

Different is good: Connectionism and dynamic systems theory are complementary emergentist approaches to development

Linda B. Smith¹ & Larissa K. Samuelson²

¹Department of Psychology, Indiana University, 1101 E. 10th St., Bloomington, IN 47405

²Department of Psychology, E11 Seashore Hall, University of Iowa, Iowa City, IA 52240

To appear in: Spencer, J.P. & Thelen, E. (Eds.) (2002). Connectionism and dynamic systems theory: Are these really different approaches to development? [Special issue]. *Developmental Science*.

Connectionist and dynamic systems approaches to development are similar in that they are both emergentist theories that take a very different perspective from more traditional symbolic systems. Moreover, they are both based on similar mathematical principles. Nevertheless, connectionism and dynamic systems differ in the approach they take to the study of development. We argue that differences between connectionist and dynamic systems approaches in terms of the basic components of the models, what they see as the object of study, how they view the nature of knowledge, and their notions of developmental change mean that they each stand to make different and unique contributions to a more complete theory of development. We present an example from our work on how children learn to learn words that illustrates the complementary nature of connectionist and dynamic systems theories.

The purpose of this special issue is to discuss the common assumptions of dynamic systems theories and connectionism, to evaluate the unique strengths of each, and to explore whether these are actually the same approach to development. In the first section of our contribution to this issue, we note important commonalities between the two kinds of theories and conclude that there may be no in-principle differences in the range of phenomena that each can explain. In the following sections, we note that there are, nonetheless, important differences between the two approaches in the goals of the theorists. We argue that these differences are critical and suggest that the two approaches are valuable complements to one another. Importantly, both stand to make a unique contribution to a more complete theory of development. In the final section, we illustrate this complementarity with an example from our work on children's word learning.

Fundamental similarities in emergentist accounts

The enemy of my enemy is my friend. This chestnut gives us a standard by which to judge the similarities of the two kinds of accounts. Dynamic systems and connectionist accounts of development stand in opposition to the classic symbol system view of cognition (see also Munakata & McClelland, this issue). In the traditional view, the core of human cognition resides in symbolic representations. Representations stand for events in the world and are operated on by internal processes that manipulate their discrete and enduring forms. Since no one has any idea how such symbolic representations might be initially formed, theories that take this classic representational stance end up as nativist theories of development. Both connectionist and dynamical systems theories of development were founded in opposition to this classic cognitivist idea and argued instead that cognition was an emergent phenomenon, grounded in lower,

simpler, and non-symbolic processes. Thus, in their early days, both dynamic systems and connectionist models eschewed the notion of representations.

The target articles make clear that at least some dynamic and connectionist theories now want to lay claim to the idea of representations. But these neo-representational claims differ from the classic symbolic stance. According to the authors of the target papers, all that is meant by representations in the connectionist and dynamical systems account is that the *theorist* can see correspondences between internal patterns and regularities in the world. For example, the activation patterns on an internal layer may be said by the theorist to “represent” categories because they stand in a stable relation to category decisions by the network. But notice, those patterns of activation do not “stand for” anything as far as the network is concerned. The transitory patterns of activation in a connectionist network or a dynamic field are not used as representations by the network; they are not discrete enduring forms that are input to another level. Instead, they are emergent patterns within the processes of the model that yield category decisions. This is an important distinction and one that should be carefully noted because at their core, dynamical systems and connectionist accounts are alike in that they are emergentist accounts and *not* representational symbol systems. This is precisely why they are potentially powerful developmental theories; they promise an explanation of how something more (e.g. cognition, categories, language) can emerge out of something less.

Another measure by which connectionist and dynamic systems theories are at least similar is in the fact that they are mathematically related. Despite the different names in the two kinds of accounts—learning rules versus time evolution equations, attention weights versus cooperatively active representations, latent representations versus memory input—the mathematical notions behind these ideas are very much the same. Indeed, many connectionist models *are* dynamical systems and are routinely analyzed and characterized in terms of their attractor states (see chapters in Smolensky, Mozer, & Rumelhart, 1996). However, the relation between dynamical systems and connectionist models is not one of equivalence. There are many dynamical systems which are not connectionist models (and share none of their properties) and there are some connectionist models that are not dynamical systems. Nonetheless, if one takes the mathematics as defining of sameness of theories, these are theories of the same general class.

Thus, in terms of their common enemy, their common emphasis on emergence, and similar mathematics (see Thelen & Bates, this issue, for other similarities), connectionist and dynamic systems theories are more alike than they are different. Given this, one might expect that they would naturally lead to specific models that are similar as well. As we will see below, this is not generally the case.

In-principle differences or differences in principals?

The three target articles offer two different emergentist accounts of at least one phenomenon – the A not-B error. Are the strengths and weaknesses of these specific accounts revealing of in-principle differences in the strengths and weaknesses of the two classes of emergentist theories? How essential to an account is it that it is couched in the connectionist or dynamical systems framework? Could there be a connectionist version of every dynamic systems account or a dynamic systems version of every connectionist account? We think there is a good possibility that the answer to this last question could be “yes.” As an illustration, consider the connectionist and dynamic systems accounts of the A-not-B error.

According to target articles in this issue, these models differ on the issues of learning and embodiment. There is, as yet, no dynamical systems account of the learning process—of how an

organism incorporates, over the long-term, the repeated regularities in interactions with the environment. Likewise, there is, as yet, no connectionist account that incorporates the role of the body-environment interaction in cognition. But are these in-principle failures? The answer is “no.” A dynamical systems account could include time-evolution laws that describe change over the long-term (e.g. Schöner, 1989; van Geert, 1998) and indeed could readily do so in ways mathematically consistent with the learning processes assumed within connectionist theories. Connectionist accounts of development have, to date, concentrated mostly on cognitive and linguistic phenomena and thus ignored the role of bodies and actions, but again this is not an in-principle failing. Indeed, there is a growing movement toward more neurally-based connectionist models (e.g. Bullock & Grossberg, 1988; Medina & Mauk, 2000), ones that include architectures based on known neural wiring characteristics and that are constrained by the mechanics of the body. These models may incorporate perception-action loops as well as learning about the statistical regularities that are engendered by them.

The differences between connectionist and dynamic systems accounts on the issues of learning and embodiment thus stem from the specific models that happen to have been offered, and not in-principle differences between the more general theories. In brief, Munakata’s and Thelen, Schöner, and Spencer et al.’s accounts of the A-not-B error do not differ because one is connectionist and the other is a dynamic systems account. They differ because Munakata’s account offers an explanation of learning over developmental time whereas Thelen et al.’s account does not. They also differ because Thelen et al.’s account explains why posture and body changes matter, but Munakata’s account does not. It might seem, then, that the relevant scientific dispute is about the very specific strengths and weaknesses of two very specific accounts, not two distinct and opposing classes of theories. We believe, however, that the differences between these accounts of the A-not-B error are actually revealing of larger differences in the core principles behind connectionist and dynamic systems approaches to development.

Different theoretical goals

Connectionism and dynamic systems theory may have a common enemy, share similar mathematics, and, in principle, cover the same range of theoretical ideas, but these similarities are not the whole story. The differences seen in connectionist and dynamic systems accounts of the same phenomenon reflect an important difference: Connectionist and dynamical systems theories have different historical origins and theorists from these two perspectives have different goals. We use Table 1 to outline what we take to be the most relevant differences in their approaches. As we have already discussed, both theories are emergentist—novel, more complex behavioral forms emerge from the interaction of well-specified, more simple components. The components from which novel forms emerge, however, are quite different between the two approaches. The connectionist enterprise starts with a basic set of universal elements that can, through their own activity, change their connections to each other. In brief, this approach starts with the building blocks of a simplified and idealized brain. These components are theoretical entities themselves, not observables. In contrast, a dynamical system, by definition, consists of (1) *observable* components and (2) their relations such that future states can be predicted from current states. The interactions of these observables—in a task—are specified by equations that describe the trajectory of the states of the components. These observables can be at any level of analysis, from the patterns of activity of populations of neurons, to a reach, to the words uttered, to the resistance offered by the floor, or the distance between hiding wells on a table, but they

must be observable because the theoretical task in dynamic systems approaches is to explain how these observables evolve in time.

The two types of theory also differ in the object of study, that is, what each is trying to explain. The object of study for connectionist theories *is* those elementary neural building blocks and the learning process that produces a change in behavior. In contrast, the object of study for the dynamic systems theorist is the change in behavior, specifically the trajectory of change and the related time-evolution laws.

Likewise, the two accounts differ in their view of knowledge. Knowledge in a connectionist network is distributed and resides in the weights of the connections between individual units. The values of these weights are determined by the history of the system in an environment that presents a particular set of regularities. Knowledge in a dynamical system is also distributed, but it is distributed over many different kinds of *processes*—perception, action, the hardness of the floor, the location of the hiding wells. There is no analogue of latent knowledge waiting to be activated; rather knowledge is emergent in the moment, in the task, out of the particulars at hand.

Connectionist and dynamic systems accounts also differ in their view of developmental change. Connectionist theories are about systems that learn statistical patterns. They take the regularities that exist in the world and internalize them in connection weights. This is a very specific claim about the nature of development. Dynamic systems, with its view of multiple causality and levels of interactions, encompasses a wider variety of kinds of causes – from strengthening of muscles, to exploration, to energy consumption, to memory.

Are these in-principle differences between connectionist and dynamic systems theories? That is, could you track the trajectory of change in the weights of a connectionist model and gain insight into the process of learning or development in the modeled system? Or, could a dynamical system learn the statistical regularities inherent in world and use them to direct and change its behavior? Surely both are possible. These are formally relatable theories. This makes the two perspectives bridgeable and unifiable in the same complete theory, but it does *not* make them the same. They are different because connectionist and dynamic systems theorists are trying to answer fundamentally different questions about development. Connectionist theorists answer the question: How can I build it? Dynamic systems theorists answer the question: How does it change over time? Indeed, we suspect that this is the main source of discomfort each kind of theorist feels regarding the approaches of the other. Given their different goals, connectionist and dynamic systems theorists are just not going to be happy with each other's theoretical answers. If your question is the form of change and how it evolves, you are not going to be satisfied with a specification of building blocks, even if they are put together to form a well functioning system. If your question is how it is built, an answer that specifies only the trajectory of change will seem inadequate. But both perspectives—how do you build it and how, in real time and in a real world, does it change—are clearly essential to a complete theory of development. We illustrate the complementary nature of dynamic systems theory and connectionism with a discussion of our own work on the accelerating rate of children's early object name learning.

A dynamic connectionist approach to early word learning

The phenomenon is this: Children begin learning and producing object names very slowly, needing repeated experiences with multiple examples of each category before they generalize the name to the appropriate range of instances in the category. However, as children's

productive vocabularies grow, they become very rapid learners of object names such that they can correctly induce the range of objects in a category from hearing a single object named (Jones, Smith, & Landau, 1991; Markman, 1989; Waxman & Hall, 1993). For example, by the time they are two, children consistently (and appropriately) extend names for solid rigid things to new categories by shape (Imai, Gentner, & Uchida, 1994; Landau, Smith, & Jones, 1988; Samuelson & Smith, 2000), and by the time they are three they consistently (and again appropriately) extend names for nonsolid things by material (Dickinson, 1988; Soja, Carey, & Spelke, 1991; Subrahmanyam, Landau, & Gelman, 1999). Importantly, an individual child's knowledge about category extensions and their speed in learning new object names appears closely related to the number of nouns that child already knows (see Smith, 2000 for a review).

In one line of research, we have sought an understanding of this developmental trend through connectionist modeling. One reasonable hypothesis is that children learn how names map to different kinds of categories as they learn more words. Connectionist modeling is ideally suited to address this possibility. Accordingly, we have analyzed the correlational structure of early learned nouns and found pervasive regularities, including the fact that solid things are named by their shape (Samuelson & Smith, 1999). We have fed those regularities into networks (Hopfield nets with hebbian learning algorithms) and found that those networks, like children, develop what we as observers see as expectations about how different kinds of categories are organized—expectations, for example, that solid things are named by shape and nonsolid things are named by material. This research program has also revealed new and unexpected insights into the developmental trend. For example, because the networks are correlational learners, they have revealed regularities in early noun lexicons of which we were not aware and made predictions about context-specific influences on children's noun extensions, predictions that we have empirically confirmed (Colunga & Smith, 2002; Samuelson, 2002; Smith, Colunga, & Yoshida, *in press*). Further, by examining different kinds of networks and learning algorithms, and then matching their predictions to children's noun extensions, we have learned more about the statistical learning processes that characterize children's early learning of object names (Colunga & Smith, 2002; Samuelson, 2002).

However, there are aspects of this developmental progression that are not well explained by our connectionist models. First and foremost, the developmental trajectory seen in children appears to be self-accelerating. That is, there is an apparent “snowballing effect” in that learning nouns that refer to shape based categories increases children's attention to shape, which leads to an increased rate of learning new names for things in shape-based categories, which in turn leads to increased attention to shape, and so on. We recently documented this snowballing effect in two training studies (Samuelson, 2002; Smith, Jones, Landau, Gershkoff-Stowe, & Samuelson, 2002). The participants in these studies were very young children who knew few object names, who learned new object names slowly, and who did not systematically attend to the shape of solid things. We trained these children to attend to shape in the context of naming cues (the sentence frames indicative of count nouns). In so doing, we accelerated the rate of noun vocabulary growth—outside the laboratory—by nearly 300% in an 8 week period (Smith et al., 2002; see also Samuelson, 2002). We have also shown that in the early stages of this snowballing growth in vocabulary, children overgeneralize the shape bias – they attend to the shapes of things even when the words are adjectives labeling other properties or mass nouns labeling material. However, as more and more nouns are acquired, the shape bias becomes both more robust and more restricted to the context of count nouns labeling concrete objects. Thus, in dynamic systems terms, it appears that children's early acquisition of names for shape-based categories first leads

to a widening shape attractor that subsequently narrows as other kinds of nouns are slowly added to the vocabulary.

We would like to specify and understand how attention to shape, the rate of acquisition of object names, the rate of acquisition of other kinds of nouns and other kinds of words all interact to create this longer developmental *trajectory*. The question of how different developmental achievements feed into each other is a classic issue in developmental theory. Note, however, that this question is more about how past and current developments influence later ones, and less about how the system is built. That is, it requires a theory in which development grows out of a system of inter-relations among observables that index different aspects of language (number of nouns of different kinds in the receptive and productive vocabulary, number of articles, determiners, verbs, etc., in the vocabulary) rather than out of changes in connectionist weights among elementary units. Thus, it is a question that may be better asked and answered in dynamic systems, rather than connectionist, terms. The challenge we face now is using what we have learned from our experiments and connectionist models of early noun acquisition to create a dynamic systems model that captures the longer developmental trajectory. In the end, this research program will result in a rich and complete understanding of the developmental process, because it will provide both an understanding of how to build a system that learns and how this complex system of multiple interacting components changes over time.

Conclusion

We have argued in this commentary that connectionist and dynamic systems approaches are similar in a number of ways. We have also argued, however, that these approaches are different in important ways. More specifically, the basic components of connectionist and dynamic systems models are fundamentally different, what they see as the object of study is different, they take different views on the nature of knowledge, and have different notions of developmental change. These differences mean that connectionist and dynamic systems approaches attract different scientists who then view the same phenomena differently, as if from different sides. Thus, connectionist and dynamic systems accounts of the same phenomenon end up being able to explain different aspects of the relevant developmental change, and do so in ways that highlight different characteristics of development. This difference is good because it means that these two approaches each provide important insights into how intelligence emerges from more ordinary and lesser processes. The fact these two approaches provide clearly different perspectives while at the same time being formally relatable is a clear plus, a strength as we seek a unified emergentist theory of development. Thus, in terms of the central question of this special issue, we believe that dynamic systems and connectionist approaches to development are importantly *not* the same—they are complementary—and that it is important to keep these differences in mind as a new grand theory of development emerges out of this discussion.

References

- Bullock, D., & Grossberg, S. (1988). neural dynamics of planned arm movements: emergent invariants and speed-accuracy properties during trajectory formation. *Psychological Review*, 95, 49-90.
- Colunga, E., & Smith, L. B. (2002). *A connectionist account of the object-substance distinction in early noun learning*. Manuscript submitted for publication.
- Dickinson, D. K. (1988). Learning names for material: Factors constraining and limiting hypotheses about word meaning. *Cognitive Development*, 3, 15-35.
- Imai, M., Gentner, D., & Uchida, N. (1994). Children's theories of word meaning: The role of shape similarity in early acquisition. *Cognitive Development*, 9(1), 45-75.
- Jones, S. S., Smith, L. B., & Landau, B. (1991). Object properties and knowledge in early lexical learning. *Child development*, 62, 499-516.
- Landau, B., Smith, L. B., & Jones, S. S. (1988). The importance of shape in early lexical learning. *Cognitive Development*, 3, 299-321.
- Markman, E. M. (1989). *Categorization and naming in children*. Cambridge, MA: MIT Press.
- Medina, J. F., & Mauk, M. D. (2000). Computer simulation of cerebellar information processing. *Nature Neuroscience*, 3(Suppl), 1205-1211.
- Munakata, Y., & McClelland, J. L. (in press). Connectionist models of development. *Developmental Science*.
- Samuelson, L. K. (2002). Statistical regularities in vocabulary guide language acquisition in connectionist models and 15-20-month-olds. *Developmental Psychology*, 38(6), 1016-1037.
- Samuelson, L. K., & Smith, L. B. (1999). Early noun vocabularies: Do ontology, category organization and syntax correspond? *Cognition*, 73(1), 1-33.
- Samuelson, L. K., & Smith, L. B. (2000). Children's attention to rigid and deformable shape in naming and non-naming tasks. *Child Development*, 71(6), 1555-1570.
- Schöner, G. (1989). Learning and recall in a dynamic theory of coordination patterns. *Biological Cybernetics*, 62, 39-54.
- Smith, L. B. (2000). Learning how to learn words: an associative crane. In K. Hersh-Pasek (Ed.), *Becoming a Word Learner. A Debate on Lexical Acquisition* (pp. 51-80). New York, NY: Oxford University Press.
- Smith, L. B., Colunga, E., & Yoshida, H. (in press). Making an ontology: Cross-linguistic evidence. In D. Rakison & L. Oakes (Eds.), *Early category and concept development*: Oxford University Press.
- Smith, L. B., Jones, S. S., Landau, B., Gershkoff-Stowe, L., & Samuelson, L. K. (2002). Object name learning provides on-the-job training for attention. *Psychological Science*, 13(1), 13-19.
- Smolensky, P., Mozer, M. C., & Rumelhart, D. E. (Eds.). (1996). *Mathematical perspectives on neural networks*. Mahwah, NJ: Lawrence Erlbaum Associates.
- Soja, N. N., Carey, S., & Spelke, E. S. (1991). Ontological categories guide young children's inductions of word meaning: Object terms and substance terms. *Cognition*, 38, 179-211.
- Subrahmanyam, K., Landau, B., & Gelman, R. (1999). Shape, material, and syntax: Interacting forces in children's learning of novel words for objects and substances. *Language and Cognitive Processes*, 14(3), 249-281.
- Thelen, E., & Bates, E. (in press). Connectionism and dynamic systems: Are they really different? *Developmental Science*.

van Geert, P. (1998). A dynamic systems model of cognitive and language growth.
Psychological Review, 98(1), 3-53.

Waxman, S. R., & Hall, D. G. (1993). The development of a linkage between count nouns and object categories: Evidence from fifteen- to twenty-one-month-old-infants. *Child Development*, 64, 1224-1241.

Table 1. Four core ideas that differ between connectionist and dynamic systems approaches.

Core idea	Connectionism	Dynamic Systems
Components	Network of simple processing units connected to represent an idealized brain	Observable elements of the nervous system, body, and environment
Object of study	The elementary units and learning	Time evolution laws
Nature of knowledge	Resides in the long-term (latent) connections which are made active by the immediate input (and also any recurrent activity)	Emergent in the moment—the product of the intrinsic dynamics, the state of the system at that moment, and the immediate input
Nature of developmental change	Learning statistical regularities and thus making internal to the system the regularities – the structure – in the world	Multiple causality and interactions over multiple levels – from posture to memory