Defending qualitative change: The view from dynamical systems theory

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Abstract

A central controversy in developmental science, enflamed by nativist accounts, is whether development is best viewed as a series of qualitative or continuous changes. This essay defends the notion of qualitative change from the perspective of dynamical systems theory (DST). Qualitative change within DST refers to the shift that occurs when a system goes from one attractor state through an instability into a different attractor state. Such changes occur on the second-to-second time scale of behavior. Thus, developmental analysis must always stay local, grounded in the real-time attractor states around which behavior is organized. This essay also demonstrates that qualitative and continuous change should not be cast in opposition. They are aligned concepts that work together across multiple time scales.

Defending Qualitative Change: The View from Dynamical Systems Theory

In his essay entitled “In Defense of Qualitative Changes in Development”, Jerome Kagan (2008) argues that the balance between claims of transformational change and continuity in development has been a central point of controversy throughout the long history of our science. This controversy has reached a head in the past two decades given the growing number of claims of continuity between infants’ abilities and the abilities of older children. Many of these claims, Kagan argues, stem from a nativist tradition that has built its reputation, in part, by demonstrating amazing infant abilities and their seeming connection to later forms of cognition (e.g., Meltzoff & Moore, 1977; Wynn, 1992). Kagan argues that such claims of continuity are exaggerated. For instance, the ability of children to use complex semantic networks is qualitatively different from the perceptual schemata formed by infants in looking tasks. Kagan also argues that the empirical evidence of early competence is on tenuous ground given that the empirical record is largely built from a single measure of infant performance—total looking time—which is known to be subject to a host of influences that are often overlooked by researchers interested in showing early competence.

We applaud Kagan’s effort to defend the notion of qualitative change. Our essay seeks to do the same; however, we take a different tack motivated by our commitment to a particular theory of development—dynamical systems theory (DST). Dynamical systems theory was introduced to developmental science in the early 1990s with the publication of *A dynamic systems approach to the development of cognition and action* by Thelen and Smith (1994; for related ideas, see van der Maas & Molenaar, 1992; van Geert, 1998). These authors, inspired by earlier work on dynamical systems theory in physics, motor control, and psychology, proposed a radical view of development as fluid, multi-determined, and grounded in perception and action (for reviews, see Spencer et al., 2006; Thelen & Smith, 2006). In the past two decades, the concepts of DST have been applied to a host of phenomena including topics in motor development (e.g., Corbetta & Thelen, 1996), cognitive development (e.g., Spencer, Simmering, Schutte, & Schöner, 2007), and socio-emotional development (e.g., Lewis, Lamey, & Douglas, 1999).

In the present essay, we use this theoretical framework to weigh in on the issue of whether development is best viewed through a qualitative or continuous lens. Our essay has two central goals. First, we will define what "qualitative" means from a dynamical systems perspective. Critically, DST provides a precise definition of this concept. This is important because the notion of qualitative development means different things to different researchers, creating conceptual confusion in the literature. Second, we will argue that qualitative changes in behavioral organization actually occur at the time scale of behavior—the second-to-second time scale of thoughts, actions, emotions. From this view, what changes over learning and development is the emergence of these qualitatively different real-time behavioral states, their stability, and the ability of the infant or child to flexibly shift from one state to another.

What Does "Qualitative" Mean?

For many developmental scientists, the term "qualitative" invokes the notion of transformational change—creating something new that was not obviously connected to the something old. A typical example is the transformation that occurs when a caterpillar emerges from a cocoon as a butterfly. What went into the cocoon bears only faint resemblance to what came out. This seems to capture the use of qualitative in the essay by Kagan. He highlights that the perceptual schemata hypothesized to underlie infants' behavior bear no obvious resemblance to the semantic networks invoked in childhood.

Although the use of the term qualitative in this context has appeal due to its face validity, there is an important tension point—we know that there must be some fundamental, biological connection between the caterpillar and the butterfly. Thus, mustn't there be continuity as well as dis-continuity or transformation? Mustn't the perceptual schemata be somehow connected to the emergence of the first semantic network?

To further compound the problem, there is now a rich body of evidence showing that apparently abrupt and transformational changes previously thought to reflect qualitative re-organizations in development appear more continuous when examined at finer levels of detail (Adolph, Robinson, Young, & Gill-Alvarez, in press; Siegler, 1994; Siegler, 1996). This work has highlighted that the measurement scale and level of analysis can critically effect the conclusions we draw from data about the nature of developmental change, as well as our ability to test theories that make claims about transformational and continuous developmental processes.

Given the diversity of thought regarding the meaning of the term qualitative, how this concept relates to developmental continuity, and how to measure different types of change, we think the time is ripe to anchor the notion of qualitative development to a detailed theoretical framework. DST has much to offer in this regard: DST offers a precise definition of qualitative change, clear empirical signatures to identify qualitative change, and clarity regarding the link between qualitative and continuous change. Although DST has much to offer, it is difficult to explain dynamical systems concepts succinctly and in a way that resonates with the interests of behavioral researchers. In an effort to achieve both goals, we describe a set of central concepts below using examples that link neural and behavioral dynamics in real time. We then extend these concepts to tackle the issue of qualitative *developmental* change.

Dynamical systems are a class of systems that can be mathematically modeled using equations that specify the rate of change of some variable or system of variables at each moment in time. The idea behind this class of equations is actually quite powerful: if you know the current state of the system and its rate (and direction) of change, that is, how fast the system is moving along some trajectory, then you can take the current state, add the amount you expect it to change, and you can predict where the system will be at the next point in time.

If we could do this perfectly, we could describe—in detail—the development of a child and predict the state of the child each step along the way. The problem is that the dynamical systems we study in development are extraordinarily complex. Because we cannot know all of the details of a complex system, we have to settle for something simpler—we have to study how the system behaves around special points called attractors, points toward which the system gravitates over time. This can get tricky, though, because these special points can actually change themselves. This is what occurs when a qualitative transition happens in a dynamical system: the system shifts from being in the local territory of one attractor to losing that attractor and gravitating toward a new one. The question is: how do we know when one attractor becomes unstable and another attractor emerges (which is formally called a bifurcation, see Braun, 1994).

Figure 1 provides an overview that answers this question. This figure also illustrates how difficult it can be to identify qualitative shifts in the dynamics of a system. Figures 1A-1C show a set of stimulus events—inputs to a hypothetical brain of a hypothetical child—turning on and off from second-to-second as might occur in an infant habituation experiment (see, e.g., Schöner & Thelen, 2006). These figures also show the activation of one simple neuron in the child's brain. Note that in all of the simulation examples in this essay, we will talk about an example neuron to pick the simplest case possible that is still directly relevant to behavior. Importantly, however, all of the concepts we introduce are applicable to the more complex neural fields described in many of our papers (e.g., Simmering, Schutte, & Spencer, 2008; Spencer & Schöner, 2003; Spencer, Simmering, Schutte, & Schöner, 2007). Moreover, these dynamics can be found in real cortical fields (Amari, 1977; Amari & Arbib, 1977) and measured in real brains using electrophysiology (Bastian, Riehle, Erlhagen, & Schöner, 1998; Bastian, Schöner, & Riehle, 2003; Erlhagen, Bastian, Jancke, Riehle, & Schöner, 1999; Jancke et al., 1999).

As can be seen in Figure 1A, the first exemplary neuron shows a rather complex pattern of behavior: its activation rises and falls with an exponential pattern as each stimulus is presented, and the overall level of activation co-varies with the stimulus strength. Given the non-linear behavior of this neuron, one might guess that a non-linear dynamical system is at work that goes up toward one attractor state when the input is on and down toward a qualitatively different state when the input is off. And because the details of the attractor state shift as the input shifts, one might invoke the idea that that system rises to a more advanced or richer encoding of the stimulus when the second input is presented.

It turns out that this analysis is only partially correct. The neuron in Figure 1A is moving toward a higher level of activation when the input is on and a lower level of activation when the input is off. Critically, however, there is no qualitative shift in the dynamics of this system whatsoever. Rather, the activation profile shown in Figure 1A was produced by a simple *linear* dynamical system with a *single* attractor state that the neural activation is moving toward across the duration of this simulation. Why does the neural activation go up and down? This occurs because the location of the attractor in activation space moves as the input is turned on and off.

In contrast to Figure 1A, the simulation shown in Figure 1B shows an example of a qualitative shift. In particular, this neuron shifts from a *resting* or off attractor state into an input-dominated attractor state we refer to as the *self-stabilized* state. In this attractor state, activation stays stably on (i.e., above 0) provided that the stimulus is present, and the strength of neural activation within this state can accurately mirror the strength of the input signal (see Figure 1B). If the input is removed for a significant period of time, however, the self-stabilized state becomes unstable and the system moves through another qualitative shift as it returns to the resting state. Indeed, there are four qualitative changes in the dynamics of this neural activation profile across the simulation shown in Figure 1B (see circled joints in the activation profile).

Conceptually, the self-stabilized state reflects a type of perceptual encoding: the shift into the self-stabilized state marks a detection decision, that is, the neuron has detected the presence of a reliable signal and it will remain in this state provided that the input remains reasonably robust. For instance, this neuron can stay in the self-stabilized state even when there are transient interruptions in the input signal as might occur when an infant moves her eyes briefly to look away from a stimulus and back again (for discussion, see Spencer, Perone, & Johnson, in press).

It turns out that the simple neuron simulated in Figure 1B can actually move into a third attractor state—the self-sustaining state—shown in Figure 1C. In this simulation, the neural activation moves from the resting state into a state where activation stays stably on (above 0) even when the input is removed. Thus, there is only one qualitative shift in the behavior of the neuron in Figure 1C (see circled joint). Once the neuron detects the stimulus, it maintains an active representation of this detection decision for the duration of the simulation. The neuron is able to enter this attractor state because it has a relatively strong self-excitation parameter. Consequently, once stimulated, the neuron is able to keep excitation around, even when the external stimulus is turned off. This strong self-excitation is evident in the strength of activation in Figure 1C: at two points in this simulation, the strength of neural activation actually rises to a level that exceeds the input strength.

Just as the self-stabilized state provides a conceptual link to notions of perceptual encoding, the self-sustaining captures a neurally-plausible form of working memory (Fuster, 1994; Simmering et al., 2008; Spencer et al., 2007; Wang, 2001). We have shown, for example, that this basic form of sustained neural activity underlies the ability of children and adults to actively maintain information in spatial working memory during short-term delays (Spencer & Hund, 2003; Spencer et al., 2007). More recently, we have shown that this form of working memory also underlies the maintenance of non-spatial features such as color and orientation (Johnson, Spencer, Luck, & Schöner, 2008; Johnson, Spencer, & Schöner, in press). And developmental changes in the ability to stably enter this working memory state can capture changes in the stability of spatial working memory over development (Schutte, Spencer, & Schöner, 2003; Simmering et al., 2008), the likelihood that infants and young children will perseverate in simple reaching tasks (Schutte et al., 2003; Spencer, Smith, & Thelen, 2001; Thelen, Schöner, Scheier, & Smith, 2001), as well as developmental changes in the capacity of the visual working memory system (Simmering & Spencer, 2008).

What determines whether a neuron or neural field is stabilized by input (Figure 1B) vs. self-sustaining (Figure 1C)? The move between these two states requires a tiny tweak to the neuron's self-excitatory strength. With weaker self-excitation, the neuron enters the stabilized state; with stronger excitation, the neuron can be self-sustaining. This highlights that there is a deep connection between the notions of continuous change and transformational change within dynamical systems theory: a continuous and subtle change in the details of a neural system can produce a qualitative transformation in the attractor states the system moves into and out of in real-time. Indeed, this tie between continuity and transformation becomes more intricate when one considers that the neural attractor states shown in Figure 1B and 1C are emergent and softly-assembled from several factors—even in this simplest of cases. One can, for instance, move the neuron into the self-sustaining state (rather than the self-stabilized state) by boosting the strength of the input (for discussion, see Simmering et al., 2008).

Thus far, we have largely just asserted that the attractor states illustrated in Figures 1A-1C are qualitatively different. One signature of the qualitative shifts are the joints in the neural activation profiles in Figures 1B and 1C that occur near an activation value of zero as the system moves from the off state into a stable on state. In Figures 1D-1F we go one step further, highlighting another key signature of behavior as a dynamical system moves through a qualitative transition—heightened variability near the transition point (van der Maas & Molenaar, 1992; Van Geert, 1998). In these simulations, we set the starting state of the neuron's activation just below zero, at zero, and just above zero, and then let neural activation change through time in the absence of input, but in the presence of a small bit of neural noise. What emerges are rather dramatic differences in how the linear system (Figure 1D), the self-stabilized neuron (Figure 1E), and the self-sustaining neuron (Figure 1F) behave.

As can be seen in Figure 1D, the linear system shows the same behavior regardless of its starting state—in the absence of input, neural activation shows exponential decay to a baseline level. This highlights that there is no special qualitative transition happening in this system as activation passes through the zero threshold. By contrast, Figure 1E behaves in a qualitatively different fashion once the initial activation level is greater than zero (see right panel in Figure 1E). Now, self-excitation is strong enough that the system can hover in an on state temporarily, even in the absence of stimulus input. Note that if we were to compute the variability of neural activation across the simulations in this panel, the variance would be dramatically higher than in all of the simulations shown in Figure 1D. The final set of simulations shown in Figure 1F shows the most dramatic case of heightened variability near a qualitative transition: when we set the neuron's initial activation state to zero (see middle panel of Figure 1F), the system shows a roughly 50-50 chance of going into the off vs. the on state.

Considered together, the simulations in Figure 1 illustrate what the concept of qualitative change means within DST. Three points are critical. First, the notion of qualitative change in DST is all about a change in the attractor states of a system—a shift from one stable state, through an instability, into a different attractor state. Second, you cannot judge a qualitative transition by its cover, that is, by just watching the system behave through time. Even simple systems with no qualitative changes in dynamics (a single attractor state) can exhibit complex patterns of behavior through time. To discover whether a qualitative transition has occurred, one must look deeper for signatures of transformational change such as high variance near transition points. Third, there is a deep connection between continuity and qualitative change within DST: qualitative transformations can arise from continuous changes in multiple aspects of the system, such as when a small change in self-excitation moves a neural system from a perceptual to a working memory state.

What about Qualitative Transitions in Development?

Although the dynamical behavior of the simple neuron in Figure 1 is interesting, it is a far cry from the types of developmental transitions typically studied in developmental science. What does this notion of qualitative change from DST buy us when thinking about qualitative *developmental* change?

Developmental changes in the dynamics of a system are often depicted as a shifting landscape of attractor wells. Figure 2 shows an early depiction of this notion from Waddington (1954), as well as an updated view from Muchisky and colleagues (1996). In these figures, the organism is represented by the ball moving along a landscape. As each new valley opens up over development, qualitatively new states are available to the organism. For instance, the wells in Figure 2B capture different categories of action that emerge as infants shift from reaching, to crawling, to walking, and so on. Thus, the collection of wells at some moment in development captures the landscape of potential actions. And the depth of each well captures the stability of that particular action type (a deeper well is more stable).

Although this depiction of development is pervasive, there is an odd thing about depicting development in this manner. As deeper wells form as a function of skill acquisition, practice, consolidation, and so on, the system—the ball—will have a harder time getting out of the most stable states. This is a good thing if we are talking about the stability of an adult's walking pattern on bumpy ground, but it is not a good thing if we are talking about an adult's ability to flexibly shift from one stable action pattern (walking) to another (dancing). Skill involves stability (deep wells), but it also involves the ability to de-stabilize one pattern and move into another. Skill, therefore, involves qualitative change. How does the ball manage that nifty trick?

It turns out that the developmental landscape picture is a bit off in this regard. Although one can think of the ball getting kicked from one well to another to capture movement from one pattern to another, this does not effectively capture skilled behavior. Why? Empirical evidence shows that flexible, skilled behavior involves moving from one stable attractor state through an instability into another stable attractor state (see, e.g., Scholz & Kelso, 1989). This is precisely what our neuron did in Figure 1. Although one can think of this as having two wells and moving a ball back and forth, the more accurate picture is that the ball is in one well, *then that well disappears,* and the ball rolls to a newly formed well nearby. By this view, attractor states are not sitting around; they are not competencies waiting to be tapped. Rather, attractors come and go in real time—the attractor landscape is dynamic and changing on the time scale of behavior (for related ideas, see Spivey, 2007).

It is important to note that the developmental landscapes in Figure 2 are not wrong; they are just limited. They provide a temporally averaged view of the real dynamics that are taking place. This can offer a useful survey of the terrain, but it can blur some important details, in this case, that the qualitative shifts that are taking place in development actually come and go and emerge and morph in real-time.

How can we put the notion of real-time qualitative shifts (see Figure 1) together with a developmental landscape (see Figure 2)? Figure 3 shows one view of this integration, returning to our simple neural example from the previous section. The first thing we have done in this simulation is run it for many, many time steps—41,000 here compared to 400 in Figure 1. Thus, this figure is showing real-time changes in the behavior of our neuron (or neural field) over a time scale that might encompass a day or two of experience.

What is the neuron experiencing? Figure 3A shows the input to the neuron. The duration of the inputs vary to reflect some of the natural variations an infant might encounter as she moves from context to context. We have also simulated a simple form of developmental change. In particular, Figure 3B shows a slow, continuous (linear) change in the strength of self-excitation. This type of change might arise from a simple Hebbian process that strengthens synaptic connections that are repeatedly active (for related ideas, see Mareschal et al., 2007; Schutte et al., 2003; Simmering et al., 2008; Spencer, Dineva, & Schöner, in press).

As can be seen in Figure 3C, the combination of variations in input, random fluctuations in activation, and changes in self-excitation lead to the emergence of qualitatively new attractor states over the course of development in this simulation. At the start of the simulation, the neuron lives in a resting state (see the solid line above the neural activation profile). It shows some fluctuations up-and-down that mimic the input pattern, but it never enters the self-stabilized state.

As development unfolds, however, there is a qualitative shift in the neuron’s behavior: it becomes more and more likely that the neuron will enter the self-stabilized state where it encodes the presence of a stimulus (see dotted line above the activation profile). Critically, although the neuron spends more time in the self-stabilized state, it is still moving into and out of this state through real-time. Toward the end of this long simulation, the system first enters the self-sustaining or working memory state (see grey line above the activation profile). Again, we emphasize that this state first emerges in real-time in the context of a particular stimulus input; however, over time, the system more reliably enters this state as self-excitation strengthens.

Figure 3D shows a developmental landscape that we created by transforming the categorization of the neuron's attractor states through time (see solid, dotted, and grey lines in Figure 3C) into a well diagram. Note that this landscape looks different from the images in Figure 2, in part, because time runs from left to right rather than from top to bottom. But there is also a more critical difference in how the wells change over time. Rather than having the emergence and deepening of new wells over time (Figure 2), *a qualitative change in the attractor layout occurs each time the neuron goes from one state to another in real time* (the first such occurrence is marked by the circle in Figure 3D). Over development, new states emerge in real time (first the self-stabilized state, then the self-sustaining state), these states become more stable (i.e., deeper), and the states are entered more reliably.

In summary, Figure 3 shows how qualitative shifts in behavior emerge in real-time and cohere over the longer time scales of learning and development to give rise to the attractor states commonly depicted in developmental landscapes. Critically, Figure 3 clarifies how multiple time scales can be integrated within a developing system, making static wells dynamic in real time.

Implications of DST for Developmental Science

What are the implications of a dynamical systems view of qualitative change for developmental science? First, there is something very special about the notion of qualitative change within DST. This concept is about creating something new—a new attractor state—out of something old—the existing, diverse, and complex components that are newly assembled. It is about the emergence of new forms in real time as infants and children behave in real situations, and how these new forms come to repeatedly cohere over learning and development.

Second, the integration of dynamics over multiple time scales highlights that developmental stability and change is always connected to the local details of behavior. Consequently, studying qualitative shifts in behavior over broad stretches of time—while often useful as a starting point—can sometimes reveal relatively little about the organization of behavior in real time. In this context, we agree with Kagan that claims of continuity across broad stretches of time that attempt to link infant behaviors with the behaviors of much older children must be treated as place-holders—approximations that should always be viewed with a critical eye. Importantly, however, this same critique applies whether we extend the arrow of time forward in development from infancy to childhood, or backward in development from infancy to the prenatal period and purported biological (or evolutionary) predispositions (Spelke, 1998; Spelke & Kinzler, 2007). Approximations that extend far in both temporal directions should be treated with much more care in our science (Spencer, Blumberg, et al., in press).

The third implication of a dynamical systems view is that understanding qualitative developmental shifts is extremely complicated. One cannot just observe the local behavior of a system and extract the attractor states around which behavior is organized. Rather, one must look for the unique signatures that separate one state from another. And given that attractor states are softly-assembled and multiply-determined, it can be difficult to understand why they come and go, especially when the components that make up behavior are linked in non-obvious ways. These behavioral realities—which have been born out in many well-studied empirical examples—provide even more reason to think about development locally and be highly dubious of claims of long-term continuity, nativist or otherwise (see Spencer, Blumberg et al., in press).

In conclusion, the challenge of a dynamical systems view is that to understand development, we must understand how the dynamics of a system change over multiple time scales: how qualitatively new attractor states emerge in real time, and how those attractors become more accessible, more stable, and more tuned to the particulars of the situation over development. Thus, we agree with a central theme of Kagan's (2008) essay: qualitative shifts in development occur, and they should be defended because they are fundamental to what emergence over development is all about. But qualitative change should not be put in opposition to gradual, continuous change as Kagan’s essay implies. Continuity and change go hand-in-hand. We think DST offers a firm defense of qualitative development, a formal framework for understanding the link between qualitative development and continuity, and a charge to push our understanding of development to the more local time scale where emergence and continuity come together to truly create something new out of something old.

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Author Notes

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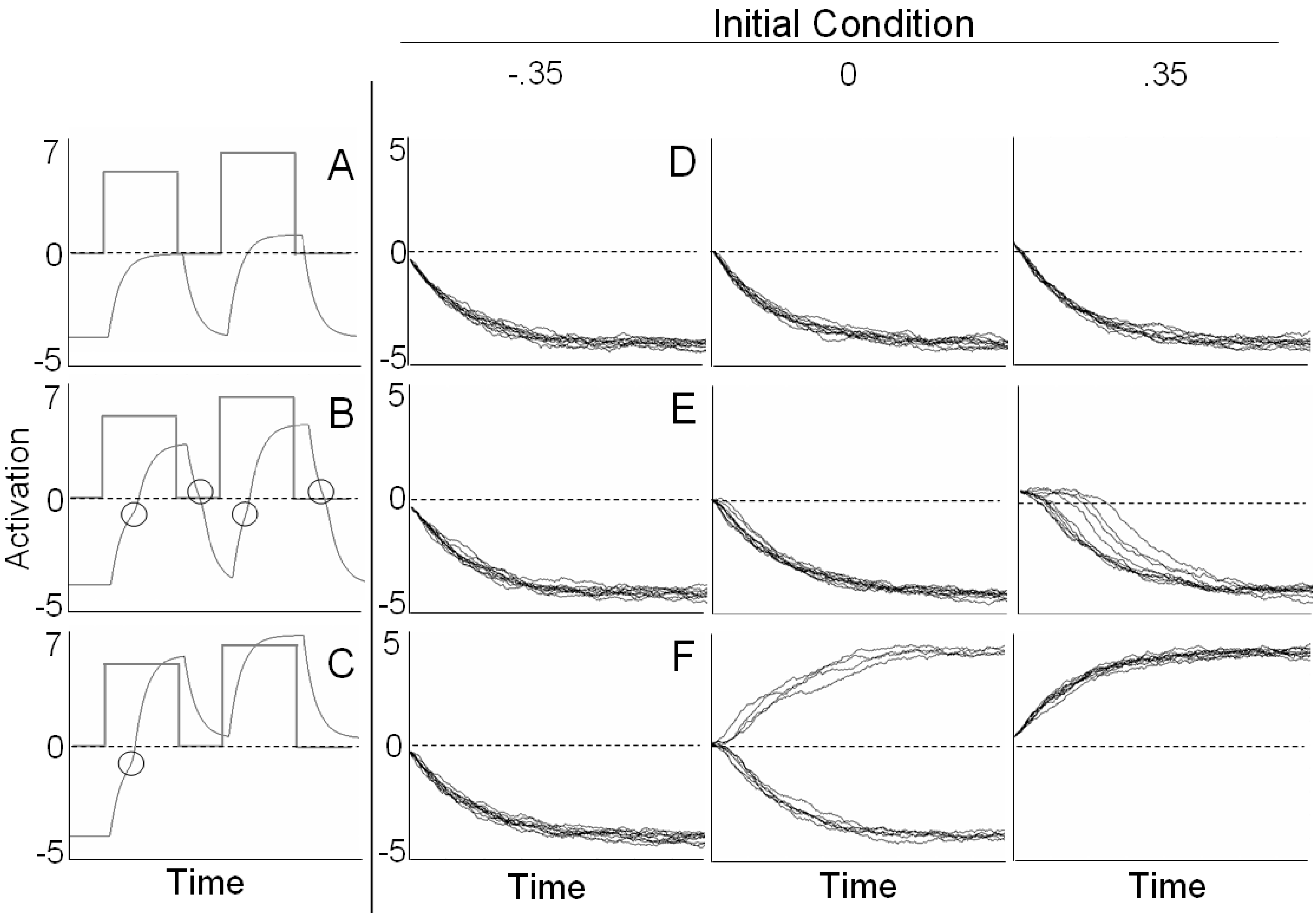
Figure Captions

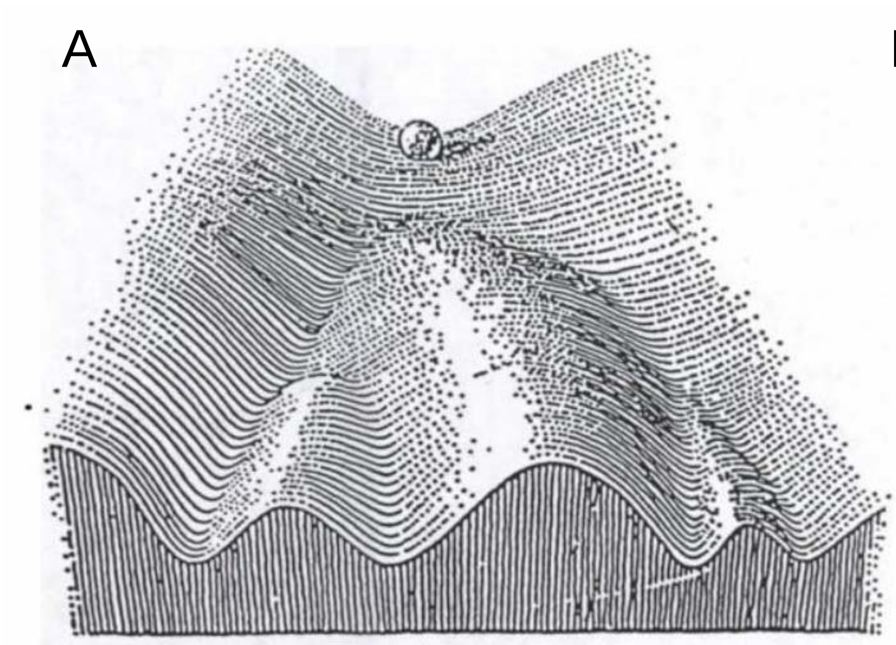
Figure 1. Simulations of a simple neural system to illustrate the concept of qualitative change within dynamical systems theory. (A) The behavior of a neuron with linear dynamics in response to input; (B) the behavior of a self-stabilized neuron; (C) the behavior of a self-sustaining neuron. Rectangular inputs are shown in grey. Circles denote qualitative transitions in neural activation. Panels in (D), (E), and (F) show repeated simulations of the neurons simulated in (A), (B), and (C) with different initial activation values (-0.35, 0, or 0.35) and a small amount of noise.

Figure 2. Depictions of developmental landscapes that invoke the concepts of dynamical systems theory. (A) Epigenetic landscape described by Waddington (1954); (B) Developmental landscape described in Muchisky et al. (1996).

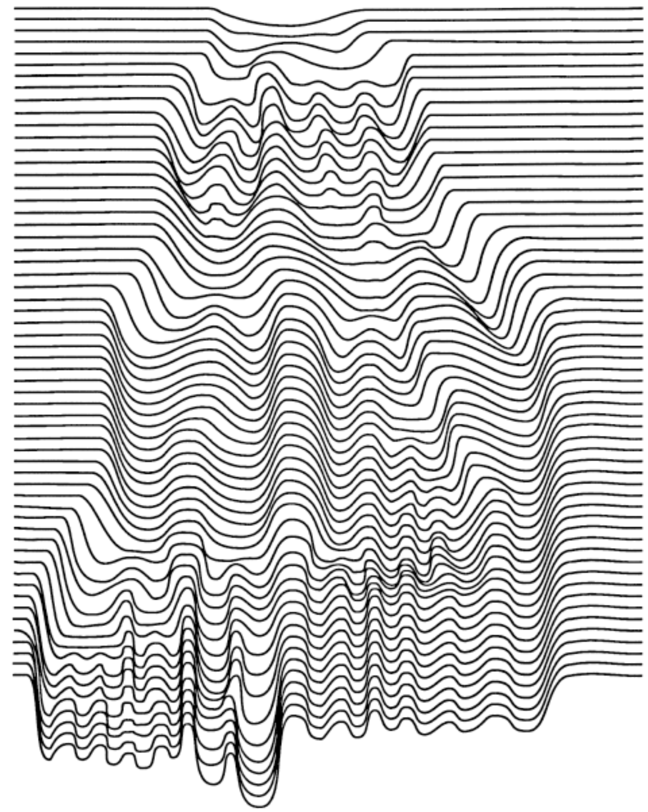
Figure 3. Simulation of a simple neural system in real time across a long time span to illustrate the integration of time scales within dynamical systems theory. (A) Pattern of rectangular inputs over time; (B) Linear increase in the neuron's self-excitation strength over time; (C) activation of the neuron over time. Thick line above the neural activation profile indicates the attractor state the neuron is in at each moment in time (solid line = resting state; dotted line = self-stabilized state; grey line = self-sustaining state). (D) A developmental landscape constructed by mapping the attractor states shown above the activation profile in (C) onto a well diagram. Arrows show example of mapping for each attractor state. Circled transition marks the first qualitative transition in real time from the resting to the self-stabilized state. Depth of each well is scaled based on cumulative frequency of each attractor state over time.

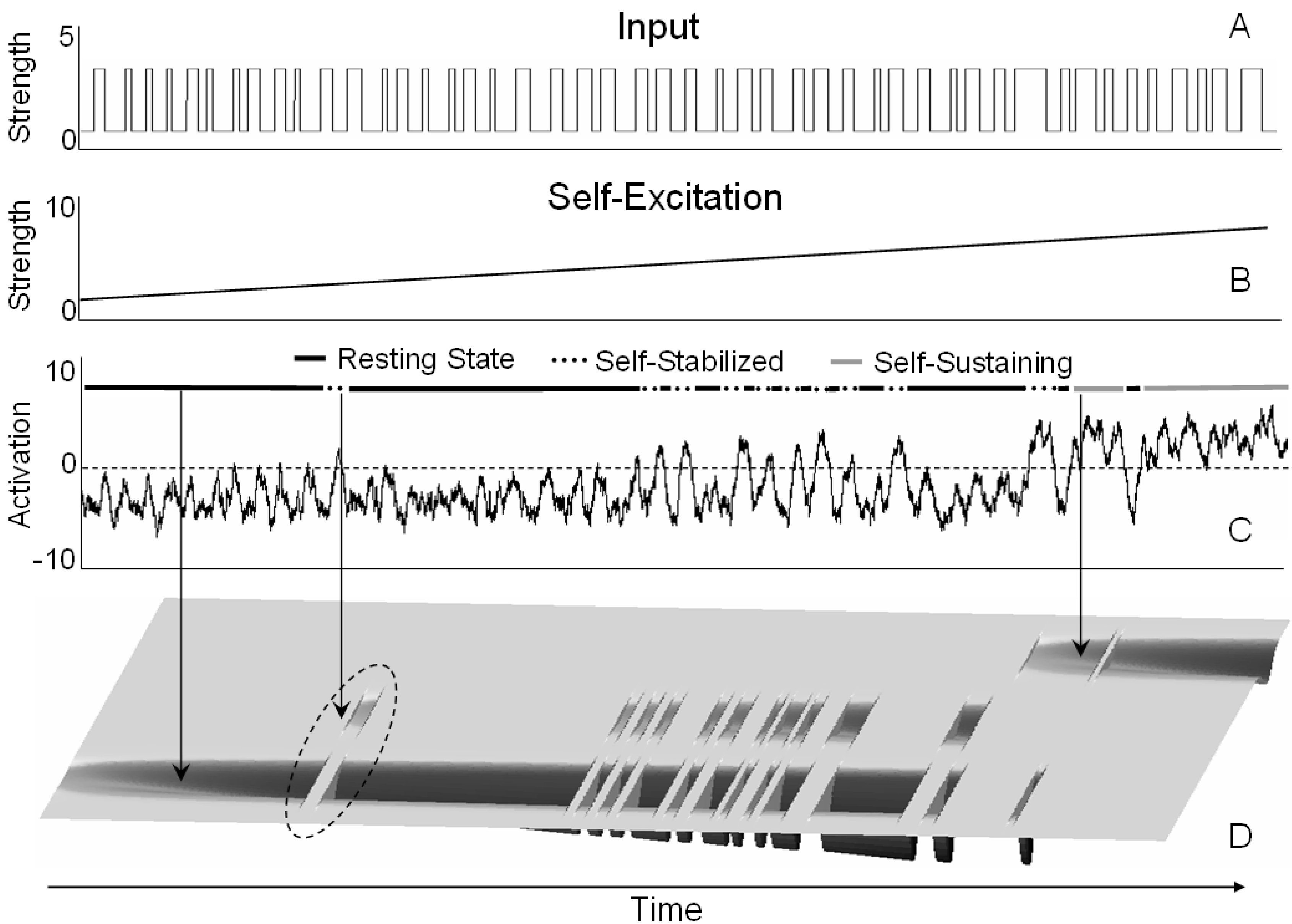

Initial Condition
-.35
0
.35
Activation
7
0
-5
A
B
C
5
D
E
F
Time
Time
Time
Time

A



B





Input
A
Strength
5
0
Self-Excitation
B
Strength
10
0
Resting State
Self-Stabilized
Self-Sustaining
Activation
10
0
-10
C
D
Time