Kloos, H. & Van Orden, G.C. (2009). Soft-assembled mechanisms for the grand theory. In J.P. Spencer, M. Thomas, & J. McClelland (Eds.), *Toward a New Grand Theory of Development? Connectionism and Dynamics Systems Theory Reconsidered*, (pp. 253-267). Oxford University Press.

CHAPTER 12

Soft-Assembled Mechanisms for the Unified Theory

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Do connectionist and dynamic-systems models converge on a unified theory? The answer depends on the kind of mechanism that the two models attempt to unravel. Two views of mechanism avail themselves to contemporary scientists. One view of mechanism represents cognitive activity as reducible to a cognitive architecture of separate cognitive components. Another view sees cognitive activity as emergent and highly dependent on fine details of the contexts in which behavior emerges. We will argue in this chapter that connectionist and dynamic systems models complement each other and collectively move toward a unified theory of development if they subscribe to the second view of mechanism, one that treats behavior as soft assembled in the immediate context.

The chapter organization is as follows. In section Where Models Converge in Stalemate, we address why models aimed at reducing behavior to cognitive components cannot make clear headway. The argument is that a reduction of behavior requires human performance to be relatively context free. Yet, as we show with the example of balance task performance, human performance is highly context dependent, even in the sterile laboratory context of balance experiments. In section Taking Context Effects Seriously, we elaborate on what such context dependence could mean. While not conclusive on its own, strong context dependence is consistent with the idea that cognitive activity is softly assembled to suit the immediate task environment. Soft assembly offers a plausible alternative to hard-assembled cognitive functions—functions that exist prior to and independently of the task context. We review more pointed evidence for soft assembly and discuss why models that take soft assembly seriously—connectionist or dynamic systems—anticipate the unified theory.

WHERE MODELS CONVERGE IN STALEMATE

At the center of the argument is strong context dependency in human performance. We develop this argument around well-studied examples from developmental psychology, in particular children's performance on balance scale tasks. However, our points pertain to cognitive modeling more generally.

Balance Scale Performance and Associated Models

Picture a child in a balance scale experiment. The balance scale straddles a fulcrum and has pegs along its surface on which to set weights (see Fig. 12.1). The experimenter sets some weights and asks the child to predict the behavior of the scale. Will it stay balanced, will the right side tip, or will the left side tip? To perform correctly in every case, the child must take into account the number of weights on each side of the bar, the distance of each weight from the fulcrum, and their product.

Different children give different kinds of answers to balance scale problems of this sort, but four kinds of answers seem reliable and systematic (Siegler, 1981). (I) One class of answer appears to reflect an exclusive focus on

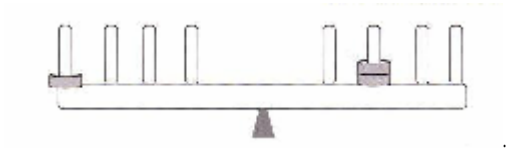

Figure 12.1. Schematic illustration of a balance scale apparatus
The balance scale apparatus depicted has four pegs on each side; the number of weights on each side varies during the balance scale task.

the amount of weight on each side of the fulcrum. Children who answer this way consistently expect the side with the most weights to tip. When there are equal numbers of weights on each side, children in this group expect the balance scale to stay level, ignoring distance from the fulcrum. (II) A second class of answer appears to take into account distance from the fulcrum, but only when weights are equally distributed on both sides. Children who produce this kind of answer predict that the heavier side will tip. But when both sides have the same numbers of weights, they predict that the side with weights furthest from the fulcrum will tip. (Ill) A third class of answer takes into account both weight and distance from fulcrum, but does not suggest a systematic integration of the two dimensions. Children who produce this class of answers correctly predict the effect of weight when the distances are the same, and they correctly predict the effect of distance from fulcrum when the number of weights is equal. However, when both weight and distance from fulcrum differ, then these children simply guess. (IV) A final, fourth class of answers appears to take into account both relevant dimensions (number of weights and distance from the fulcrum) and integrate dimensions appropriately when the two dimensions are pitted against each other.

A variety of models have been proposed to explain the four kinds of answers and the transition from one type of answer to the next more sophisticated. Production-rule models suggest that children's performance derives from rule-like algorithms or strategies that can change rather suddenly as a result of experience (e.g., Klahr & Siegler, 1978; Langley, 1987; Sage & Langley, 1983; Schmidt & Ling, 1996). Connectionist models, on the other hand, suggest that children's performance is not a function of explicit rules but rather a gradual adaptation to statistical relations between balance scale appearance and response (e.g., McClelland, 1989, 1995; Shultz, Mareschal, & Schmidt, 1994; Shultz, Schmidt, Buckingham, & Mareschal, 1995). Finally, dynamical systems models capture developmental changes as sudden jumps in the cusp catastrophe—a rule-like response looses stability and changes suddenly in a phase transition or bifurcation to a new rule (e.g., Van Rijn, Van Someren, & van der Maas, 2003).

The condensed overview of these models indicates some disagreement among them about the causal mechanism that could underlie balance performance. One solution to the disagreement has been to evaluate the degree to which the output of a model can capture human performance overall (Van Rijn et al, 2003). For instance, one could find a way to calculate overall fit across models in a single score and conclude that the model with the best score must be using the correct mechanism—the mechanism that best mimics the underlying cognitive architecture. On the grounds of this logic, production-rule models might receive a low score because they have difficulty capturing the developmental transition to a more sophisticated rule. And connectionist models might receive a low score because they do not capture rule-like human performance unless the rules are part of the statistical relations in the training set (Raijmakers, van Koten, & Molenaar, 1996).

We suggest, however, that such a solution is premature because it does not adequately consider how context figures into the disagreement. The models that presently compete emphasize the axiom that behavior can be the same across different laboratory contexts. They emphasize that psychological constructs are motivated by "behavioral consistency over varying contexts" (Embretson, 2006, p. 50; Cronbach & Meehl, 1955). Unquestioning adherence to this axiom rules out context-sensitive behavior as a topic of study. Or, at least, it ascribes context effects to secondary performance limitations that come and go with task, rather than to a participant's primary competence. Thus, the models that would compete for best overall fit tend to assume that scientifically informative behavior stands outside of context. This stance would beg the question of context effects, accepting before the fact that only context-free behavioral effects adequately pick out underlying mechanisms. But as we argue next, context effects actually distinguish between the models.

Balance Scale Performance Is Context Sensitive

Adults, children, and even toddlers move through uncountable varieties of physical and social contexts with fluid ease—from outdoor play on the slippery slide to indoor play on the paintball court, from being a peer to being a child or parent, and from quietly drawing to arguments about bedtime. Even in the artificial and somewhat sterile environments of cognitive laboratories, context effects are paramount.

Take again the example of balance scale studies. The four types of balance scale behaviors described above—rules I, II, III, and IV—are well known and often cited. But it would be grossly misleading to suggest that this typology captures children's full range of balance behaviors. In fact, it captures only a limited set of options allowed within the particular task context (Hardiman, Pollatsek, & Well, 1986). Limits come from a variety of methodological choices that are rationalized in terms of good experimental design. In this section, we discuss some of these choices in more detail.

One methodological choice is to give or hold back feedback during children's test performance. In the standard balance scale task, a child is presented with a balance scale scenario in each measurement trial, and after predicting the behavior of the balance scale, the child progress immediately to the next trial. But feedback during testing changes the likelihood that a child's performance will adhere to one of the four rules, especially when feedback is tailored to a child's beliefs (Hardiman et al., 1986; Kliman, 1986). Siegler and Chen (1998), for example, carefully constrained the feedback provided to preschoolers to stop them from forming the rule *greater distance goes down* instead of rule I *(ignore distance]* or rule II *(pay attention to distance only if weight is equal).*

Another choice is the kinds of response options that children are allowed to give. In the standard task, children are allowed only three answer options: *left side down, right side down,* or *balance.* If children are provided with more flexible options, as when they are allowed to adjust the number of weights and the position of weights on the scale, children's performance can follow an entirely different rule called the *addition rule.* Under these circumstances, children integrate both the number of weights and their distance from the fulcrum according to an additive algorithm (Normandeau, Larivee, Roulin, & Longeot, 1989; Wilkening & Anderson, 1982). That is to say, they do not focus on one dimension only (rule I-III), nor do they integrate dimensions according to the correct multiplication algorithm (rule IV).

Yet another choice of method is the rather limited range of possible balance scenarios presented to participants. Only four pegs are fitted on each side of the fulcrum and only four weights can be placed on the pegs. This yields rather small discrepancies between the left and right arms of the balance scale. As it turns out, the magnitude of discrepancy between left and right side matters—an effect known as the *torque effect.* Children perform better with larger differences in torque when predicting the behavior of the balance scale (Ferretti & Butterfield, 1986; Ferretti, Butterfield, Cahn, & Kerkman, 1985; Jansen & Van der Maas, 1997).

The list goes on. Another design choice balances out the number of trials of each type. In the standard task, the dimension number-of-weights is pitted against the dimension distance-from-fulcrum in half of the trials, while either one or both dimensions are held constant in the other half. Tasks that allow a greater and unbalanced variety of configurations of weights do not elicit performance of the four rules (Kliman, 1986). Children no longer form rules on the basis of differences in weights or distance from the fulcrum; they form rules about mathematical relations, specific to their narrow experience. For example, a child will abstract from examples like *"one* weight on the *ninth* peg balances *nine* weights on the *first* peg" to become *"one* weight on the nth peg balances *n* weights on the *first* peg." Yet the child will generalize this belief no further, not even to accommodate two or more weights on the nth peg.

Finally, a fifth methodological choice puts limits on proprioceptive information available to the child. Children in the standard task are provided with proprioceptive information about weight (children are encouraged to hold the weights), but not about how distance of weights affects balancing. The lack of proprioceptive information about how distance affects balance selectively increases the difficulty for children to correctly take into account distance (Hardiman et al, 1986). In particular, exclusive proprioception of weight could bias children's performance toward rule I *(greater weight goes down)* and rule II *(if weight is the same, greater distance goes down),* but against a rule based on distance alone. In fact proprioceptive information about distance leads children to perform as though the rule is *(greater distance goes down)* but completely ignore differences in weight (KarmilofT-Smith & Inhelder, 1974). And children will sustain this rule for some time despite contradictory evidence, suggesting that this *distance rule* is at least as stable as rules I-IV.

Strong context dependence is of course not limited to balance scale tasks. Quite the opposite is the case. Context-dependent performance is the rule in developmental psychology, not the exception (e.g., Gigerenzer & Richter, 1990; Lawton, 1993). One could even argue that the most salient outcome of American-style post-Piagetian research has been to demonstrate extreme context sensitivity. Indeed, changes in task design can yield more and more sophisticated competence in younger children, making contextual support an important causal variable (c.f. Keen, 2003). Nonetheless, despite omnipresent context effects, the effect of context is rarely studied in its own right.

Explaining Away Context Effects

One common argument is that differences in performance due to contexts can be ignored because they do not reflect children's true competence. Instead they are mere performance limitations due to underdeveloped language skills or memory limitations, for example. Yet where does performance end and competence begin? To illustrate this dilemma, take children's performance in another integration task, one that tests children's integrative understanding of distance, velocity, and travel time (Wilkening, 1981). In one task context, children estimated the distance an object traveled, after observing its velocity and travel time. In a second task context, children estimated the time an object traveled, after observing its velocity and travel distance. And in the third task context, children estimated an object's velocity, after observing the time and distances traveled. Each of these three contexts is a permutation of the relations among distance, velocity and travel time. And each permutation asks the child for a prediction of one factor based on the other two factors as antecedents. The important finding for our argument was that each permutation yielded a qualitatively different outcome. For example, 5-year-old children integrate speed and time multiplicatively to estimate the distance traveled, but they integrate speed and distance additively to estimate the time traveled, and they used distance exclusively to estimate speed—three qualitatively different outcomes.

Another way to treat task effects is to assume that they are a simple add-on to other factors, notably to cognitive functions. For instance, if children simply performed better in one balance task than another, then, all other things being equal, task effects are superposed on

other effects. In this case, one could legitimately partition out task context as an independent source of variation in data. In a model, task context would then become a fixed parameter. But task and context effects rarely combine so straightforwardly, in balance performance or any other developmental phenomenon. As our review illustrates, children tested in a balance task do not simply perform better or worse. They exhibit different qualities of performance in different task contexts.

Still another way to treat contexts effects is to equate different effects with separate components of the mental architecture. Successful performance in one context might reflect implicit knowledge, for example, while performance in a different context reflects explicit knowledge. This solution may appear clear-cut when tasks differ conceptually. For instance, tasks that require a physical action such as balancing a rod can appear conceptually different from tasks that require a verbal judgment of balance (c.f. Kirst, Fieberg, & Wilkening, 1993; Levin, Siegler, & Druyan, 1990). A physical action might shed light on implicit knowledge, while verbal action might shed light on explicit knowledge—two distinct forms of representation. However, even if we ignore stalemates that have emerged over supposedly clear-cut distinctions (Cleeremans, 1997; Farah, 1994), this approach runs aground when tasks are conceptually alike. For example, it is not clear how a balance scale task with a small number of weights and pegs differs conceptually from balance scale tasks with a large number of weights and pegs. Both should entail the same knowledge; so finding a difference in performance leaves one guessing intuitively about what the separate components might be. But to merely equate effects with components, what has been called the *effects = structure* fallacy (Gibbs, 2006; Lakoff, 1987), yields a theoretical enterprise that is unpredictable, circular, and likely to end in stalemates among competing intuitions.

Finally, the most widely practiced response to task effects is to argue about which context is more transparent to mental functions, or equivalently which task context produces more *pure* data than another. In the example of the balance scale performance, Siegler (1981) defends the highly structured and methodologically precise task context of his assessment procedure, and Wilkening and Anderson (1982) justify the legitimate expansion of task contexts to explore the task space. But in truth, there is simply no empirical basis on which to decide which task context is best. All task effects refer equally to changes in outcome measures of performance. Distinctions among task effects are supported only by intuitions about competence based on convention or esthetics, but not evidence. Consider, however, that task effects might not be superficial aspects of performance, but rather that context is always and fundamentally constitutive of children's performance.

Arguments about the purity of data have not fared well in other domains. Conventional studies of adult cognition have virtually run to stalemate on the question of which task's data best reveal the architecture of cognition. Details of apparent stalemates have been described for perception (Uttal, 1990, 1997), language and reading (Goldinger & Azuma, 2003; Van Orden & Kloos, 2005; Van Orden, Pennington, & Stone, 2001), and memory processes (Watkins, 1990; Weldon, 1999). Similarly, functional neuroimaging of adult cognition shows signs of running to stalemate because subtle changes in task context cause cognitive functions to be in different parts of the brain (c.f. Cabeza & Nyberg, 2000).

In sum, we have reviewed how task context effects determine our laboratory pictures of children's knowledge. Such context effects demonstrate that a child's performance is an interaction of the child's knowledge and the specific task constraints within which they act. The solutions discussed so far hold onto the idea that context-free performance exists and should be given priority for a reduction to specific cognitive components. But these solutions have also, so far, led to stalemates about which tasks can separate context from components most successfully. In the next section, we discuss a more conservative solution to context sensitivity—one that takes context sensitivity at face value and accepts that context is constitutive of human behavior.

TAKING CONTEXT EFFECTS SERIOUSLY

In the remainder of this chapter, we describe a path to circumvent stalemates about cognitive components and task contexts and thereby situate connectionist and dynamical systems models within a unified theory. The argument rests on the distinction between soft-assembled and hard-assembled cognition introduced by Turvey and Carello (1981). In what follows we describe this distinction in more detail and show how soft assembly provides a new way to think about context and behavior. We then return to the issue of modeling and discuss how connectionist and dynamical systems models can complement each other and point toward a new unified theory.

Soft- Versus Hard-Assembled Mechanisms

Most of the research discussed so far is grounded in the assumption that cognitive activity is based on hard-assembled mechanisms. These mechanisms exist off-line in some form of inactive or dormant state and are activated in a particular task. Going back to the balance scale research, a hard-assembled mechanism could be a child's rule about what makes a balance beam tip, a recurring strategy that a child pursues in order to figure out the answer, or simply a child's knowledge about the effects of relevant dimensions. Hard-assembled mechanisms are independent of the immediate task context, they reveal themselves across multiple contexts, and are therefore discovered in context-independent performance.

By contrast, soft-assembled mechanisms emerge in contextually constrained, collective action of the brain and body. They come into existence with enaction, and they are only realized within the immediate context of enaction. An example of a soft-assembled system is the kinematics of a limb in a particular action. The mind and body in context will together create unique kinematics, and if the movement is repeated, each repetition will reveal unique kinematics (Berkinblit, Feldman, & Fukson, 1986; Bernstein, 1967). Looking across repeated movements, one sees a family resemblance, but no context-free mechanism exists to tie these movements together. Of course muscles and tendons and neuropil continue to exist throughout, but the instantaneous play of emergent control is realized in the movement itself, an enacted limb movement that is unique in each instantaneous context (Turvey, 1990).

Self-organized criticality is proposed as the mechanism that underlies soft-assembled cognitive activity (Juarrero, 1999; Turvey & Moreno, 2006; Van Orden, Holden, & Turvey, 2003), a concept borrowed from physics (Bak, 1996; Jensen, 1998). Criticality refers to a preparatory state of a system, also referred to as critical state, that emerges immediately before a response occurs. This preparatory state consists of several potential responses, all of which are contextually appropriate, although maybe not accurate. In the balance scale example, the potential responses will include the kinematics of indicating whether the scale will stay balanced, tip to the right, or tip to the left.

Self-organized criticality is brought about by local interactions among processes of the system. Those interactions that satisfy contextual constraints are strengthened, and thereby recruit other processes to their configuration. As a result, these local interactions extend to the periphery of the body and create interdependence among all component processes. It is this interdependence that allows components to act together, to express one of a potential set of contextually appropriate outcomes. Thus soft assembly creates poised, situated, state dynamics across the brain and body. Immediately prior to action, the final contextual contingencies of the trial, including the stimulus, will collapse the critical state to one response option, the response that the child will enact (c.f. Jarvilehto, 1998).

Two features make self-organized criticality ideal to explain context effects. First, as noted, a critical state is a situated state, meaning that it is directly linked to the immediate constraints of the task context. Preparative cognition stays in the loop, so to speak, to create continually updating, contextually appropriate, critical states ready for action. This situated cognitive activity ensures that the child will respond appropriately (though not always accurately)

with the response options that the experimenter allows. A cognitive act within an arbitrary context requires a situated preparatory state to anticipate the situated future—for instance, a child poised to stay on task in novel or familiar stimulus conditions and to make a balance scale response. Perpetually changing relations among context, brain, and body situate cognitive activity within an oncoming task.

Second, self-organized criticality ensures coordination across multiple scales of time and space. Even aspects of the artifactual balance scale environment change at different rates. Trial-by-trial changes in the distribution of weights occur on a relatively fast timescale, whereas the static laboratory backdrop changes on a much slower timescale. In another example, millisecond changes in the acoustics of a conversation co-occur with second-by-second, minute-by-minute, and more drawn out scales of change in structure, content, contextual backdrop, shared knowledge, turn-taking, and other facets of the conversation. Likewise there are many scales of change entailed in the optical flow of a walker, from nearby bumps in the road to landmarks or scenery, flowing by at different rates depending on relative size and proximity, to meandering detours and even changes of destination, to name just a few. Perpetual coordination of cognition is necessary because the environment changes perpetually on multiple timescales.

The brain, the body, and other biological systems are likewise organized on hierarchies of timescales (Soodak & Iberall, 1987). Each hierarchy spans faster and slower changes in neural activity and other physiological processes, timescales of change in limb and torso movements, and in fascia and skeletal movements. Self-organized criticality organizes the processes of the brain and body to act together, simultaneously, across their various scales of space and time. This organization across the brain and body allows context to work simultaneously at all scales, to fully and subtly situate the brain and body within the changing environment (Kello, Beltz, Holden, & Van Orden, 2007).

Local interactions among embodied processes on different timescales weave the intrinsic fluctuations of the component processes into a coherent fabric of flux, despite inherent tendencies of the different processes to vary at their own different rates (on their own timescales). Competitions among local rates of change strike a precise balance with globally emerging cooperative activity. In the precise balance of (or near) the critical state, they produce a long-range correlated, aperiodic pattern of change or flux in behavior—a complex fractal pattern of long-range correlations. The aperiodic flux is called *1/f noise, pink noise, 1/f scaling, fractal time,* and other names, and is a generic prediction of systems in critical states.

Evidence for Soft Assembly

What is the evidence that human cognition is soft assembled? As discussed above, soft-assembled processes have two characteristics that come from self-organized criticality: (1) pre-preparedness of critical states, rather than a dormant system that is merely reactive to a stimulus, and (2) long-term coordination and correlation of processes, rather than independent and static components. We present evidence next for these two features.

Pre-prepared critical states. Findings of ultrafast cognition provide evidence that cognition is pre-prepared. Take for example the results of Grill-Spector and Kanwisher (2005): The time it takes a participant to know that a picture was flashed on the screen is sufficient to know whether the picture showed a bird or a car. Perceivers apparently required no more time "for object categorization than for object detection" (Grill-Spector & Kanwisher, 2005, p. 157). Such ultrafast cognition has been found even when participants are asked to categorize novel pictures on the basis of animacy (i.e., *animate* versus *inanimate),* an archetype of high-level cognitive activity (Fabre-Thorpe, Delorme, Marlot, & Thorpe, 2001).

Ultrafast cognition is surprising and unexpected from the perspective of hard-assembled cognition. If cognition begins only after a stimulus onset, then substantial information processing remains to be completed prior to a categorization response. If cognition were one part of a hard-assembled chain of events that

unfolds across a single timescale, then some measurable time should pass between successful object detection and successful object categorization. We are led to expect a longer time delay between stimulus and response than is observed in ultrafast cognition (Fabre-Thorpe et al., 2001; Kirchner & Thorpe, 2006). Nevertheless, ultrafast cognition is possible when the mind and body are pre-prepared to act immediately in one cascading lunge. Given pre-prepared cognition, an impulsion favoring one particular action trajectory can sometimes realize its action in an ultrafast cascade.

Long-term Coordination. Evidence for long-term coordination of embodied processes comes from ubiquitous I// scaling in human performance. Recall that long-term coordination among processes that change at different timescales predicts a pattern of long-range correlation or I//scaling in repeated measurements of an organism's behavior. Figure 12.2 illustrates the I// pattern in simple reaction time data. The time series is about 8000 trials worth, collected in one sitting, for about 3 hours. The upper right of the figure shows the wavy, aperiodic, fractal pattern of variation in reaction time from trial to trial. Below this trial data graph is a spectral portrait of *l/f*. It is derived by artificially parsing the aperiodic pattern into multiple periodic component frequencies, usually sine waves. Examples of such sine waves are shown on the left hand side of the figure, the top left graph showing slow, lower-frequency oscillations, the left bottom graph showing rapid higher-frequency oscillations, and the middle two graphs showing intermediate frequencies (y axes are adjusted to make the higher-frequency sine waves visible). One can artificially segregate component waves of variation to yield higher frequencies plus intermediate frequencies plus lower frequency oscillations.

Emergent properties of the fractal pattern dictate the relation between amplitudes and frequencies. The remarkable finding is the lawful scaling relation between amplitudes of variation and frequencies of variation (on log scales). In this particular example, the relation between

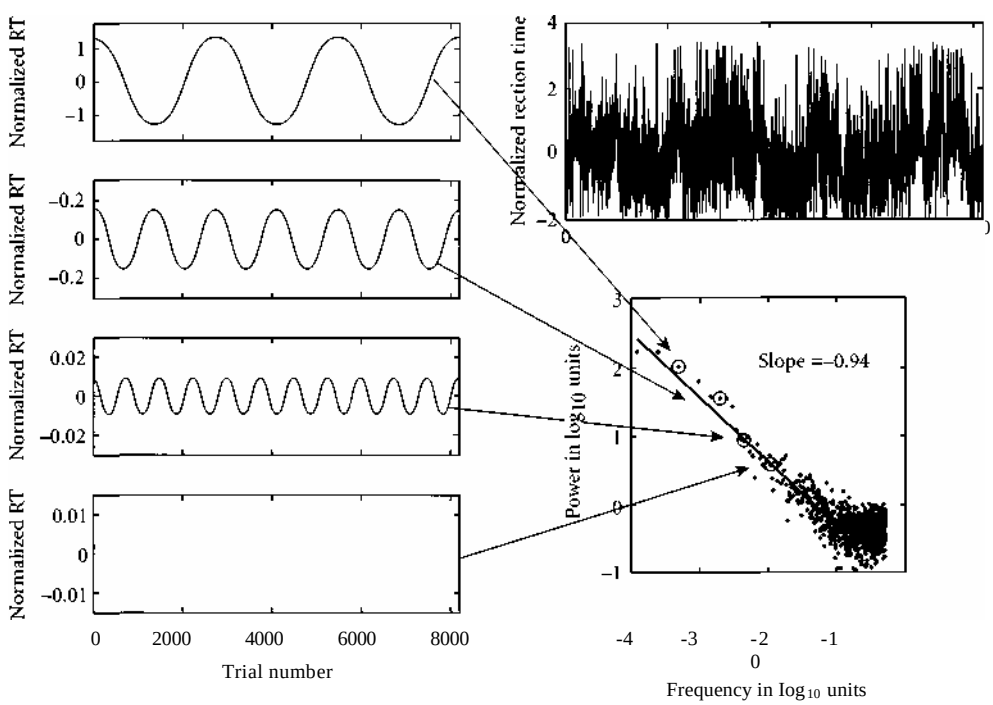

Figure 12.2. Spectral portrait of *l/f* scaling

amplitudes and frequencies has a linear slope of -0.94. Amplitudes of oscillations with periods of tens of trials, for example, find their values on the same line that captures amplitudes for oscillations across periods of hundreds or thousands of trials.

Similar patterns of fractal long-term correlations are ubiquitous in physiology and human behavior (Bassingthwaighte, Liebovitch, & West, 1994; Gilden, 2001; Kello et al, 2007; Raichle & Gusnard, 2005; Riley & Turvey, 2002; van Orden et al., 2003; West, 2006). In fact, it begins to appear, as Machlup (1977, p. 157) suggested decades ago, if you have not yet found the fractal pattern, you have not taken enough data, "you have not waited long enough. You have not looked at low enough frequencies."

The initial response to I// scaling patterns has been a cautious reluctance to interpret these findings as evidence of soft assembly and self-organization (e.g., Wagenmakers, Farrell, & Ratcliff, 2005). Any complex pattern in data can be modeled by a linear decomposition into smaller patterns—that is how the spectral analysis works. This means that it will always be possible to model a particular *IIf* pattern of a particular data set (Beran, 1994). The crippling paradox for hard assembly, however, is that a model's success becomes tied too closely to arbitrary details of how data are collected (Mandelbrot & Wallis, 1968/2002). Success depends too literally on the number of data points collected. One need only collect more data to, in effect, falsify the model.

As more data are collected, variation will grow in amplitude because the I// pattern will extend outside of the limits of sampled data points, and a larger sample will pick up more of the scaling relation. A longer data set reveals more of the lower frequencies, frequencies that are associated with much larger amplitudes of variation. So variation will grow in the larger sample. Consequently, the hard-assembled model must invent additional new components every time a longer data set is collected, out to natural limits of data collection (van Orden, Holden, & Turvey, 2005). As a consequence, no successful hard-assembled alternative has yet been put forward (Thornton & Gilden, 2005).

In addition, success of mimicking a I//process depends too literally on the particular kind of measurement taken for the observed behavior. One need only collect different kinds of measured values in the same behavior to, in effect, falsify the model. For example, a spoken word can be measured in parsing its acoustic spectrum into frequency bins and measuring the spectral intensity of the component frequency bins (300 Hz wide, evenly spaced up to 13.5 kHz, in Kello, Anderson, Holden, & Van Orden, 2008). If this same word is repeatedly spoken and an acoustic spectrum is computed for each repetition, then the repeatedly measured intensity values of the component frequency bins will all fluctuate in the pattern of I// scaling. Thus each arbitrary bin, 90 total, can be equated with a separate stream of variation, and each varies in the pattern of I//scaling. Thus a hard-assembled model must invent 90 distinct sources of I//scaling, one for every repeatedly measured value that is examined (see also Kello et al., 2007; Wijnants, Bosnian, Hasselman, & Cox, 2007).

A hard-assembled model must invent a source of I// scaling for each measured value that fluctuates in the pattern of I//scaling. Yet I//scaling may extend outside the sampled values under consideration and appear in an indefinite set of different measured values that have not yet been considered. The absurdity descends from the idea that variation in measured values comes from independent hard-assembled sources, that measured values are transparent to causal properties of the component sources. The consequent paradoxical, endless additions to ad hoc models also stem from thinking that variation in measured values can be equated with components of cognition—that one's measured values are context-free and thereby transparent to state variables of cognitive components.

The paradoxes disappear, however, once we allow that cognitive activities are soft assembled. In other words, one moves past the paradox in recognizing that measured values are emergent products of dynamic linkages among component systems, including the system that comprises the context of measurement (Flach, Dekker, & Stappers, 2007; Turvey & Moreno, 2006). In soft

assembly, context is causally entwined with the measurement of behavior (Van Orden, Kello, & Holden, in press). Consequently, measured outcomes differ in quality from the embodied processes from which they emerge. On-coming contingent details of task demands and immediate task contexts are constitutive of behavior. Contingent details, as fluid changes in constraints, change the interaction among the component processes from which behavior emerges.

Context Constrains the Body

We have argued in previous sections that context effects are not simple add-ons to so-called real effects. Instead, pervasive context effects indicate different design principles altogether. This argument expands upon a famous description of development by connectionists—namely, that development entails "interactions all the way down" (Elman et al, 1996). Elman and colleagues use a newly hatched duck to illustrate how preparative constraints set up the potential for imprinting that is subsequently determined by the interaction with the environment. Beyond nature and nurture, a duck, or a child, is pre-prepared for developmental milestones, and the milestones are realized in interactions with the environment. Development reflects local details of the environment as a consequence. Likewise cognition itself is preparative and realized in local interactions with the environment (Turvey & Fitzpatrick, 1993).

Currently, dynamical systems and connectionist models address context effects by accounting for children's performance in more than one context, usually by additions to their architectures. For example, the dynamical systems model of Van Rijn and colleagues (Van Rijn et al., 2003) simulates rules I-IV, as well as the torque effect described by Ferretti and colleagues (e.g., Ferretti et al., 1985). McClelland's (1989) connectionist model can account for a difference in salience between weight and distance that could explain the discrepancy in performance when children are given proprioceptive information about weight versus distance. These attempts are insufficient in the present light, however. And this not only because they fail to capture the addition rules proposed by Wilkening and Anderson (1982) or the idiosyncratic rules discussed by Kliman (1986). Even if a model could be rigged to account for children's behavior in all the discussed contexts, it will not anticipate the inevitable next round of context effects.

Context effects are not exhausted at the level of the larger task contexts illustrated in the first part of this chapter. Context effects permeate the brain and body well below the level of trial judgments in particular tasks. That is to say, the context effects discussed in previous sections are just tips of icebergs, so to speak, and soft-assembled icebergs are context sensitive all the way down. Below the iceberg tips, each instantaneous muscle flex and each pattern of rhythmic cortical firing creates a context for every other muscle flex and every other pattern of neural firing (c.f. Belen'kii, Gurfinkel, & Pal'tsev, 1967; Freeman, Holmes, Burke, & Vanhatalo, 2003; Marsden, Merton, & Morton, 1983; Raichle & Gusnard, 2005).

Take, for example, the coordination of speech after an unexpected pull to a person's jaw (Kelso, Tuller, Vatikiotis-Bateson, & Fowler, 1984; Shaiman & Gracco, 2002). Articulation compensates with movements in the upper and lower lips to preserve the flow of speech such that a listener cannot distinguish between perturbed and unperturbed speech. The compensation entails cortical interactions, the fluid matrix of neuromuscular interactions in the lips, modulation of the force of breath and the pace of respiration, and all else that makes up speech. Most important, the fluid compensation stays within the limits of contextual constraints. Context in this case equals the unfolding of a spoken word as co-articulated speech. This context of constraints, specific to the particular co-articulation, exists in a particular configuration at the point at which the experimenter perturbs the jaw. This configuration constrains the fluid compensation, limiting potential compensations to those that insure intelligibility, all the way down.

The example illustrates how global and local context are embodied in local interactions as limits (or constraints) on cascading interactions among excitable neuromuscular media. These

limits are demonstrated widely in motor coordination and also in the neuroscience of perception and action. In laboratory experiments, brain and body demonstrably reconfigure, in an instant, to accommodate local changes in the task environment. For example, a slight change in a motor coordination task—increasing the stimulus pace of the coordinated movements—leads to a new pattern in behavior in a virtually instantaneous phase transition across brain and body (Kelso, 1995). To accomplish this, active constraints must anticipate the phase transition, and must define a potential set of changes in concurrent interactions among excitable media. Active constraints maintain perpetually updated, context-specific potential sets of actions, which anticipate which actions are appropriate, necessary, and possible. Human and nonhuman animals prefigure how to act to satisfy their contexts of action. They must do so to keep apace of perpetually changing relations between actors and environments. In effect, brain, body, and context combine constraints to poise the actor perpetually ready for action.

IMPLICATIONS FOR MODELING

Contemporary models do not usually represent context as a source of constraints. Context is usually implemented as activation or some other causal force. The pace at which activation is updated defines the primary timescale of a model's dynamics, and activations from context and other sources are usually integrated on this single timescale. A typical connectionist model will also include a second timescale of change in connection weights, but the model is always limited to a definite (usually small) number of timescales. This is true of dynamical systems models as well if they equate parameters and variables with hard-assembled mechanisms. Parameters and variables amount to a few explicit timescales of hard-assembled dynamics. However, for all their strengths, contemporary models grossly underestimate the number of temporal scales on which cognitive activity is actually assembled.

Actual cognitive activity unfolds across an indefinite number of timescales in a coordinated fractal pattern that hard assembly does not anticipate. We have explained this fact keeping in mind a picture of cognition that has a primary preparative function (c.f. Raichle & Gusnard, 2005). In the concrete terms of a laboratory experiment, cognition situates a person to participate. Contemporary models do not capture the situated behavior of participants and thereby fail to reveal the situated mechanisms of behavior. Instead, the most widely practiced modeling strategies have emphasized regularities across participants, central tendencies in data, or gross features of developmental change. These phenomena, though legitimate, do not reliably define a mechanistic level of explanation.

A different target for theory, modeling, and explanation is a level of emergent control, above the component details of enacted mechanisms. This *strategic reduction* captures causal properties of systems that are not transparent in component causes. A theory of emergent control makes progress so long as there actually are general principles of control to be discovered. This point about general principles takes a lesson from dynamical systems models. The cusp catastrophe, for example, is a very general account of control and qualitative change (Gilmore, 1993). And the search for empirical flags of the cusp catastrophe illustrates how one goes about establishing that cusp principles of control actually apply (van der Maas & Molenaar, 1992). However, if one grounds the ensuing model in hard-assembled components, then the paradoxes we have described come along for the ride.

At the level of emergent control, task context effects are equated with task constraints in a model's control parameters (Van Orden, Holden, Podgornik, & Aitchison, 1999). A control parameter is a ratio among constraints. Values of the ratio will favor one or another of the probabilistic outcomes. Control parameters are most often associated with dynamical systems models, but they are also discussed in the context of connectionist models (Kello, 2003; Kello, Sibley, & Plaut, 2005; Rueckl, 2002). For example, the ratio of weight to distance trials in a balance scale task could be conceived as a

control parameter. The values of the ratio that favor distance trials yield different rules than the values of the ratio that favor weight trials. In a connectionist model, the ratio of weight versus distance trials is made explicit in the training regime and implicit in the weight matrix. In a dynamical systems model, this ratio could appear explicitly as a parameter in a system of equations. In both cases, the ratio controls competing outcomes that live on opposite sides of a critical value. The critical value defines the point of equally distributed constraints, an imaginary point of no decision, a state of criticality, and a precisely balanced tug of war between equally compelling rules.

This is a different view of modeling and control compared to previous schools of psychology. Models do not stand outside of history, in the sense of a cognitive architecture, except in the principles of their design. Most important, they do not capture phenomena outside of history. Models capture and make explicit the control of behavior emerging in time. Previous schools of psychology relegated control of behavior to relatively static loci in the environment *(behaviorism)* or the organism *(cognitivism).* The new unified theory will locate control in the perpetually changing interaction of child and environment.

CONCLUSION

Hard-assembled cognition must inevitably treat context effects after the fact or as methodological problems of experimental control. Context effects are either something to be explained later, once the basic architecture is in place, or something that undermines data that could otherwise be equated with cognitive components. Nonetheless, cognitive performance is unduly dependent on the particulars of context. A unified theory of cognition and cognitive development must find its beginnings in the particulars of context sensitive phenomena. As for modeling, mimicking the control structure of human behavior captures the available causal basis of behavior. Control of behavior, even qualitative changes in control structure, can be simulated in both connectionist and dynamical system models. Therefore, a unified theory of soft-assembled cognition and development may embrace both dynamic systems and connectionist models. These attractive possibilities, perhaps inevitabilities, can be achieved by discarding hard assembly, by accepting that performance is not transparent to hard-assembled competence. Fluid soft assembly of cognition is the essential human competence and performance is transparent to this competence. Competence as context sensitivity and performance as sensitivity to context are two sides of the same coin.

ACKNOWLEDGMENTS

We thank Michael Riley, Kevin Shockley, and the reviewers for comments and questions that improved this chapter. We also acknowledge funding from the National Science Foundation to Heidi Kloos (DRL # 723638) and to Guy Van Orden (HSD #0728743; BCS # 0642716).

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