlighted (yellow dot on the green patches, see Figure 2). Learners were told that there were no hidden complexities and these rules governed the behavior of the ants (by pressing the 'cover' command). To explore the simulation, students could draw food, add ants to the system, move ants, and randomize the ants' positions. They were also encouraged to explore various parameters (described as controlling factors) of the system, the
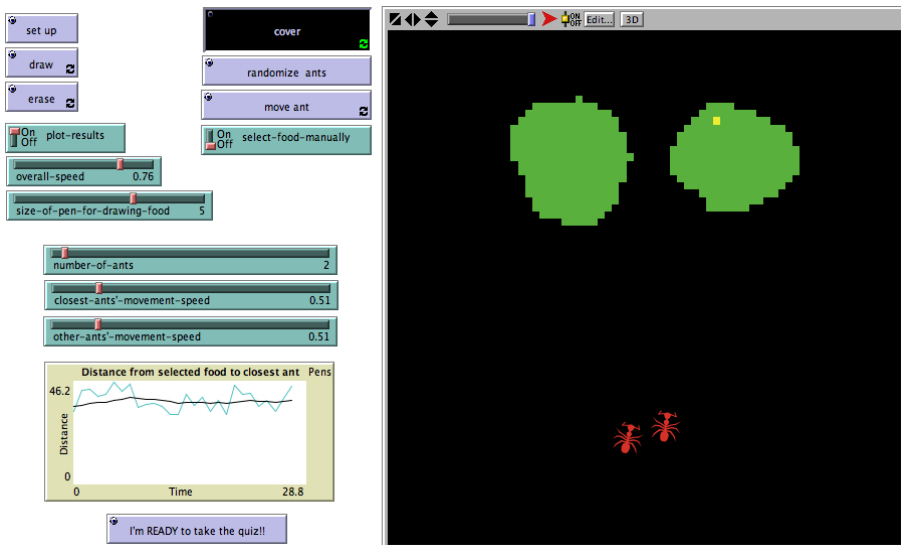

Figure 2. Screenshot of Ants and Food simulation created with NetLogo. Randomly selected food pieces (one is shown by the small yellow square) are sampled from the green regions drawn by the user. The ants move toward the sampled food with parametrically controllable speeds.

critical ones being the 'closest-ant-movement-speed' and 'other-ants-movement-speed' that could be adjusted on sliders (see Figure 2). We will call these parameters the 'closest rate' and the 'not closest rate.'

To guide their explorations of the parameters, a worksheet with several steps asked students to think about and perform a number of actions to the simulation (this worksheet and corresponding simulation can be downloaded at http://jys.bol.ucla.edu/simulations). (1) Students were asked to consider how to achieve an efficient covering solution such that the pieces of food each have an ant nearby. (2) Students were asked to manually place ants far away from the food in nonoptimal configurations and note that the graph (in the bottom left corner of Figure 2) depicting the average distance between selected food to the closest ant was high. Then students were asked to manually place the ants in optimal configurations (i.e., one on each region) and note that the graphed distance was low. (3) Students were asked to randomize the position of the ants and have the ants automatically
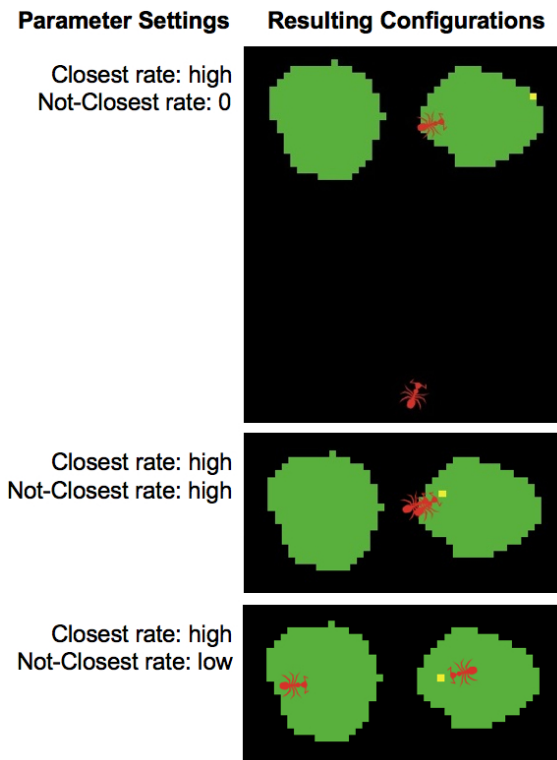

Figure 3. Resulting configurations from various parameter settings of the Ants and Food simulation. Only when the ant closest to randomly selected pieces of food moves quickly and the other ants move slowly does the optimal covering pattern (lowest panel) emerge.

achieve this optimal configuration by finding parameter values (instead of the manual 'move ant' command) to achieve low average distance.

Starting with the initial configuration of two ants and two food patches shown in Figure 2, the results of different parameter settings are shown in Figure 3. If only the closest ant moves, and the not-closest ant does not move at all, then the ant slightly closer to the food will move closer to all of the food regions because the food regions are all relatively close together. In subsequent iterations, this ant will continue to be the closest ant no matter what piece of food is selected. The other ant will never get the opportunity to be the closest ant and will never move at all. On the other hand, if both closest and not-closest rates are equally high, all ants will move closer to the food. However, because all ants will be moving equally quickly toward selected food regardless of their initial positions, their movements and positions become identical after several iterations. These are both sub-optimal parameter settings because either one ant or a group of ants are trying to cover the entire food space instead of specializing for different regions. In these cases, either one or all ants will eventually hover around the center of mass of the available food. The solution for competitive specialization is instantiated by having the closest ant move quickly while the other ants only move very slowly. Even if one ant starts off covering most of the available food, soon the other ants will come close enough to cover peripheral patches. Eventually, each ant will occupy a local center of mass (the entire space is divided by the number of available ants).

4.2 Specialization in metaphorical space

This second type of simulation involves agents specializing over a different kind of space, similarity space. Inspired by self-organizing neuronal sensors (Von de
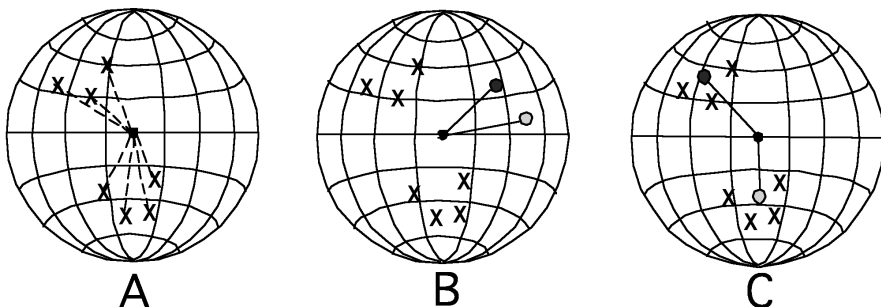

Figure 4. Rumelhart and Zipser's (1985) geometric construal of competitive learning shows (A) input patterns, represented by x's, as vector endpoints in a multidimensional space, (B) initially random pattern sensors are circles, and (C) the result when a sensor that "wins" the competition adapts towards the selected input while the other sensor adapts more slowly towards the input.

Malsburg 1973), the Sensors and Inputs simulation shows how initially homogenous sensors — sensors that react similarly to all inputs — become specialized to a certain range of inputs. The simulation is based on Rumelhart and Zipser's competitive learning algorithm (1985) used to find clusters of patterns in neural network inputs. They provide a geometric construal of pattern learning that is useful to review here. Imagine each input as a vector in a multidimensional feature-space (vector endpoints are illustrated in Figure 4 in a hypersphere). Inputs that share many features, a classic view of similarity, have endpoints that are close together and dissimilar inputs are far apart. Sensors start off with random feature values (feature weights in the original competitive learning algorithm), in other words as random points in the high-dimensional space. Applying the rules of competitive specialization, (1) an input is randomly presented, (2) the sensor that is most similar is chosen as the winner, and (3) the winner adapts a large amount towards the presented input and the losers adapt by a small amount.
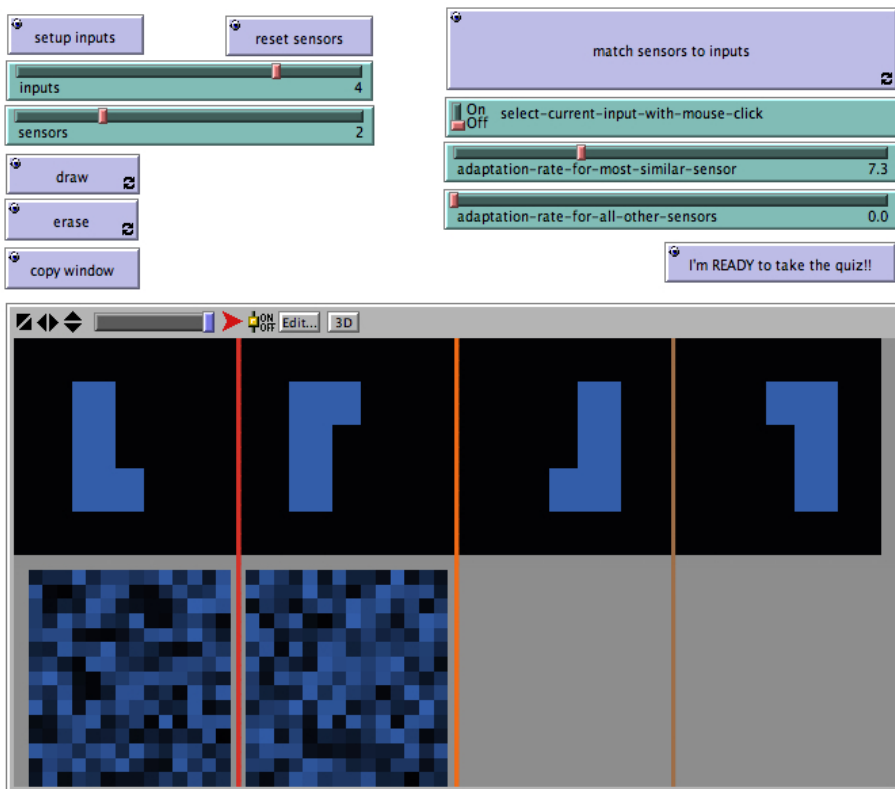

Figure 5. Screenshot of Sensors and Inputs simulation. Four input pictures (top row) have been drawn by the user and the two sensors (bottom row) are initialized with random pixel values.

This technique roughly produces sensors that capture general similarities among groups of instances (for improvements to this algorithm, see Goldstone 2003). Specialized sensors react to inputs that are close in multidimensional space just as the specialized ants in the previous section react to points of food that are close in 2-dimensional space. Although this simulation was created based on this more abstract conceptualization of spatial proximity, the user-interface only indirectly reflected this (see Figure 5). A sensor adapting toward an input, distance reduction in the high-dimensional space, merely looks more similar to the input.

In the simulation, inputs are drawn in on the first row and sensors are randomly initialized on the second row. Inputs are defined as arrays of pixels such that inputs that are "close" in multidimensional space have many overlapping pixels and look like each other. As the sensors are adapted towards inputs, they come to share more pixels and look like them. The key parameters in the Sensors and Inputs simulation are 'adaption-rate-for-most-similar-sensor' and 'adaption-rate-for-all-other-sensors' (which we will refer to as the most-similar and other rates).

Students can control these parameters, draw inputs, set the number of inputs and sensors to explore the simulation. Once again, the rules governing the system were explicated to students in a worksheet (worksheet and simulation available for download) and they were told that the command 'match sensors to inputs' would execute the rules iteratively. Students were generically asked to think about how sensors could become specialized for similar inputs by following the three rules. Unlike the simulations for specialization in literal space (i.e., ants and food), this simulation did not have a series of exercises mapped out for students. They were allowed to freely explore this simulation.

Consider Figure 5's set of initial input patterns drawn by a user and two random sensors. Figure 6 demonstrates how changing the two critical adaptation parameters results in varying degrees of specialization. If only the sensor most similar to a randomly selected input pattern adapts and the other does not adapt at all, the sensor that starts off a bit more similar to the patterns becomes even more similar to the inputs (which happen to be similar to each other by virtue of their black backgrounds). This sensor reacts to all inputs and comes to looks like all the inputs superimposed on top of each other, while the other sensor never reacts to any input. If all sensors (the most similar and others) adapt at the same rate, they all react to all inputs, again a sub-optimal solution. Specialization occurs when the most-similar sensor adapts at a faster rate and the others adapt more slowly. Even though one sensor might start off adapting towards all four inputs, the other will also be adapting toward them. Eventually, the closer, winning sensor, by virtue of adapting to one of the inputs, will be pulled away from the other inputs. The other, losing sensor can then adapt quickly, because it is the most-similar sensor to these inputs. The resulting sensors are each similar to some subset of the inputs, and
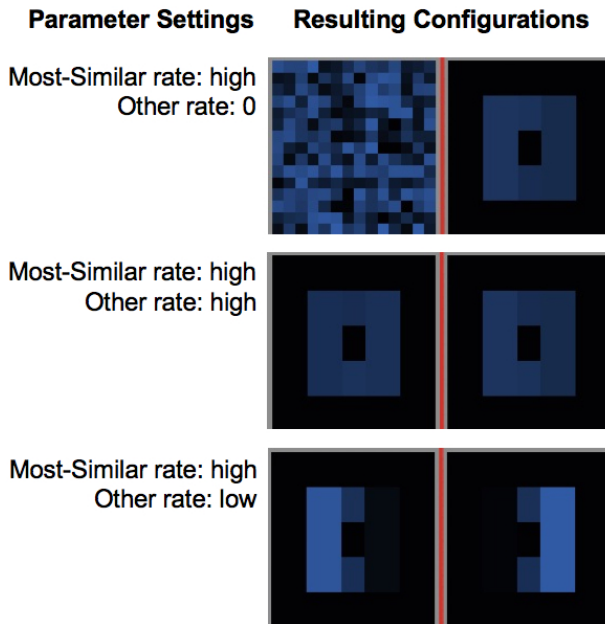
Parameter Settings   Resulting Configurations

Most-Similar rate: high
Other rate: 0

Most-Similar rate: high
Other rate: high

Most-Similar rate: high
Other rate: low

Figure 6. Resulting sensors from various parameter settings of the Sensors and Inputs simulation. Optimal covering of the sensors to the input patterns is achieved only when the sensor most similar to a randomly selected input pattern adapts quickly and the other sensor adapts slowly. In this case, when an optimal covering is found, the sensors spontaneously group the input patterns into subsets according to their similarity.

these subsets form groups according to similarity. These three combinations of adaptation rates show results that are analogous to the literal-space parameter results shown in Figure 2. These instances from both literal-space and metaphorical-space are equivalent under the abstract description of competitive specialization. Our studies examine the conditions under which students can come to appreciate this equivalence.

5.   Experimental findings

Two situations being analogous does not predict whether students will be able to appreciate the analogy. However, in education the aim is two-fold: To help students appreciate the relations *between* phenomena, the analogies, but also deeply understand the phenomena themselves, the individual analogs. Although concreteness typically leads to good understanding of particular situations, it often endangers transfer between them (Bransford, Brown, and Cocking 1999). Idealization has been characterized as necessary for transfer (Singley and Anderson 1989) but may

not provide enough understanding to transfer in the first place. There is an inherent tension between these two design directions, but the potential for grounded understanding that transfers has been tempting enough to draw several theoretical attempts to put together the advantages of concrete situated contexts with idealized, generalizable abstractions. These combination attempts range from "situated abstraction" (Noss, Hoyles, and Pozzi 2002) and "situated generalization" (Carraher, Nemirovsky, and Schliemann 1995) to "abstraction in context" (Hershkowitz, Schwarz, and Dreyfus 2001).

Despite the implications of empirical research that shows promise for combining concreteness and idealization, there have been few attempts to find design principles that emphasize the advantages of each. We will summarize several previously published studies examining the effects of graphical concreteness and idealization. Then we present three new studies examining the effect of concretely intuitive versus idealized descriptions and the best way for combining concrete/idealized graphics and descriptions.

5.1 Perceptual concreteness and idealization

Our initial foray into teaching competitive specialization to undergraduates was simply to examine whether there was an effect of training with concrete or idealized graphics on transfer (Goldstone and Sakamoto 2003; Goldstone and Son 2005). All participants were trained in an earlier version of the Ants and Food simulation with concrete graphics (black ants and small fruit) or idealized elements (black dots and green blobs) as shown in Figure 7. Afterwards they were able to explore the Sensors and Inputs simulation. Participants answered multiple-choice questions after each simulation that probed their knowledge of the embedded competitive specialization principles. Although these questions were always written in context-specific terms (i.e., "when the ant moves towards the food", "when
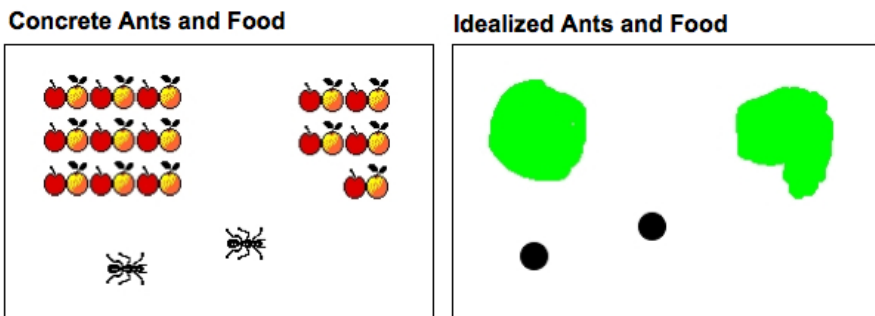

Figure 7. Graphical concrete/idealized manipulations used in the Ants and Food simulations (Goldstone and Sakamoto 2003; Goldstone and Son 2005).

the sensor adapts towards the input"), they could only be answered correctly by applying the principles of competitive specialization. These questions were written to be analogous across the two contexts (ants and sensors) and examples are provided in the Appendix. This procedure helps distinguish the effect of perceptual concreteness on both initial learning (Ants and Food simulation) and transfer (Sensors and Input simulation).

Even these relatively minor manipulations of concreteness — after all line drawings of ants are not that much more concrete than black dots — were found to have impact on both initial learning on the Ants and Food quiz and transfer to the Sensors and Inputs quiz. Participants in the concrete condition, with drawings readily perceptible as ants, showed better initial quiz performance than those in the idealized condition (39.8% and 33.8%, respectively). However, despite an initial disadvantage, the idealized condition showed better transfer to the Sensors and Inputs quiz (41.3%) than the concrete condition (36.4%). In particular, learners who had a poor understanding of the initial learning situation transferred better with idealized simulations.

These results can be described by the complementary advantages of concreteness and idealization. Although the concretely detailed ants and food graphics allowed students to learn effectively from that simulation, their knowledge may have been tied down to that domain. Students do well as long as they remain in the domain but fail to adapt their knowledge to new isomorphic situations. However, the idealized dots, because they were ambiguous and perhaps less intuitively connected to ants, had to be interpreted as ants, introducing difficulties in learning. However, this very ambiguity allows the idealized dots to serve as a useful representation for transfer, interpreted through the context of other isomorphic systems.

What is so striking about these results is how trivial the difference between conditions is. Looking from the ants and dots (Figure 7), the "idealization" seems insignificant. But in some sense, this physical change, stripping away the details such as ant legs and fruit stems to leave generic dots and blobs, is abstraction. Research from schema development (Fivush 1984) and the creation of mental models (Schwartz and Black 1996) suggest that the psychological process of forgetting or removing details creates structural representations. An external training that mimicked such processes might act as an aid to structural transfer.

Our first effort to combine the advantages of both concrete and idealized graphics was "concreteness fading," to start users with concrete graphics that transition into more abstract idealizations. Given that concrete similarities to corresponding real-world elements may have helped users gain an advantage in initially comprehending the simulation, concrete graphics are introduced first. But after this link has been established, the ants shift to dots and the fruit patches shift to blobs as a means of "fading" out the details that may have initially helped but also

hurt transfer to new domains. We compared fading to "concreteness introduction," where the idealized simulations became more detailed over time. Both of these conditions could potentially promote transfer because it is frequently advantageous to introduce multiple versions of the same analog (Gick and Holyoak 1980, 1983; Reeves and Weisberg 1990). To examine the effect of variability, consistent conditions (only concrete or only idealized) were also included in the experiment.

The same simulations from Goldstone and Sakamoto (2003) were used for teaching and probing transfer. In variable conditions, such as concreteness fading, 10 minutes after participants explored the concrete ants and food simulation, this message appeared, "We are now changing the appearances of the food and ants, but they still behave just as they did before." Then the alternative graphics appeared for another 10 minutes before the participants took the ants and food quiz. The concreteness introduction condition received 10 minutes of the idealized simulation, followed by the concrete one. There were no switches in the consistent conditions that received 20 minutes of the concrete simulation or 20 minutes of the idealized one.
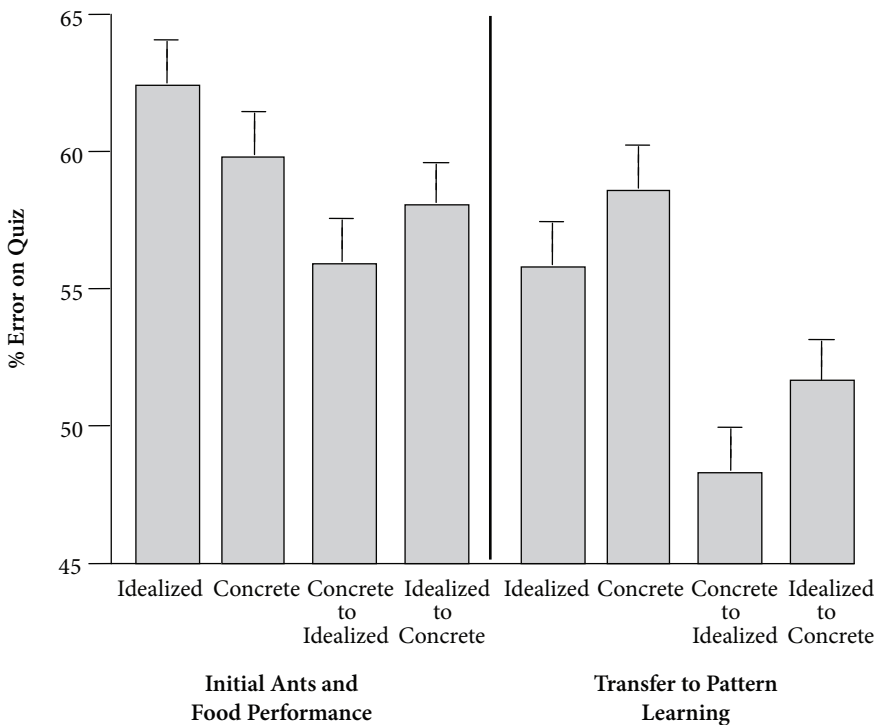

Figure 8. Results from Experiment 1 reported in Goldstone and Son (2005).

The results revealed several informative aspects of presenting both concrete and idealized graphics. By combining concreteness fading and introduction conditions into a "variability" condition and the idealized and concrete conditions into a "consistency" condition, we found an aggregate advantage of variability over consistency for both learning (61.3% to 56.8%, respectively) and transfer (57.5 to 50.1%, respectively). In addition, there was a more pronounced advantage when the variation in graphics was in the direction from concrete to idealized than vice versa (shown in Figure 8). A second experiment showed these effects in two measures of comprehension, quiz scores as well as problem-solving within the simulation environment.

The advantage of variability fits with theoretical intuitions that both concreteness and idealization contribute to learning and generalization. It is often difficult to focus on structure apart from rich details (Ratterman and Gentner 1998) or the context it is embedded in (Catrambone and Holyoak 1989; Holyoak and Koh 1987). Knowledge has even been characterized as completely dependent on these contextual details (Lave 1988; Lave and Wenger 1991). Researchers have documented housewives and fishermen carrying out complex mathematical computations for problems in familiar contexts without being able to demonstrate these skills in less familiar settings (Nunes, Schliemann, and Carrahar 1993). These results have been interpreted as evidence for domain-specific knowledge of mathematics. Concrete graphics might represent a situation where both structure and concrete context are present to support learning. However, this can produce a highly contextually tied specific construal helpful for understanding the presented situation. Idealized graphical representations cut those ties, fostering the learning experience to transfer to new situations. Being exposed to both construals seems to be additively advantageous because both concreteness fading and introduction conditions experience benefits to both learning and transfer.

It may seem as though participants in the variable condition were given a clue as to the more abstract commonality between the two spatial instances (ants and dots) of competitive specialization. Furthermore, even though informal interviews suggest that participants easily treated these instances as the "same thing" (Goldstone and Son 2005, 100), this practice in expanding their equivalence class of competitive specialization exemplars may have played a significant role in promoting the noticing of structural similarities. Several studies from analogical and symbolic reasoning have shown that comparison between two highly similar instances enhances attention to relational information (Loewenstein and Gentner 2005; Markman and Gentner 1993).

Although having both concrete and idealized graphics are better than just one or the other, the distinctive advantage of concreteness fading indicates an additional advantage of positioning concrete graphics first. One of the disadvantages,

and advantages, of idealized simulations is that they can be multiply interpreted. This is advantageous in transfer since the idealized learning can be re-used for new interpretations. But this ambiguity makes initial learning difficult. Presenting concrete graphics first is beneficial because ambiguous objects are interpreted in light of previously seen unambiguous objects (Leeper 1935; Medin, Goldstone, and Gentner 1993; Moore and Engel 2001). The perceptual scaffolding provided by concrete details provides a link between real world elements and the elements of the model. Stripping away seemingly unimportant elements of that scaffolding helps learners become more sensitive to the scaffold itself.

5.2 Intuitive concreteness

Our characterization of concreteness fading largely depends on the idea that the influence of concreteness comes from activating past knowledge to provide an intuitive basis for comprehending new material. If this is indeed the case, intuitive concreteness does not have to be instantiated purely perceptually. After all, the verbal description of "ants and food" provides a concrete situational interpretation for the perceptual elements of a simulation. One of the advantages of concrete pictures is that they match with their concrete interpretations. However, just as these matching intuitions might facilitate comprehending the current domain, we wondered if the complementary disadvantage to transfer might also result from this intuitive background.

In an attempt to separate the effects of a concrete description with an intuitive one, we changed the contextual descriptions applied to the spatial covering simulation. Although ants covering food is a concrete example of agents efficiently covering space, competitive specialization is not a very common way of understanding ant behavior. However, a highly intuitive example comes from the sports domain: Zone defense, a strategy in soccer or basketball where players defend zones of a playing field. The same general rules for competitive specialization can be described in the zone defense context: A shooter is randomly selected from the available shooting regions, the closest defender moves towards the selected shooter quickly while all other defenders move more slowly. Figure 9 shows the ants and food simulation modified to reflect zone defense. These rules seem to genuinely reflect what players might actually do on the soccer field (the defender closest to a shooter should run quickly towards that player!) rather than being abstract rules imposed upon a system. A poor soccer team has one player that defends the entire field while the rest of the defenders sit by. Conversely, a whole team of individuals trying to pursue every shooter is not very good either, as any parent of a six-year old soccer player will attest. Only when individuals specialize does the entire team cover the entire field. Experiment 1 examined whether these intuitive descriptions
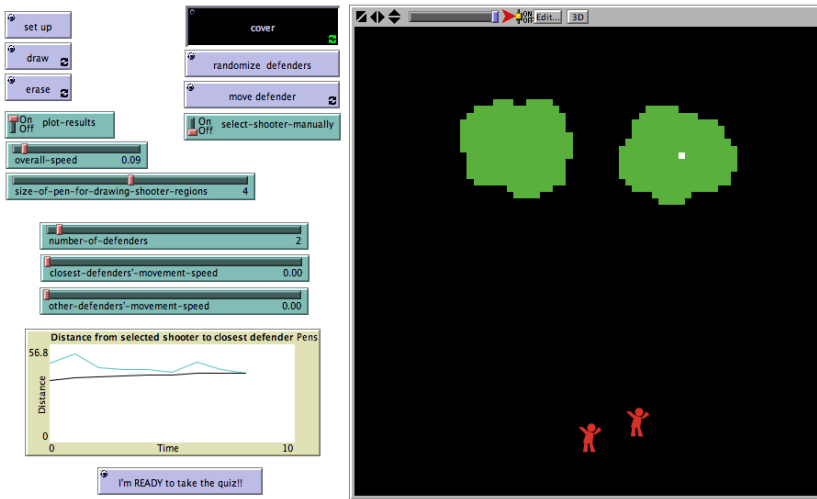
Figure 9. Screenshot of Defenders and Shooters simulation.

enable understanding and/or foster transfer, and Experiment 2 incorporated idealization to make better use of intuitions. Experiment 3 further examined the interpretability of idealized graphics.

6. Experiment 1

Space frequently provides a perceptual metaphor for understanding more abstract structures (Gardenfors 2000; Goldstone and Barsalou 1998) so both ant and defender simulations might foster good understanding of competitive specialization. Highly intuitive examples might foster even better understanding of competitive specialization. However, if the goal of CAS simulations is to produce *transferable* understanding, will these intuitive construals transfer to highly dissimilar situations? Does spatially grounded learning transfer to non-spatial situations?

6.1 Method

Participants. Thirty-seven undergraduates from Indiana University participated in this experiment for credit. Participants were randomly placed in one of two learning conditions: 18 received Concrete descriptions ("ants and food") and 19 received Intuitive descriptions ("defenders and shooter zones").

Materials and Procedure. All of our simulations were instantiated in NetLogo and are described more fully in Section 4. Both of the learning simulations were instantiations of specialization over physical space while the transfer simulation

was over similarity space. The "Ants and Food" simulation was a combination of concrete and idealized graphical elements used in previous studies (Goldstone and Sakamoto 2003; Goldstone and Son 2005) with line drawings of ants as agents and blobs depicting the food regions. In the "Defenders and Shooters simulation", defenders were depicted as stick figures and blobs depicted shooter regions. Participants received a packet of instructions and were given examples of configurations. They were guided through several combinations of parameters to help them discover the settings that would result in efficient specialization. After participants explored the first simulation, they took a seven-question multiple-choice quiz modified from previously used quizzes.

The transfer simulation was the Sensors and Inputs simulation shown in Section 4. There was a handout of instructions but no guidance as to useful parameter settings. Participants were instructed to explore this simulation before going on to a seven-question quiz with elements comparable to the learning quiz. All materials (including the NetLogo simulations) are available on our website (http://jys.bol. ucla.edu/simulations). Afterwards, participants were debriefed and asked whether they where familiar with zone defense.

6.2 Results

Because our manipulation of "intuitiveness" hinges on whether students were already familiar with zone defense, we used the debriefing question to determine whether it was a known concept. Zone defense seems to be a general concept among our undergraduates because only one person in our Intuitive condition and three in the Concrete condition reported that they did not know what a zone defense was.

The quiz results are shown in Figure 10 and were analyzed with a 2 (quiz-type: learning, transfer) x 2 (description condition: Concrete, Intuitive) repeated-measures ANOVA. There was a significant effect of test, $F(1, 35) = 21.40$, $p < .001$, and an interaction between test and description, $F(1, 35) = 5.27$, $p < .05$. A paired T-test revealed that the average score on the learning quiz (59.9%) was significantly higher than the transfer quiz (39%), $t(36) = 4.43$, $p < .001$. Closer examination of the interaction revealed that this was mostly caused by the Intuitive condition which performed 30.8 percentage points better on learning than transfer, $t(18) = 5.05$, $p < .001$. On the other hand, the concrete condition did not show a significant difference, only 10 percentage points better on learning than transfer tests, $t(17) = 1.60$. Although T-tests between the two description conditions were not significant, $p > .15$, it seems that whatever learning the intuitive condition might have shown did not come across for transfer performance.

To further examine this possibility, we examined the correlations between test scores between the two training conditions and the transfer test. The concrete
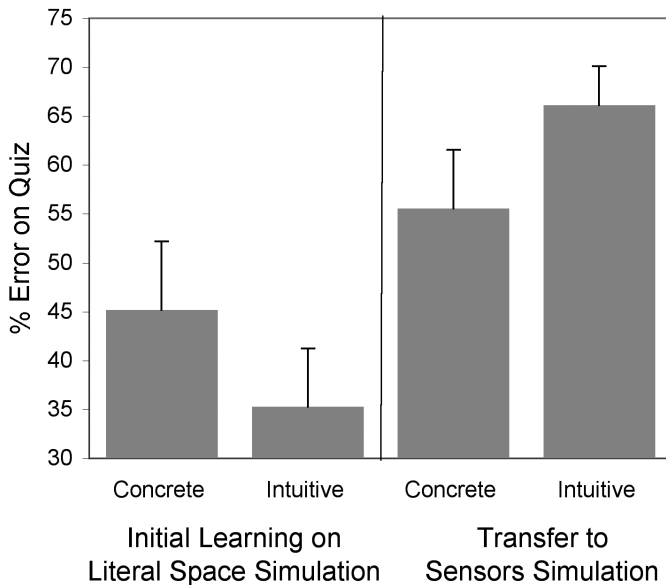
Figure 10. Results for Experiment 1. The intuitive condition does well (few errors) on the initial simulation, but shows less transfer to an analogous situation than does the concrete condition.

condition showed a significant correlation between learning and transfer performance across participants, $r = .53$, $p < .05$, suggesting that those who understood the Ants and Food simulation well also did well on the Sensors and Inputs quiz. However, the intuitive condition's training and testing quiz scores were not significantly correlated, $r = .38$. This, combined with the paired T-test results, suggests that what students learned during training in the intuitive condition did not transfer well to the analogous but superficially unrelated simulation.

These results are interesting because defender and shooter are relational terms and zone defense is a structurally proper instantiation of competitive specialization. Additionally, through this simulation participants can invoke other context-specific intuitions that support this structure. Informal observation of written notes on the instruction packets showed that participants in the Intuitive condition used sports-specific terms to describe particular states of the system. For example, when describing the "clumping" that happens when all agents move at the same rate (see Figure 11), participants called this "bunch ball" and when describing a state where some defenders are not covering anything, participants used descriptions such as "shooters [are] being left wide open" or "inefficient block." Contrast this to the domain-specific comments made by those in the concrete condition: "the rest stay hungry", "ants dying out", "ended up on the grass", "wiggle around", "chewing food". These statements neither describe competitive specialization nor
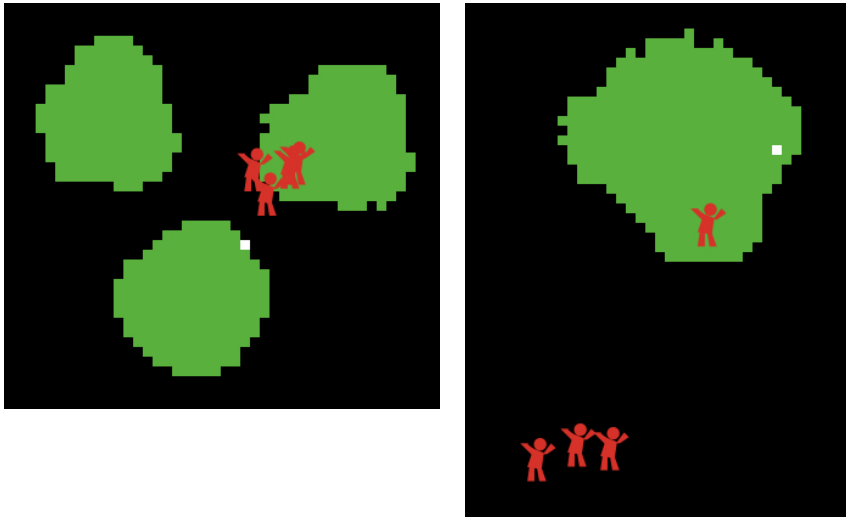
Figure 11. (a) This state on the left is the result of all defenders moving at the same rate. (b) The state on the right is the results of only the closest-defender moving at all. These results were described in sports-specific terms such as "bunch ball" or "shooters being wide open," respectively.

are related to particular parameter settings. This contrast illustrates one of the learning benefits from intuitive simulations — that the relation between the world and the model becomes transparent thus allowing domain-specific intuitions from the world to help students interpret the model. However, taken to the extreme, these benefits can also become detrimental, particularly for transfer.

When situations are too intuitive and the model-to-modeled-world link too transparent, the model ceases to become a general representation of the rules of competitive specialization. Instead the model simply provides an interpretation of zone defense. This learning example strongly tied to the sports domain allows learners to use their intuitions about sports to answer the learning quiz questions, but without the support of domain specific knowledge, they did not have any previous learning that could help them in a dissimilar transfer situation. All of this supporting contextualization that helped during the learning quiz may have acted as a crutch rather than a scaffold (Pani, Jeffres, Shippey, and Schwartz 1996). By drawing upon so much rich knowledge, participants may not have learned anything new about the competitive specialization principles underlying zone defense. In some sense, the relations were so deeply embedded in the zone defense context that participants could not separate them out.

Another way to construe this tight model-to-modeled-world link is that although zone defense clearly demonstrates this link, it also prevents learners from making the model-to-*modelable*-worlds link. This link requires learners to understand the

model's potential referents beyond merely understanding the model itself. Here it may be useful to invoke DeLoache's dual-representation hypothesis (1995) which proposes that transfer between a model and a referential object comes from understanding two things: (1) the model itself as well as (2) the model's referential role. DeLoache's studies (1995, 2000) examine children's use of scale models as maps for larger rooms. In these studies, young children are shown a small Snoopy doll hidden under a small piece of furniture in a small model room. They are taken to a larger room that is set up in the same way and asked to find big Snoopy in the corresponding location. Typically 2.5-year-olds have trouble using the model while 3-year-olds use the model location to find Snoopy. DeLoache (2000) proposes that in order to transfer information from the model to the larger room, children must represent both the shown location as well as the referential relation between the model and the room. Thus, when younger children are shown the model behind a pane of fiberglass, strengthening the model's referential role, they make better use of the model in the finding task. Distance from the model directs more attention to the room that is being modeled rather than the model itself. Additionally, if the older children are given an opportunity to play with the model before the finding task, weakening the referential understanding by making the model an interesting object in its own right, their ability to use the model declines.

Our intuitiveness manipulation may have similarly weakened the referential role by making the model itself an object with interesting properties. This probably contributed to increases in actual understanding of the model as well, as shown in Experiment 1. Following DeLoache's lead, one solution for making effective use of intuitive models might be to make the model less interesting as a domain in and of itself, and strengthen the model-to-modelable-worlds link. Experiment 2 is an attempt to put our own "fiber glass" in front of the model.

7.   Experiment 2

Experiment 2 is an effort to make the zone defense simulation less evocative of real-life zone defense in order to foster improvements in generalization. We used the insight from previous studies on perceptual idealization and created a generic spatial covering simulation in NetLogo with dots and blobs. Dots can be described as people, animals, defenders, or oil drills so the two descriptions ("defenders" and "ants") from Experiment 1 were each applied to the dot simulation. This experiment thus distinguishes whether the differences found between concrete interpretations and intuitive ones are mediated by their matching pictures or solely by these descriptions. If intuitive descriptions are always detrimental to transfer, we should see the same pattern of results as Experiment 1. If they are not detrimental
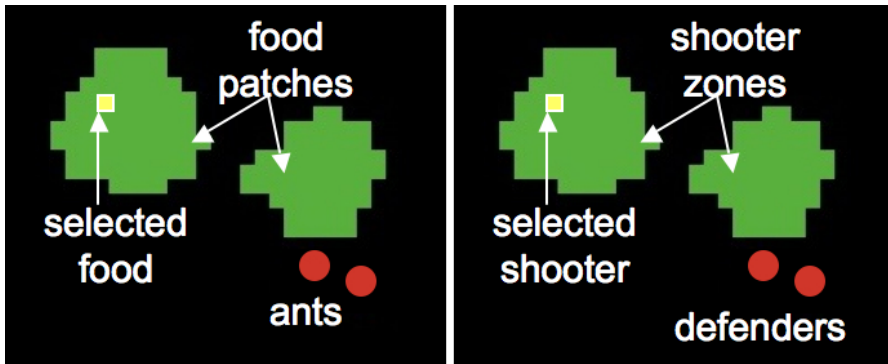
Figure 12. Pictures from the instruction packets of Experiment 2.

when applied to idealized dots, this provides further support for the benefits of idealized simulations.

7.1 Method

Participants. Forty-seven undergraduates from Indiana University participated in this experiment for credit. Although all participants learned with a simulation that had dots and blobs, they were described in two ways: 22 had Concrete descriptions ("ants and food") and 25 had Intuitive descriptions ("defenders and shooter zones").

Materials and Procedure. The procedure is identical to that of Experiment 1. The only change is in the elements depicted in the learning simulations. The ants in the Ants and Food simulation were changed to dots and the people in the Defenders and Shooters simulation were also changed to dots (Figure 12). Transfer was measured with the Sensors and Inputs simulation used previously.

7.2 Results

There were several participants who reported that they did not know zone defense (6 in the Intuitive condition and 5 in the concrete condition) but this was not a significant factor by any analysis. The main quiz results are shown in Figure 13 and were analyzed with a 2x2, quiz-type (learning, transfer) x description condition (Concrete, Intuitive) repeated-measures ANOVA. There was a significant effect of test, $F(1, 45) = 45.00$, $p < .001$, but no effect of description, $F(1, 45) = .171$, nor interaction, $F(1, 35) = 1.78$. A paired T-test revealed that scores on the learning quiz were 14.2% higher than on the transfer quiz, $t(46) = 3.88$, $p < .001$. Collapsing across concrete and intuitive conditions, scores on the two quizzes were correlated
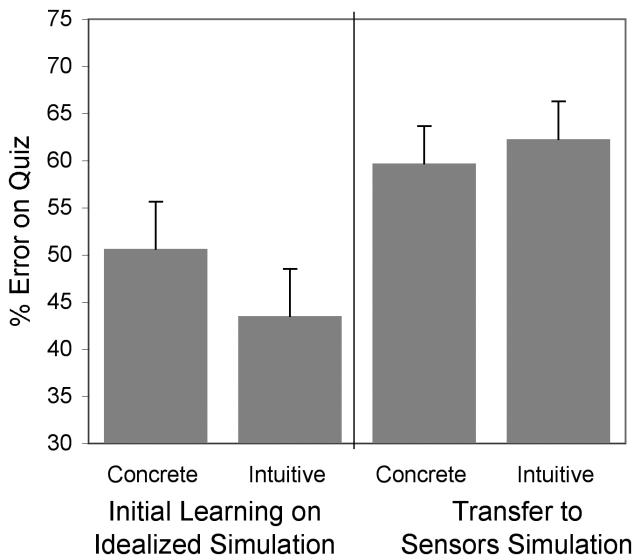
Figure 13. Results from Experiment 2. The graphical elements for all participants were idealized, but the descriptions associated with these elements could either be concrete (e.g., ants) or intuitively related to competitive specialization (intuitive). Pairing idealized graphics with the intuitive defenders background story yields good understanding of the training simulation (low error rate on quiz), and equivalent transfer to the concrete story.

across participants, $r = .38$, $p < .01$. Although the intuitive condition still performed significantly better on learning than transfer (18.8%), $p < .001$, their scores on these two quizzes are now also significantly correlated, $r = .51$, $p < .01$. On the other hand, the concrete condition's 9% difference between the tests was not reliably difference, $t(21) = 1.60$, nor were participants' training and test scores correlated, $r = .28$. T-tests between the two description conditions were not significant for either quiz, $p > .30$.

In Experiment 1, intuitive descriptions seemed to have value for learning but was devastating for transfer. By using idealized simulations, the major disadvantage of using intuitive descriptions, lack of transfer, seems to have been mitigated. There were two reasons that intuitive stories hurt transfer in Experiment 1: (1) by embedding the rules of competitive specialization too deeply in one domain and (2) by weakening the model's referential role. Idealized pictures could help alleviate both of these effects on transfer. By being visually less similar to the zone defense context, idealized graphics may have forced students to work harder to make the link between the simulation elements and zone defense, but this effort could enable more transfer. Turning defenders into more context-neutral dots gave students practice with interpreting rich and complex scenarios using the lens of competitive specialization. This practice is helpful when students are then given

the sensors simulation because it employs competitive specialization in an even subtler manner. By this account, students benefit not only from exposure to clear principles, but perhaps even more importantly by receiving training in the critical cognitive skill of interpreting model elements according to the principles. This suggestion is consistent with Bransford and Schwartz's (1999) framing of transfer in terms of giving students skills for future learning. Additionally, by virtue of being interpretable in more ways, simple dots are more applicable to the wide variety of competitive specialization instances than little people.

However, idealized simulations also seem to compromise some of the advantages of using concrete descriptions. Concrete visual situations described concretely have a strong model-to-modeled-world link providing a frame for the abstract principles of competitive specialization. Idealized graphics reduces this meaningful link, thus reducing the amount of learning in the initial simulation. This may have contributed to a similar level of decrease in transfer.

A priori, an important design aspect seems to be how simulations get linguistically described. They typically can be described in a number of ways and some of these descriptions may be more helpful for later needs than others. According to constructivist theories of learning, most notably Piaget (1980), knowledge is constructed by coordinating multiple instances or representations. With the rise of multimedia educational tools, there is a greater need for understanding the integration of both visual information and linguistic descriptions (Mayer 1993; Schnotz 1993). There are several theories posing a form of dual coding (e.g., Baddeley 1992; Mayer 1992; Paivio 1986; Schnotz 1993) that suggest that these two streams must be coordinated with each other for effective learning (Clark and Paivio 1991; Mayer 1984). Paivio (1986) referred to a process of "building referential connections" that may be relevant to the linguistic interactions with concrete and idealized graphics. Although descriptions that match their perceptual elements have strong referential connections already (i.e., "ants" is strongly linked to pictures of ants), in order to foster generalizable knowledge, we need to create a new link, not to ants but to "originally homogenous agents that become specialized." Ambiguous visual stimuli weaken the referential link to ants per se but may allow this more abstract class to be formed instead. An interesting prediction might be that using these ambiguous visual stimuli with multiple linguistic descriptions (e.g., first calling the elements "ants" and then "defenders") might result in better internalization of the underlying principle.

Although the studies reported here examine the impact of using concrete and intuitive linguistic descriptions to understand multiply interpretable perceptual events, it is possible that there is a way to use abstract linguistic descriptions to interpret concrete perceptual events. We have made several unsuccessful attempts to find ways to build this referential connection in the opposite direction. Pilot
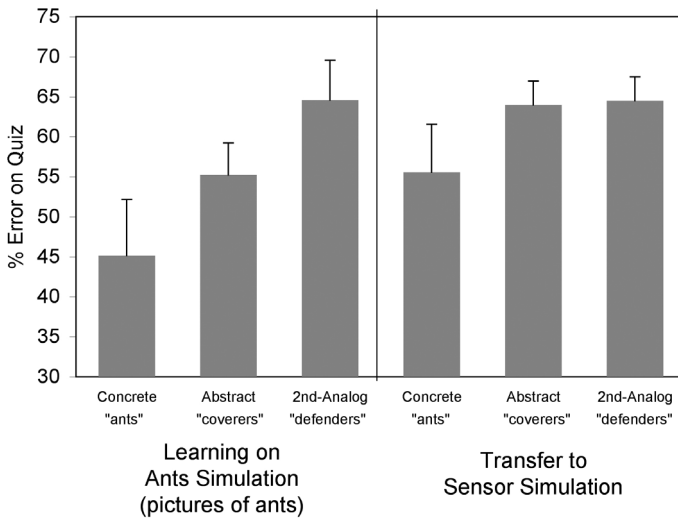
Figure 14. Results of pilot studies on abstract descriptions. The graphical elements for all participants were ants, but the descriptions associated with these elements could be either abstract (e.g., "coverers") or a second analog (e.g., "defenders"). These descriptions yield generally poor understanding of the training simulation (high error rate on quiz) and similarly poor transfer.

studies have examined the effects of describing the concrete depictions of ants in abstract ways, such as "coverers and resources," with the aim of combining graphical concreteness and linguistic idealization. We have even tried teaching with two analogs simultaneously by showing pictures of ants but describing them as "defenders and shooters." However, both of these training conditions result in marginally detrimental effects on both learning and transfer. Pilot results from abstract and second-analog description conditions are shown in Figure 14. As of yet we have not found a successful way of combining concrete pictures with abstract words, in contrast to the beneficial effects of idealized pictures with concrete and intuitive descriptions shown in Figure 14. Through these failed attempts, we realize how difficult it is to create words that helpfully capture the wide array of agents that can take part in competitive specialization. One way of "abstracting" without being abstract per se is to describe perceptual ants as "insects" or "animals." Although we have not tested such descriptions, this may be able to foster a wider appreciation for the types of things that could be agents of competitive specialization. However, it may be more effective to teach with idealized images describable in multiple ways than to have one abstract description applied to multiple concrete instances. Although scientific efforts for universal principles are typically aimed towards the latter, the pedagogical aims of teaching science may be better achieved through the former.

8.   Experiment 3

Experiment 3 may more clearly illustrate the benefit of idealized images to take on a broad range of descriptions. In an effort to come up with a general but meaningful term to capture agents that 'cover' both physical and metaphorical space, the simulation depicting ants was modified in terms of "lids specializing over pots." The same descriptive modifications were made to the idealized dot simulation. For both ant and dot depictions, the rules of competitive specialization are described as follows: A pot is randomly selected, the closest lid moves towards it with one rate, while all other lids move toward it with a different rate. "Lids and Pots" is not at all an intuitive cover story but it is a concrete one. Lids and pots are about physical covering situations and are relatively concrete simple objects. There is no a priori reason to believe that this description should help anyone understand competitive specialization, much less show transfer to the domain of sensors and inputs, and this was true for those who received the ants simulation described as "lids".

8.1 Method

Participants. Thirty-one undergraduates from Indiana University participated in this experiment for credit. Although all participants learned with a simulation described as "lids covering pots," this was applied to two different graphics: 12 participants learned with Concrete ants and 19 with Idealized dots.

   Materials and Procedure. The procedure is identical to that of Experiment 1 and 2. The elements depicted in the learning simulations were literal space instantiations of competitive specialization with element depicted as either ants or dots. Both were (somewhat oddly) described as "lids". The Sensors and Inputs simulation provided a measure of transfer.

8.2 Results and discussion

The main quiz results are shown in Figure 15 and were analyzed with a 2x2, quiz-type (learning, transfer) x learning graphics (Concrete ants, Idealized dots) repeated-measures ANOVA. There was a significant effect of test, $F(1, 29) = 10.15$, $p < .01$, and a significant effect of graphical elements, $F(1, 29) = 4.93$, $p < .05$, but no interaction, $F(1, 29) = .11$. A paired T-test revealed that scores on the learning quiz were 13.8% higher than on the transfer quiz, $t(30) = 3.40$, $p < .01$, and these scores were significantly correlated, $r = .46$, $p < .01$. Learning with ant graphics resulted in significantly worse performance on both learning, $t(30) = 5.44$, $p < .05$, and transfer quizzes, $t(30) = 4.4$, $p < .05$. Describing idealized dots as "lids and pots" allowed
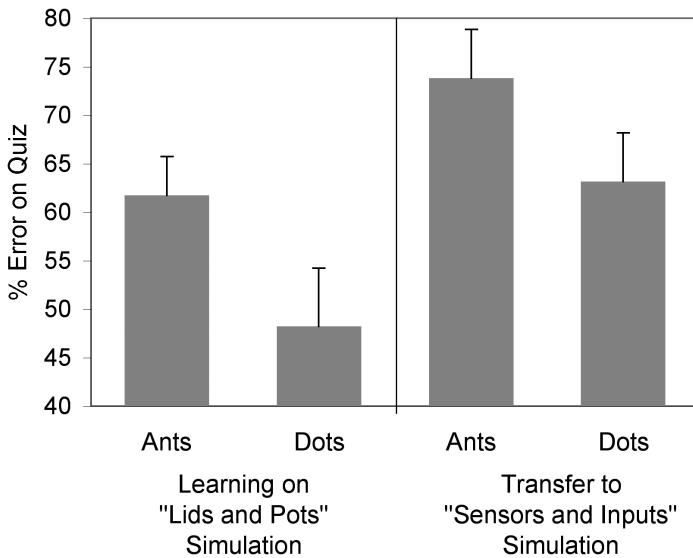
Figure 15. Experiment 3 results illustrating the flexibility of idealized depictions of simulation elements. The two graphical conditions, ants versus dots, represent the depicted elements in the learning simulation described as "lids and pots." However, as odd and unintuitive as this description may be, the idealized graphics allow students to learn and transfer better than concrete graphics.

participants not only to learn and transfer better than those who were shown concrete ants, but also to learn and transfer at levels comparable to participants from Experiment 2 who had more meaningful descriptions applied to the dots.

Considering how odd the description of "lids covering pots" is (at least compared to ants covering food and defenders covering shooters), it is surprising that any graphical elements could allow participants to learn competitive specialization from it. This is a demonstration of the advantage of idealized graphics. Their flexibility, to be interpreted in multiple ways, gives them an advantage over more specific and less interpretable concrete graphics. Whereas participants were confused when a line drawing of an ant was called a "lid", they were apparently more amenable to calling an idealized dot a "lid".

9. Some design principles for interactive simulations

With regard to concreteness and idealization, as well as an eye on both learning and transfer, there are a few design principles that emerge from these experiments:

Get the best of both worlds

Both educators and cognitive scientists have realized the advantages that come from both concrete learning instances as well as abstract representations of structure. A simple design suggestion is to present multiple instantiations of the same idea in easily relatable ways. In many ways, presenting students with multiple linked representations is not a new idea; however, our research suggests some strategies for traversing across the different types of representations. For example, although sparse equations and highly concrete instantiations of them are relatable, one problem is that they are too different from each other to reconcile properly. Simulations can range over a continuum of concreteness, from virtual reality all the way down to simple dots. Learners may benefit by taking small manageable steps across that continuum. Highly concrete simulations invite learners to involve their past knowledge and intuitions. Shifting those simulations towards increasingly idealized forms may help by providing connection to that past knowledge while removing some of the irrelevant specific details.

Be wary of too much concrete intuition

Although highly intuitive learning situations seem to be easier for learners to grasp, educators should be aware of the potential detriment to transfer. Intuitions that are highly tied to a context may only be effective in that context. One danger is that these intuitions often allow students to excel in domain-specific tests of knowledge, where intuitions are consistent with the correct answer (Dror, Peron, Hind, and Charlton 2005). The disadvantage is only seen in tests of transfer to dissimilar contexts. Thus, students and teachers may feel that students have learned more with a model grounded in intuition, but the student may be less able to apply their knowledge to new analogs. Scientific simulations should be designed with the primary goal of *fostering* scientific intuitions rather than simply *depending* on these intuitions. This emphasis on creating new ways of seeing and interpreting situations implicates being able to transcend specific contexts. So it is important to test the effectiveness of simulations for later transfer as well as immediate performance (see also Bransford and Scwhartz 1998). However, combining intuitions with other more abstract design elements, such as idealized graphics, allows students to use their intuitions more effectively for transfer.

When in doubt, idealize perceptual elements

Perceptual simulations instantiate models. Experience with simulations may potentially provide building blocks for mental models and idealized elements may

provide particularly efficient building blocks that can be used to model a variety of situations. This effective portrayal may also be the advantage of extreme or caricatured examples which exaggerate critical features (Dror, Stevenage, and Ashworth 2008). Furthermore, idealized perceptual elements, by being less connected to specific real-world categories, can illustrate a greater diversity of contextually specific descriptions than concretely similar elements. In this way, idealized simulations appear to provide effective mental manipulatives for building future models.

Additionally, since it is rather difficult to find abstract descriptions that students immediately grasp, using idealized graphics can draw upon their already well-developed perceptual capabilities. Idealized graphics seem relatively resilient to the dangers of intuitive descriptions, while more concrete elements must be described in particular ways to be effective.

10. Conclusions

For a long time, scientific models were visually presented by the insertion of pictures or graphs in text. The possibilities present in complex interactive simulations for radically affecting science as well as science education are enormous. However, to make use of all of that potential, we must design simulations that respect psychological, not just technical, constraints. The psychology of analogical problem-solving and other forms of relational reasoning often draws evidence from mathematical and scientific learning because these domains are aimed at precisely encapsulating structure, stripping away irrelevant details. Scientific explanations, by using the same mathematical or formal abstractions, reflect a level of description useful for problem-solving in a variety of situations, thereby allowing these disparate situations to be similar. We propose that simulations may be able to help students create models that explain a wide variety of phenomena. However, there is always the danger that learners will deal with these learning technologies in superficial or otherwise inadequate ways, so research on relevant aspects of design aspects is vital.

The interesting claims that come out of science can be counterintuitive. Complex systems have that flavor because most people assume that in order to explain high-level behavior, one must have a high-level plan (Chi 2005). In trying to foster the opposite intuition, that some high-level phenomena can have low-level emergent solutions, educational technologies will play an important role in helping create new intuitions. Combining the advantages of seeing appropriate simulations with compelling intuitive explanations may be an efficient way of using available resources to create effective learning opportunities.

References

Anderson, J.R., Greeno, J.G., Reder, L.M., and Simon, H.A. 2000. "Perspectives on learning, thinking, and activity". *Educational Researcher* 29: 11–13.

Anderson, J.R., Reder, L.M., and Simon, H.A. 1996. "Situated learning and education". *Educational Researcher* 25: 5–11.

Bransford, J., Brown, A.L., and Cocking, R.R. (eds). 1999. *How People Learn: Brain, Mind, Experience, and School.* Washington, D.C.: National Academy Press.

Baddeley, A. 1992. "Working memory". *Science* 255: 556–559.

Ball, P. 1999. *The Self-Made Tapestry.* Oxford: Oxford University Press.

Bar-Yam, Y. 1997. *Dynamics of Complex Systems.* Reading, MA: Addison-Wesley.

Barnett, S.M. and Ceci, S.J. 2002. "When and where do we apply what we learn? A taxonomy for far transfer". *Psychological Bulletin* 4: 612–637.

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

Bassok, M. and 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. 2005. *Cities and Complexity: Understanding Cities with Cellular Automata, Agent-Based Models, and Fractals.* Cambridge, MA: The MIT Press.

Beals, R., Krantz, D.H., and Tversky, A. 1968. "Foundations of multidimensional scaling". *Psychological Review* 75: 127–142.

Bentley, W.A. and Humphreys, W.J. 1962. *Snow Crystals.* New York: Dover.

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

Brooks, R.A. 1991. "Intelligence without representation". *Artificial Intelligence* 47: 139–159.

Carraher, D.W., Nemirovsky, R., and Schliemann, A.D. 1995. "Situated generalization". *Proceedings of the 19th Annual Meeting of the International Group for the Psychology of Mathematics Education* (Vol. 1). Recife: Universidade Federal de Pernambuco, 234.

Carraher, D. and Schliemann, A.D. 2002. "The transfer dilemma". *The Journal of the Learning Sciences* 11: 1–24.

Casti, J.L. 1994. *Complexification.* New York: HarperCollins.

Casti, J.L. 1997. "Would-be worlds: Towards a theory of complex systems". *Artificial Life and Robotics* 1: 1433–5298.

Catrambone, R. and Holyoak, K.J. 1989. "Overcoming contextual limitations on problem-solving transfer". *Journal of Experimental Psychology: Learning, Memory, and Cognition* 15: 1147–1156.

Clark, J.M. and Paivio, A. 1991. "Dual coding theory and education". *Educational Psychology Review* 3: 149–210.

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., and Glaser, R. 1981. "Categorization and representation of physics problems by experts and novices". *Cognitive Science* 5: 121–152.

Dede, C. 1995. "The evolution of constructivist learning environments: Immersion in distributed, virtual worlds". *Educational Technology* 35: 46–52.

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., Kolstad, D.V., and Anderson, K.N. 1991. "Physical similarity and young children's understanding of scale models". *Child Development* 62: 111–126.

DiFonzo, N., Hantula, D.A., and Bordia, P. 1998. "Microworlds for experimental research: Having your (control and collections) cake and realism too". *Behavioral Research Methods, Instruments, and Computers* 30: 278–286.

Dixon, J.A. and Bangert, A.S. 2004. "On the spontaneous discovery of a mathematical relation during problem solving". *Cognitive Science* 28: 433–449.

Dror, I.E., Stevenage, S.V., and Ashworth, A.R.S. 2008. "Helping the cognitive system learn: Exaggerating distinctiveness and uniqueness". *Applied Cognitive Psychology* 22: 573-585.

Dror, I.E., Peron, A.E., Hind, S.-L., and Charlton, D. 2005. "When emotions get the better of us: The effect of contextual top-down processing on matching fingerprints". *Applied Cognitive Psychology* 19: 799–809.

Duschl, R.A. 1990. *Restructuring Science Education*. New York: Teachers College Press.

Flake, G.W. 1998. *The Computational Beauty of Nature*. Cambridge, MA: The MIT Press.

Garcia-Ruiz, J.M., Louis, E., Meakin, P., and Sander, L.M. 1993. *Growth Patterns in Physical Sciences and Biology*. New York: Plenum Press.

Gardenfors, P. 2000. *Conceptual Spaces*. Cambridge, MA: The MIT Press.

Gentner, D. and Rattermann, M.J. 1991. "Language and the career of similarity". In S.A. Gelman and J.P. Byrnes (eds), *Perspectives on Language and Thought: Interrelations in Development*. Cambridge: Cambridge University Press, 225–277.

Gentner, D. and Toupin, C. 1986. "Systematicity and surface similarity in the development of analogy". *Cognitive Science* 10: 277–300.

Gick, M.L. and Holyoak, K.J. 1980. "Analogical problem solving". *Cognitive Psychology* 12: 306–355.

Gick, M.L. and 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 and C. Olson (eds), *Perceptual Organization in Vision: Behavioral and Neural Perspectives*. Mahwah, NJ: Lawrence Erlbaum, 233–278.

Goldstone, R.L. and Barsalou, L. 1998. "Reuniting perception and conception". *Cognition* 65: 231–262.

Goldstone, R.L., Landy, D., and Son, J.Y. 2008. "A well grounded education: The role of perception in science and mathematics". In M. de Vega, A. Glenberg, and A. Graesser (eds), *Symbols, Embodiment, and Meaning*. Oxford: Oxford University Press, 327-355.

Goldstone, R.L., Medin, D.L., and Gentner, D. 1991. "Relational similarity and the nonindependence of features in similarity judgments". *Cognitive Psychology* 23: 222–264.

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

Goldstone, R.L. and Son, J.Y. 2005. "The transfer of scientific principles using concrete and idealized simulations". *Journal of the Learning Sciences* 14: 69–114.

Grady, S.M. 1998. *Virtual Reality: Computers Mimic the Physical World*. New York: Facts on File.

Heim, M. 2000. *Virtual Realism*. New York: Oxford University Press.

Hershkowitz, R., Schwarz, B.B., and Dreyfus, T. 2001. "Abstraction in context: Epistemic actions". *Journal for Research in Mathematics Education* 32: 195–222.

Holyoak, K.J. and Koh, K. 1987. "Surface and structural similarity in analogical transfer". *Memory & Cognition* 15: 332–340.

Jackson, S., Stratford, J., Krajcik, S., and Soloway, E. 1996. "Making system dynamics modeling accessible to pre-college science students". *Interactive Learning Environments* 4: 233–257.

Kaminski, J.A., Sloutsky, V.M., and Heckler, A.F. 2005. "Relevant concreteness and its effects on learning and transfer". In B. Bara, L. Barsalou, and M. Bucciarelli (eds), *Proceedings of the XXVII Annual Conference of the Cognitive Science Society*. Mahwah, NJ: Erlbaum, 1167–1172.

Kaminski, J.A., Sloutsky, V.M., and Heckler, A.F. 2006. "Do children need concrete instantiations to learn an abstract concept?". In R. Sun and N. Miyake (eds), *Proceedings of the XXVIII Annual Conference of the Cognitive Science Society*, Mahwah, NJ: Erlbaum, 411–416.

Kirkpatrick, S., Gelatt, C.D., and Vecchi, M.P. 1983. "Optimization by simulated annealing". *Science* 220: 671–680.

Klahr, D. and Carver, S.M. 1988. "Cognitive objectives in a logo debugging curriculum: Instruction, learning, and transfer". *Cognitive Psychology* 20: 362–404.

Lave, J. 1988. *Cognition in Practice: Mind, Mathematics, and Culture in Everyday Life.* New York: Cambridge University Press.

Lave, J. and Wenger, E. 1991. *Situated Learning: Legitimate Peripheral Participation.* Cambridge, MA: Cambridge University Press.

Lederman, N.G. 1992. "Students' and teachers' conceptions of the nature of science: A review of the research". *Journal of Research in Science Teaching* 29: 331–359.

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

Levin, J.R. and Mayer, R.E. 1993. "Understanding illustrations in text". In B. Britton and A. Woodward (eds), *Learning from Textbooks: Processes and Principles.* Hillsdale, NJ: Erlbaum, 95–134.

Markman, A.B. and Gentner, D. 1993. "Structural alignment during similarity comparisons". *Cognitive Psychology* 25: 431–467.

Mayer, R.E. 1992. "Guiding students' cognitive processing of scientific information in text". In M. Pressley, K.R. Harris, and J.T. Guthrie (eds), *Promoting Academic Competency and Literacy in School.* San Diego: Academic, 243–258.

Mayer, R.E. 1984. "Aids to prose comprehension". *Educational Psychologist* 19: 30–42.

Mayer, R.E. and Anderson, R.W. 1992. "The instructive animation: Helping students build connections between words and pictures in multimedia learning". *Journal of Educational Psychology* 84: 444–452.

Medin, D.L., Goldstone, R.L., and Gentner, D. 1993. "Respects for similarity". *Psychological Review* 100: 254–278.

Miller, C.S., Lehman, J.F., and Koedinger, K.R. 1999. "Goals and learning in microworlds". *Cognitive Science* 23: 305–336.

Moore, C. and Engel, S.A. 2001. "Neural response to perception of volume in the lateral occipital complex". *Neuron* 29: 277–286.

Narayanan, N.H. and Hegarty, M. 1998. "On designing comprehensible interactive hypermedia manuals". *International Journal of Human-Computer Studies* 48: 267–301.

Noss, R., Hoyles, C., and Pozzi, S. 2002. "Abstraction in expertise: A study of nurses' conceptions of concentration". *Journal for Research in Mathematics Education* 33: 204–229.

Nunes, T., Schliemann, A.D., and Carraher, D.W. 1993. *Mathematics in the Streets and in Schools.* Cambridge: Cambridge University Press.

O'Reilly, R.C. 2001. "Generalization in interactive networks: The benefits of inhibitory competition and Hebbian learning". *Neural Computation* 13: 1199–1242.

Paivio, A. 1986. *Mental Representations: A Dual Coding Approach.* Oxford: Oxford University Press.

Pani, J.R., Jeffres, J.A., Shippey, G.T., and Schwartz, K.J. 1996. "Imagining projective transformations: Aligned orientations in spatial organization". *Cognitive Psychology* 31: 125–167.

Penner, D.E. 2001. "Complexity, emergence, and synthetic models in science education". In K. Crowley, C.D. Schunn, and T. Okada (eds), *Designing for Science.* Hillsdale, NJ: Erlbaum, 177–208.

Rattermann, M.J. and Gentner, D. 1998. "The effect of language on similarity: The use of relational labels improves young children". In K. Holyoak, D. Gentner, and B. Kokinov (eds), *Advances in Analogy Research: Integration of Theory and Data from the Cognitive, Computational, and Neural Sciences.* Sophia: New Bulgarian University, 274–282.

Reeves, L.M. and Weisberg, R.W. 1994. "The role of content and abstract information in analogical transfer". *Psychological Bulletin* 115: 381–400.

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

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

Rumelhart, D.E. and Zipser, D. 1985. "Feature discovery by competitive learning". *Cognitive Science* 9: 75–112.

Schank, R.C. and Farrel, R. 1988. "Creativity in education: A standard for computer-based teaching". *Machine Mediated Learning* 2: 175–194.

Schnotz, W. 1993. "On the relation between dual coding and mental models in graphics comprehension". *Learning and Instruction* 3: 247–249.

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

Shepherd, R.N. 1958. "Stimulus and response generalization: Tests of a model relating generalization to distance in psychological space". *Journal of Experimental Psychology* 55: 509–523.

Singley, M.K. and Anderson, J.R. 1989. *Transfer of Cognitive Skill.* Cambridge, MA: Harvard University Press.

Smith, L.B. and Gasser, M. 2005. "The development of embodied cognition: Six lessons from babies". *Artificial Life* 11: 13–29.

Turing, A.M. 1952. "The chemical basis of morphogenesis". *Philosophical Transactions of the Royal Society of London* B 327: 37–72.

Uttal, D.H., Liu, L.L., and DeLoache, J.S. 1999. "Taking a hard look at concreteness: Do concrete objects help young children learn symbolic relations?". In L. Balter and C. Tamis-LeMonda (eds), *Child Psychology: A Handbook of Contemporary Issues.* Philadelphia: Psychology Press, 177–192.

Uttal, D.H., Scudder, K.V., and 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.

Wilensky, U. 1997. *NetLogo Traffic Basic Model.* Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL. http://ccl.northwestern.edu/netlogo/models/TrafficBasic.

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

Wilensky, U. and 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.

White, B.Y. 1993. "ThinkerTools: Causal models, conceptual change, and science education". *Cognition and Instruction* 10: 1–100.

White, B.Y. and Fredericksen, J.R. 1998. "Inquiry, modeling, and metacognition: Making science accessible to all students". *Cognition and Instruction* 16: 3–118.

Willows, D.M. and Houghton, H.A. 1987. *The Psychology of Illustration.* New York: Springer.

Winn, W. 2003. "Learning in artificial environments: Embodiment, embeddedness, and dynamic adaptation". *Technology, Instruction, Cognition and Learning* 1: 87–114.

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Appendix

Selected questions from Ants and Food Quiz
1. To make the ants as a population spread out evenly over the food, which strategy is best:
   a. Have all the ants move as quickly as possible.

b. **Make the ant that is closest to a piece of food move more quickly than all the other ants.**

c. Make the ant that is closest to a piece of food move more slowly than all the other ants.

d. Early on, make the closest ant move more quickly than the others, but later on, make the closest ant move more slowly.

2. Why don't the ants cover the food well if the closet ant and all of the other ants all move with the same speed?

a. The closest ant will quickly cover food but the other ants will have to quickly find other food that needs covering.

b. **If other ants move as fast as the closest ant, then when a piece of food is selected, all of the ants, close and far, will move towards it. The ants will all be covering the same piece of food.**

c. If all the ants move with the same speed, then they will all get an equal opportunity to cover food but there is a limited supply of food for everyone.

d. If the closest ant moves as fast as the other ants, then it will get to the food first, and will prevent the other ants from covering it. The other ants will only cover food after the closest ones have finished.

3. To have the ants cover the food well, it is necessary to have the ants become specialized for particular food patches. Which action most directly allows for this specialization?

a. Make sure that there are not very many ants on the field. That way, no matter what speed they are moving at each ant can be far away from other ants.

b. Make sure that there are many ants on the field. That way, no matter what speed they are moving at each ant become specialized for a tiny patch.

c. **Make the ant that is closest to the chosen piece of food move quickly to the food, but other ants should only move slowly towards it.**

d. Make the ant that is closest to a chosen piece of food move slowly to the food, but other ants should move more quickly towards it.

4. If there are two equally sized patches of food and only one ant, what usually happens after a long time?

a. The ant will alternate between the patches, but only if it moves very slowly.

b. **Pieces from both food patches will be randomly chosen so ant will end up halfway between the two patches.**

c. Pieces from both food patches will be randomly chosen so the ant will have to select one of the patches and stay there.

d. The ant will not move toward either of the patches unless it is very close to them in the first place.

Selected questions from Defenders and Shooters Quiz (Analogous questions to Ants and Food Quiz)

1. To make the defenders as a population spread out evenly over the shooters, which strategy is best:

a. Have all the defenders move as quickly as possible.

b. **Make the defender that is closest to a shooter move more quickly than all the other defenders.**

    c. Make the defender that is closest to a shooter move more slowly than all the other defenders.

    d. Early on, make the closest defender move more quickly than the others, but later on, make the closest defender move more slowly.

2. Why don't the defenders cover the shooters well if the closet defender and all of the other defenders all move with the same speed?

    a. The closest defender will quickly cover shooters but the other defenders will have to quickly find other shooters that need covering.

    b. If other defenders move as fast as the closest defender, then when a shooter is selected, all of the defenders, close and far, will move towards him. The defenders will all be covering the same shooter.

    c. If all the defenders move with the same speed, then they will all get an equal opportunity to cover shooters but there is a limited number of shooters for everyone.

    d. If the closest defender moves as fast as the other defenders, then he will get to the shooters first, and will prevent the other defenders from covering them. The other defenders will only cover shooters after the closest ones have finished.

3. To have the defenders cover the shooters well, it is necessary to have the defenders become specialized for particular shooters. Which action most directly allows for this specialization?

    a. Make sure that there are not very many defenders on the field. That way, no matter what speed they are moving at each defender can be far away from other defenders.

    b. Make sure that there are many defenders on the field. That way, no matter what speed they are moving at each defender become specialized for very few shooters.

    c. Make the defender that is closest to the chosen shooter move quickly to the shooter, but other defenders should only move slowly towards him.

    d. Make the defender that is closest to a chosen shooter move slowly to the shooter, but other defenders should move more quickly towards him.

4. If there are two equally sized regions of shooters and only one defender, what usually happens after a long time?

    a. The defender will alternate between the regions, but only if he moves very slowly.

    b. Shooters from both regions of shooters will be randomly chosen so defender will end up halfway between the two regions.

    c. Shooters from both regions of shooters will be randomly chosen so the defender will have to select one of the regions and stay there.

    d. The defender will not move toward either of the regions unless he is very close to them in the first place.

Selected questions from Sensors and Inputs Quiz (Analogous questions to Ants and Food Quiz)

1. To make the sensors best represent the natural groups in a set of inputs, you should:

    a. Have the sensors adapt as quickly as possible.

    b. Make the sensor that is most similar to a selected input adapt more quickly than all the other sensors.

    c. Make the sensor that is most similar to a selected input adapt more slowly than all the other sensors.

d.   Early on, make the most similar sensor adapt more quickly than the others, but later on, make the most similar sensor adapt more slowly.

2. Why aren't specialized sensors formed if all of the sensors (the most similar and the others) all adapt equally quickly?
    a.   The most similar sensor will quickly become responsible for inputs but the other sensors will have to quickly find other inputs that need matching.
    b.   **If other sensors adapt as quickly as the most similar sensor, then when a new input is selected, then all sensors will adapt to it. The sensors will all try to match the same input.**
    c.   If all of the sensors adapt with the same speed, then they will all get an equal opportunity to look like the selected input but there is a limited number of inputs available for matching.
    d.   If the most similar sensor adapts as quickly as the other sensors, then it will match the input first, and will prevent the other sensors from matching it.

3. To create sensors that can accommodate the whole range of inputs naturally, it is necessary to have the sensors become specialized for different inputs. Which action most directly allows for this specialization?
    a.   Create just a few sensors. That way, no matter the rate of adaptation each sensor can be very dissimilar from the other sensors.
    b.   Create more sensors than there are inputs. That way, no matter the rate of adaptation each sensor can become very specialized.
    c.   **Make the sensor that is most similar to the selected input adapt quickly to that input, but the other sensors should only adapt slowly to it.**
    d.   Make the sensor that is most similar to the selected input adapt slowly to the input, but the other sensors should adapt quickly to it.

4. There are two inputs and only one sensor, what usually happens?
    a.   The sensor will alternate between matching the two inputs, but only if it adapts very slowly.
    b.   **The sensor will be a blend of the two inputs, highlighting parts shared by the inputs.**
    c.   The sensor will become specialized for one of the inputs only.
    d.   The sensor will not become adapted to either input, unless it is highly similar to them in the first place.