Self-Organization of Cognitive Performance

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Background noise is the irregular variation across repeated measurements of human performance. Background noise remains after task and treatment effects are minimized. Background noise refers to intrinsic sources of variability, the intrinsic dynamics of mind and body, and the internal workings of a living being. Two experiments demonstrate $1/f$ scaling (pink noise) in simple reaction times and speeded word naming times, which round out a catalog of laboratory task demonstrations that background noise is pink noise. Ubiquitous pink noise suggests processes of mind and body that change each other's dynamics. Such *interaction-dominant dynamics* are found in systems that self-organize their behavior. Self-organization provides an unconventional perspective on cognition, but this perspective closely parallels a contemporary interdisciplinary view of living systems.

Psychological science usually ignores the background noise in behavioral data. Background noise is what is left over when task demands, experimental manipulations, and other external sources of variability have been eliminated or minimized. What we call background noise is treated as random variability in most research, the nuisance factor in factorial experiments. We argue, to the contrary, that background noise reveals the kind of dynamics that coordinate the mind and the body. Background noise contains the dynamical signature of purposive behavior.

Two new experiments examined background noise in the trial-by-trial variation of response times. The pattern of background noise motivates a plausible story about purposeful behavior and intentional contents. These ideas come out of a cross-disciplinary perspective that departs fundamentally from the dominant view in psychology. We introduce this perspective to make our case, which prompts this friendly notice: The present introduction is much longer than those for most articles in this journal and goes substantially beyond the empirical issue of noise in response-time data. To better communicate our ideas, we describe physical metaphors for self-control and choice and explain the scaling relations found in background noise and what they could mean. The organizing theme is how scaling relations are anticipated from conjecture about purposive behavior and intentional contents.

Intentional Contents

Occasionally, someone participates in our experiments with no intention to cooperate. Maybe they resent the required participation for course credit, or maybe they are put off by the experimenter. In any case, usually, we judge their intention from a pattern of responding. Wayward intentions may be inferred from nonsense patterns, as though the person pressed keys or filled out forms oblivious to instructions. Admittedly, it would be tricky to sort out who is willfully derelict and who is merely incompetent, but that is beside the point. For now, it is enough that uncooperative behavior happens. That obvious fact makes salient the intentions of cooperative participants.

Cooperative participation in a laboratory task requires a cooperative intention to perform the task. Cooperative participants take on a directed set of laboratory goals as their own, and these intentional contents must figure in the facts of observed performances (Vollmer, 2001). Perhaps, then, explanations of laboratory performances should begin with a story of how purposeful behavior can happen. Such explanations are partly anticipated by theory in applied psychology. To properly design airplanes or an airplane factory, one first considers the purpose of the larger system along with the embedded actors' goals—one first specifies a hierarchy of

intentional contents (Rasmussen, Pejtersen, & Goodstein, 1994; Vicente, 1999). However, such explanations are not common in the dominant streams of basic research.

The dominant research program views intentional contents as representations. Representations function as internal causes of behavior (Markman & Dietrich, 2000; Wegner & Wheatley, 1999). Speaking metaphorically, behavior is the end result of chains of billiard-ball-type interactions among representations. In this way of thinking, Newtonian efficient cause serves as a theory-constitutive metaphor that largely defines the content and limits of discussion. Intentions are representations that set in motion a causal chain. To have the intention to act is to cause the act to happen.

The metaphor of efficient cause dictates the designs of experiments and the conventional use of statistics, as well as the range of theoretical possibilities. The metaphor strictly limits discoveries to cause-and-effect relations (Van Orden & Holden, 2002). However, more inclusive metaphors are needed to understand purposive behavior. Otherwise, intentional acts remain forever groundless, open ended, mysterious, or magical. How do intentions come into existence? What is the cause of the cause of purposive behavior? Purposive behavior requires metaphors closer to the complex behavior of living systems, systems with a capacity for self-control and choice.

Self-Control

Simple physical systems exhibit self-control as spontaneous changes in the pattern of their behavior. The systems organize themselves by themselves. Self-organizing phenomena cannot be reduced to a lower level of cause and effect. Fluid convection illustrates these facts. Convection depends on how interactions among molecules are situated within a larger system, not simply on the causal properties of molecules. This example concerns nonliving systems, but it introduces a different way of thinking about living systems (cf. Depew & Weber, 1995; Kelso, 1995; Kugler & Turvey, 1987; Shaw 2001; Ulanowicz, 1997).

Picture yourself holding a large, deep, flat-bottom pan. Add some cooking oil to form a shallow pool, enough to submerge a french fry, and set the pan on a cooker. As the pan heats up, it also heats the oil. In the beginning, haphazard collisions among molecules transport heat from the pan up through the oil. Later, currents of hot oil that move oil molecules in a rotation from bottom to top to bottom emerge. These *convection rolls* transport heat more efficiently than diffusion. Spontaneous convection divides the oil into a honeycomb of cells. Convection rolls circulate within the cells.

One *control parameter* summarizes the status of the heated oil. Control parameters are second cousins to the independent variables of conventional analyses. They are distant cousins because they have different causal entailments. An independent variable is usually investigated to decide whether it picks out a causal factor. In contrast, a control parameter refers to an arrangement of causal factors that yield emergent properties. The pattern of fluid motion in convection is an emergent property. The control parameter of convection combines the amount of heat entering and leaving the oil, friction between the oil molecules, and so on in a ratio. The most prominent factor is the difference between the amount of heat entering the oil versus the amount that leaves. Just before convection rolls appear, the parameter sits near a critical value. At the critical value, the amount of heat leaving the oil is critically less than the amount coming in. This critical value marks the boundary between diffusion and convection, the *critical state*. To one or the other side of the critical value, the model system exhibits one or the other kind of behavior—haphazard collisions versus convection rolls.

Convection rolls cohere out of interdependent movements of molecules—molecules change each other's dynamics as they interact. Near the critical state, interactions among molecules coordinate the behavior of the selfsame molecules and greatly reduce their freedom of motion. Once convection rolls emerge, they subsequently control the flow of molecules and thereby become self-perpetuating. Movements of molecules both cause and are caused by convection rolls, an instance of *circular causality*. Most important, the system organizes itself by itself without an external coordinator. It is in this sense that self-organizing systems exhibit self-control, and self-control is one aspect of purposive behavior that relates to intentional contents.

Choice

A metaphor for self-control takes us part of the way, but we also require a metaphor for choice. The transition from random collisions to the rotating currents of convection includes an outcome akin to choice. The system chooses its unique pattern of rotations. In the critical state, each molecule could move either clockwise or counterclockwise; both rotations are possible for every molecule in the system. Competing rotations exist as balanced propensities at the same time everywhere in the system. Across the critical state, molecules move in the same rotation inside the same convection roll.

A critical state is a global state that is acutely context sensitive. *Criticality* refers to a precise balance among constraints; that is what it means to be in a critical state. A difference in circumstances that favors one option over another, no matter how slight, breaks the symmetry of equally poised options. A small flux in heat can change the entire pattern of interactions among molecules and choose a specific pattern of rotation. Choice of rotation happens simultaneously everywhere in the system. If one convection roll turns clockwise, then adjacent rolls turn counterclockwise.

Near the critical state, nearest neighbor interactions become correlated. This coordinates the choice across the entire system. The sudden collapse of the critical state (multiple potential rotations) chooses the molecule trajectories that are observed. The collapse of the critical state captures something essential to choice in human behavior. The details of changing circumstances choose movements that are expressed, and local movements conform to a larger global configuration of movements, a product of global emergence.

In convection, changing circumstances choose a global pattern of movement. Each molecule's trajectory is uniquely situated in these circumstances of the larger system (Prigogine, 1997). Every movement of the human body is also uniquely situated. Even scratching an itch or swinging a hammer follows a unique trajectory in each repetition (Berkinblit, Feldman, & Fukson, 1986; Bernstein, 1967). The following example of catching soap taken from Gibbs and Van Orden (in press) illustrates human movements uniquely situated in circumstances that define their intentional content.

Picture yourself in the shower grasping a bar of soap. Somehow, your hold on the slick bar propels the bar up and out of your hand. You react immediately, and, although you may bobble a bit, quick inexpert juggling brings the soap under control. You catch the soap before it gets away. The situated constraints that bring into existence the catching of the soap can be described on many different timescales. These include relatively slow timescales of cultural change in hygiene. However, they also include intermediate timescales of goal-like intentions to shower, to wash your arm, to control the soap, and so on, as well as the multiple fast timescales of the limb movements that catch the soap—a hierarchy of constraints on a hierarchy of timescales.

Notice that an explicit goal to retrieve the soap could not have existed before your juggling began. The intentional contents of grasping the soap entail controlling the soap, but the precise movements that brought the soap back under your control could not have been anticipated before they were enacted. Juggling emerges because the situation in which the soap is to be controlled changes. There is a sense in which unique details of a rapidly changing soap-bobbling situation create the intention to recover the soap as they choose unique juggling movements to recover the soap. Special circumstances choose unique movements, and all circumstances are special.

Juarrero's Conjecture

Convection supplies physical metaphors for self-control and choice, salient aspects of purposive behavior. Yet the metaphors come from simple physical systems in which a single process is at work and laboratory models that must be carefully tuned to yield criticality. In living systems, criticality itself emerges spontaneously, *self-organized criticality* (Bak, 1996). Living systems self-organize to stay near critical states. The benefits may be obvious. Criticality allows an attractive mix of creativity and constraint. It creates new options for behavior and allows the choice of behavior to fit the circumstances of behavior. Why nature is creative in this way remains a mystery, but the mystery is bounded on all sides by natural phenomena. Natural purposive behavior originates in self-organized criticality—call this claim *Juarrero's conjecture*. Our experiments are tests of Juarrero's conjecture.

Juarrero (1999) proposed that intentional contents poise human beings near critical states (see also Riley & Turvey, 2001; Shaw & Turvey, 1999; Van Orden & Holden, 2002). Intentional contents themselves are emergent dynamical structures. Intentional contents, as emergent structures, are perpetuated in time by circular causality. They are sources of constraints that persist over time. Constraints limit the degrees of freedom for interactions among the processes of the human body (Amazeen, Amazeen, & Beek, 2001; Amazeen, Amazeen, & Turvey, 1998). Intentional contents persist over time whereas bodily movements are changing on faster timescales. Slowly or infrequently changing constraints limit the possibilities for movement on faster timescales.

Like critical states, intentional contents balance the constraints that would yield one or another course of action. As in the collapse of critical states, intentional contents enfold changes in circumstance to choose among potential courses of action. Changes in oncoming immediate circumstances break the symmetry of poised options. Changing circumstances collapse the hierarchy of intentional contents (propensities for action) into purposive behavior (enacted movement). Notably, subtle changes in circumstance may

select subtly, or largely, or entirely different courses of action. In turn, action has consequences for perception and the configuration of intentional contents.

Action changes the circumstances of the mind and body, which change the opportunities for perception. Changing propensities for action seamlessly intertwine with changing opportunities for perception, like the intertwined side of a Möbius band (Turvey, 2002). Changing propensities for action introduce new opportunities for perception. New opportunities for perception entail new propensities for action and reconfigure intentional contents. This interplay among self-organizing intentional contents and perpetually changing circumstances uniquely situates ordinary purposive behavior. Remember, every swing of a hammer follows a unique trajectory.

Juarrero (1999) did not present evidence in favor of self-organized criticality—thus, the term Juarrero's conjecture. She constructed a philosophical argument against intentional contents as representations and representations as efficient causes. Her argument draws its strength from the indeterminacies of representation that she demonstrated (Adams, 2001). However self-organizing systems, including living systems, appear to have universal properties. Self-organizing systems can be very different in their structural details but behave the same way near critical points (Nicolis, 1989). Universal properties present opportunities to test Juarrero's conjecture.

Criticality predicts scaling relations, which likely refer to a universal property (Bak, 1996; Bar-Yam, 1997; Jensen, 1998). Measured behavior of model systems from physics and other disciplines exhibits particular scaling relations near critical states. The same scaling relations appear in measurements of human performance. Scaling relations supply evidence that intentional contents poise participants' bodies near critical states, evidence for Juarrero's conjecture. Our experiments tested for scaling relations, and it is important for our argument to supply a clear sense of what scaling relations are. We describe an often-used example in the next section. The example concerns measurement of length, but it illustrates a general point. It explains why some ordinary measurements of behavior are not reliable. After that, we discuss response times and then complete our introduction of technical terms.

Scaling Relations and Fractal Patterns

Colorado has a nice rectangular shape. Were one to measure the length of its border, the outcome would be essentially the same whether the measurement was taken with a kilometer scale, a meter scale, or a centimeter scale. Not so for the irregular coastal border of Britain. Measured length increases proportionally as the measuring stick is shortened. Length grows because irregular contours of bays and peninsulas not captured by a longer scale add length on shorter measurement scales. Bays and peninsulas of the coastline are composed of small and smaller subbays and subpeninsulas. Shorter scales resolve smaller features, which add to the overall length. There is no reliable fixed length for the coastline of Britain that is independent of the measuring device (Mandelbrot, 1982, pp. 25–33).

Large features of the irregular coastline nest within themselves smaller features that nest within themselves yet smaller features and so on—a fractal pattern. Fractal patterns are self-similar. They repeat similar features across nested scales of space or time. Fractal patterns are identified by scaling relations. For the coastline of Britain, the scaling relation is between the measured lengths and

the scales of measurement. It is a proportional relation between measurement scale and the results of the measurement process. The proportional relation characterizes how larger features of the coastline are related to smaller features.

In mathematical fractals, the same patterns can appear across an infinite range of scales, a precise form of self-similarity. Yet natural fractals are not pristine mathematical objects. Natural fractals display a rougher, more irregular form of self-similarity, statistical self-similarity, across a limited range of scales. We claim that the variation in response times forms a natural fractal in which larger scale deviations nest within themselves smaller scale deviations. Fractal structure would imply that no reliable estimate of variability exists, in the same way that the length of a coastline has no single value (see also Bassingthwaighte, Liebovitch, & West, 1994, pp. 33–41). The experiments described below tested for scaling relations (statistical self-similarity, fractal variation) in the measured variance of response times.

Whether variations in behavioral data form natural fractals is profoundly important. The crux of conventional statistics is whether a parameter such as variance can be reliably estimated. Experimenters trust that their samples of data have reliable means and characteristic amounts of variance. Yet suppose that the range of variability grows as more data are collected (cf. Mandelbrot & Wallis, 1969). Larger samples of the same data yield larger variance estimates up to the limits of the system. This possibility runs against the grain of all conventional analyses.

Conventional descriptive statistics are based on the assumption that a stable quantity of variability exists, a characteristic amount that is not overly sensitive to sample size. Conventional inferential statistics extend this assumption further. Inferential statistics are based on the assumption of homogeneous variance, namely, that all treatment conditions have equal amounts of variance. However, for many natural systems, these assumptions do not apply. Among these are physiological processes of living beings (Bassingthwaighte et al., 1994). When researchers take measurements of a person's behavior, they should scrutinize how variability stacks up against sample size, just in case.

Variation in Response Times

The mathematical ideas of scaling relations and fractals can shed new light on response-time behavior, a classic laboratory performance. A response time is the elapsed time in a laboratory trial between a signal to respond and an action that stops the clock. Response time is among the oldest and most widely used measurements of human performance, and a vast response-time literature exists. So, what exactly remains to be revealed? We claim that conventional studies have made the wrong assumptions about background noise in response times. Sobering discoveries in nonlinear science have demonstrated that scientists must test assumptions about background noise (Riley & Turvey, 2002). We next discuss conventional response-time models and how their assumptions are affected by scaling relations and fractal variation.

The response-time literature has almost always concerned attempts to reduce response times to elementary causal components of mind or brain (Luce, 1986). Presently, diffusion models show the most promise as candidate components. Diffusion models simulate the time to a decision in situations where there are two alternatives to decide between. For example, a participant might quickly discriminate red color patches from green color patches, or

bright lights from dim lights, or many donuts from few donuts. In a diffusion model, information that favors one choice or the other accumulates over time. Eventually, the accumulated evidence clearly favors one of the choices, at which time the model responds and its response time is noted. Many simulated decision times can be collected to compare with participants' decision times. Diffusion models correctly mimic participants' average decision times and also mimic the shapes of response-time distributions for both correct and incorrect decision times (Ratcliff, Van Zandt, & McKoon, 1999).

The diffusion framework makes two specific theoretical claims: First, information about which choice to make accrues over time. Second, choices themselves can be portrayed as opposite ends of a one-dimensional continuum, as *decision poles*. Other aspects of the decision process remain to be specified. A diffusion model is one part of a largely unspecified system. Consider that each instantiation of diffusion uses different task-specific information about color, numerosity, brightness, and so on. In fact, a diffusion model could work with very different kinds of information. Information could refer to the qualities or identities of stimuli or could refer directly to abstract decision poles or concrete response options. How responses are made is also left open. Presumably, a disembodied diffusion process would be the same whether a person said yes or no, threw a red lever or a green lever, or pedaled a bicycle faster to signal more donuts or slower to signal fewer donuts. So, how are diffusion models situated with respect to the larger reality of mind, body, and world?

To situate a model, a scientist must connect the model with other mental components, connect the mind with the brain and body, and connect the body to the world. How things are to be connected, how components are to interact, is stipulated in shared fundamental assumptions. Conventional assumptions derive from the Newtonian metaphor; all interactions take the form of cause and effect. The metaphor requires the exclusive pursuit of effects to individuate component causes. To use response time in this pursuit, it would be essential that isolable component effects occur within the time between a stimulus and response (A. Newell, 1990). Each component may work at its own rate, but operations must be initiated by the stimulus and must finish together with the response.

Background noise provides a test of whether the conventional enterprise is justified, whether it is possible to work piecemeal, effect by effect, component by component. Scaling relations and fractal variation call into question the conventional metaphor. Scaling relations imply processes that extend beyond the time boundaries of laboratory trials. These processes causally interpenetrate processes inside a trial. Interdependent processes live in a tangle of causation across the body's hierarchy of timescales. If variability in response times scales with sample size, then that fact would speak to fundamental assumptions. It would not be appeased by ad hoc changes to conventional theories. It would motivate changing the assumptions at the heart of behavioral science (Liebovitch, 1998; Van Orden & Holden, 2002; West & Deering, 1995).

Next, we continue to explain the technical terms *fractal dimension, uncorrelated noise,* and *correlated noise* and then contrast *component-dominant dynamics* with *interaction-dominant dynamics* to spell out Juarrero's conjecture. We hope that the immediate implications of these jargon terms are made clear by the end of this introduction. The following statements sum up what remains to be

explained: Self-organized criticality requires interaction-dominant dynamics; interaction-dominant dynamics produce statistically self-similar, positively correlated, background noise; and the fractal dimension of noise indicates whether it is self-similar.

Fractal Dimension

Fractal dimension can be used to evaluate variation across response-time trials. To get an intuition for fractal dimension, imagine a graph of response times. The graph's x-axis is the trial order in which response times were collected (Trial 1, Trial 2, Trial 3, and so on). The y-axis is response time itself. The graph appears as points connected by a jagged line, a *trial series*. Figure 1A presents a normalized trial series of simple reaction times. If this line were straight, it would have a Euclidean dimension of one. However, the jags away from the one-dimensional line begin to occupy area on a two-dimensional plane. In this sense, variation across response-time trials partly occupies or leaks into the second Euclidean dimension. The graph has a fractal dimension somewhere between an ideal one-dimensional line and an ideal two-dimensional plane.

Homogeneous unsystematic variability has a fractal dimension of 1.5. This is the fractal dimension of white noise. White noise is illustrated in Figure 1D. The data in Figure 1D are a randomly ordered version of the trial series in Figure 1A. The fractal dimension 1.5 indicates the extent to which white noise occupies two-dimensional space. White noise is uncorrelated noise. Uncorrelated noise implies that each trial measurement is independent of every other trial measurement. The conventional use of descriptive and inferential statistics assumes that background noise is uncorrelated noise. This assumption shapes much of what researchers think about laboratory experiments.

Uncorrelated Noise

One pearl of laboratory wisdom concerns the power of an inferential statistic to detect an effect. A marginal outcome of an experiment may become statistically reliable if the size of the data sample is increased. This idea is encoded in Equation 1.

Equation 1 portrays the familiar scaling relation between the variance statistic SE and the ratio of a population SD and sample size N. This is the equation for the standard error of the mean:

$$SE = SD_{Pop}/\sqrt{N}. \tag{1}$$

When N gets very large, SE gets close to zero. Thus, SE scales as a function of sample size N. A standardized SD_{Pop} equals one, which yields

$$SE = 1/\sqrt{N}. \tag{2}$$

Taking the logarithm of both sides of Equation 2 yields Equation 3:

$$\log(SE) = -\tfrac{1}{2} \times \log(N). \tag{3}$$

Equation 3 suggests what a plot of this scaling relation looks like on log/log coordinates: a straight line with a slope of $-\frac{1}{2}$. Figure 2 portrays this line. Fractal dimension is calculated by subtracting its negative slope ($-\frac{1}{2}$) from 1, the Euclidean dimension of a line, which equals 1½ or 1.5, the fractal dimension of white noise.

Correlated Noise

Self-organized criticality produces positively correlated noise as background noise. Self-organization coordinates the processes of the body across their hierarchy of timescales. Correlated activity across timescales produces correlated variation across time. Variation in activity takes the shape of a nested structure of positive correlations. Consequently, variation in response times appears as a natural fractal in which larger scale deviations nest within themselves smaller scale deviations.

Positively correlated noise appears less jagged than white noise (compare Figure 1A with Figure 1D). Correlated noise leaks less into the second Euclidean dimension than white noise. A dispersion analysis estimates fractal dimension and tests for correlated noise. A dispersion analysis repeatedly resamples the same data using different sample Ns (bin sizes). A variance or dispersion statistic is calculated for each bin size. The resulting pairs of dispersion statistics and bin sizes (sample Ns) can be graphed as a line on log/log coordinates. The slope of the line is used to calculate fractal dimension. The slope of the line for correlated noise is reliably less steep than $-\frac{1}{2}$, the slope of uncorrelated noise in Figure 2. Consequently, when one subtracts the less steep slope from 1, one gets a fractal dimension less than 1.5.

Interdependence among components explains correlated noise. Recall how oil molecules change each other's dynamics in convection and nearest neighbor interactions correlate changes across the entire collection of molecules. Likewise, changes in one of the body's processes are tied to changes in other processes. Loosely speaking, whatever happens to one component happens to all components. All that is left for our introduction is an explicit contrast between component-dominant and interaction-dominant dynamics.

Component-Dominant Dynamics

By convention, cognitive acts are believed to originate in loosely coupled dynamics that can be treated as component-dominant dynamics (Simon, 1973). This hypothesis about system dynamics is the core assumption of modular approaches to cognition. As the term component-dominant suggests, the dynamics inside of a component dominate interactions with other components. Component-dominant dynamics protect the integrity of component effects. They encapsulate component effects such that they can be recovered in the measured behavior of the whole.

To recover the effect of one component, say a memory component, an analysis must distinguish the memory effect from effects of other components plus internal noise—all of which accumulate in the value of a measurement. If the memory component is encapsulated, one may possibly find its effect all the way out in a measurement of human behavior. If so, then the memory effect can be attributed (reduced) to causal properties of the encapsulated memory component. In this way, measurements taken of human behavior could refer directly to causal properties of specialized components of mind or brain.

If the mind and brain are collections of specialized devices, measured behavior can be partitioned among these devices. This kind of enterprise, a program of *morphological reduction,* reduces behavior to combinations of devices, something like a table for addition (Pachella, 1974; Sternberg, 1969). If Component Effect A + Component Effect B = Behavior C, then Behavior C reduces to Component Causes A and B. The empirical cornerstones of
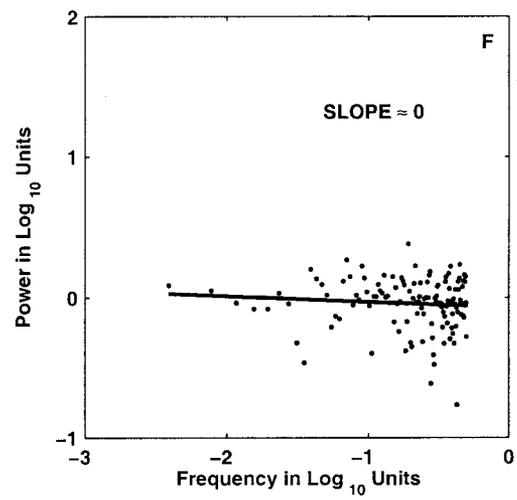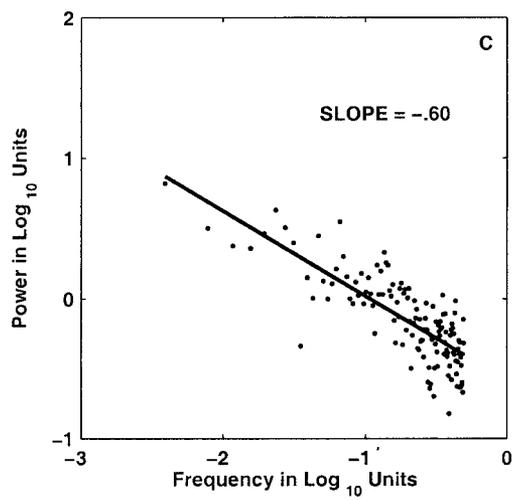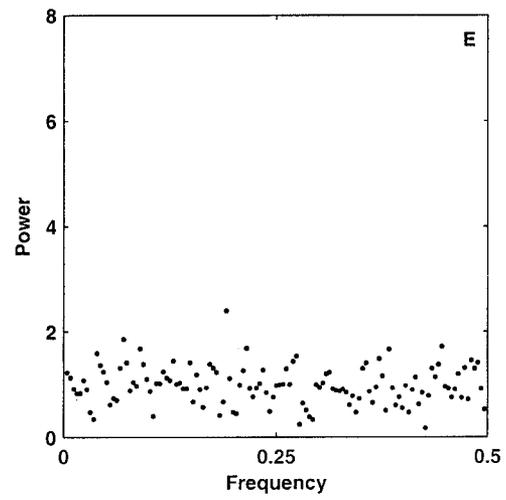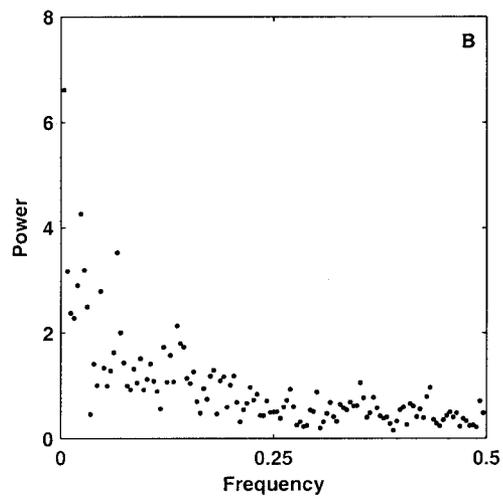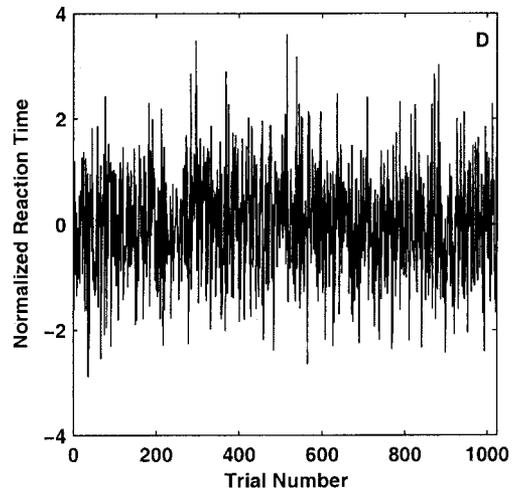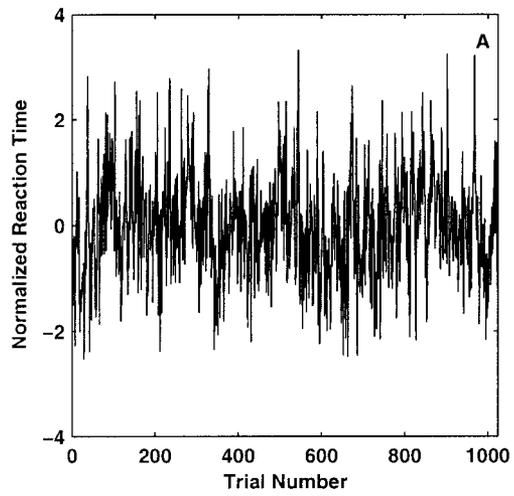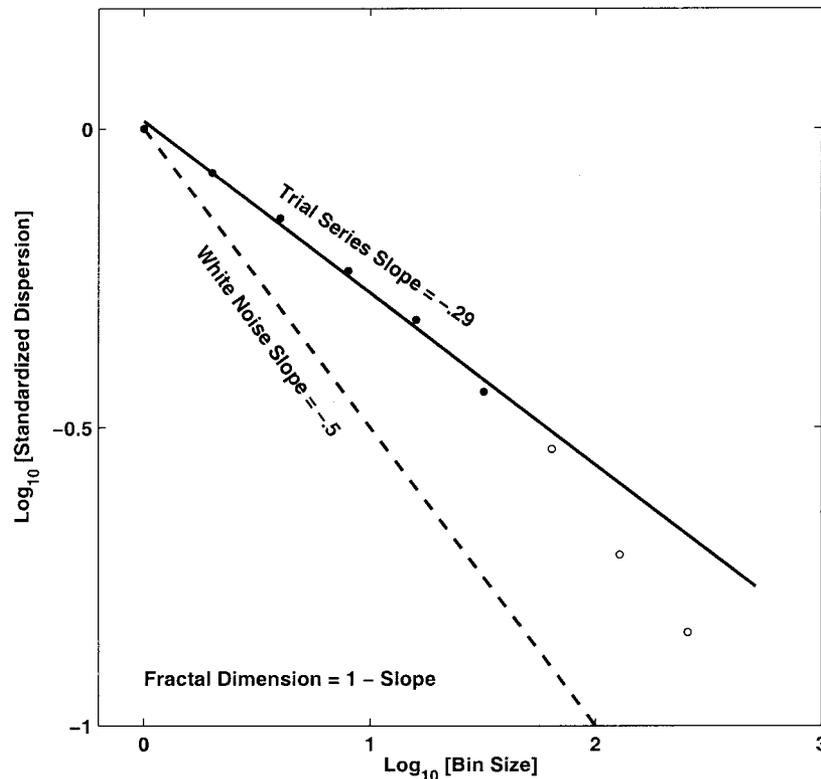
Figure 2. Standardized dispersion as a function of sample size. The figure portrays the results of a dispersion analysis on the trial series of simple reactions depicted in Figure 1A. The *x*-axis indicates the Base-10 logarithm of the number of data points in each adjacent sample (bin). The *y*-axis indicates the logarithm of the standardized dispersion at each bin size. The solid line is a least squares regression line for the six points represented by solid dots. The slope of the line is −.29. The three unfilled dots were excluded due to standard issues of detrending. The dashed line with a slope of −.5 indicates the slope of white noise.

black-box reductions are always additive effects consistent with the superposition principle (Lewontin, 1974), but additivity does not adequately describe cognitive performances.

Either additivity so far is too shy to show itself and remains to be teased out of data or it is simply the wrong assumption. We claim it is the wrong assumption. There are no encapsulated components. Ordinary things that people do—perceiving, remembering, discussing, imagining, touching, walking— have been misconstrued as components of which they are composed (Van Orden & Kloos, 2003). History finds psychology courting once again the *psychologists' fallacy*—the products of psychological processes have been mistaken for the processes themselves (Fitch & Turvey, 1978; James, 1890/1950; Turvey et al., 1980).

Interaction-Dominant Dynamics

Self-organization coordinates the body's perpetually changing processes. As the term interaction-dominant implies, neighboring

Figure 1 (opposite). Figures A–C (A: Simple Reaction-Time Trial Series; B: Simple Reaction-Time Power Spectrum; C: Power Spectrum on Log-Log Scales) step through a spectral analysis of an actual participant's trial series of simple reaction times. Figure A portrays the trial series after it has been trimmed, detrended, and normalized. Figure B displays an intermediate step in which the results of the spectral decomposition are plotted on linear axes. Frequency (*x*) is plotted against power (*y*), or amplitude squared, on linear scales. Frequency and amplitude range from low (near the origin) to high (away from the origin). Low frequency is associated with high amplitude and high frequency with low amplitude. Figure C displays the same spectral results after the frequency (*x*) and power (*y*) axes have been transformed to logarithm Base-10 scales. Again, lower frequencies have higher amplitude in the form of a scaling relation between frequency and amplitude. Figures D–F (D: Surrogate Trial Series; E: Surrogate Power Spectrum; F: Power Spectrum on Log-Log Scales) step through another spectral analysis, this time using surrogate data (a random arrangement of the data series in Figure A). The power spectrum portrayed in Figure F is the power spectrum of white noise— different frequencies all have roughly equivalent power.

processes change each other's dynamics in their interaction. Each local interaction among neighboring processes takes into account the special circumstances of the neighbors. Nearest neighbor interactions extend to the periphery of the body, to systems at the causal interface with the world at large. Consequently, the flow of circumstances in which the body is situated constrains behavior directly.

Interaction-dominant dynamics are described mathematically as in a multiplication table of interactions (Abraham, 1987). Multiplicative interactions among interdependent processes yield emergent behavior. Component processes are inextricably combined in emergent behavior. Thus, for complex systems, the object of study is interaction itself, not necessarily the details of interacting components.

Interaction-dominant dynamics coordinate the processes of the body. Coordination across the timescales of the body is the source of correlated noise. Interdependence allows the behavior of each process to reflect something of the behavior of the whole. This is a recipe for fractal properties. The variation of the whole is present, in some sense, in each of its parts. Consequently, variation across measurements of a person's behavior takes the form of a natural fractal.

To characterize the variation in background noise is to discover the signature of purposive behavior. A cooperative participant in a laboratory experiment takes on a set of directed intentions consistent with a laboratory protocol. The model system in this case is a person constrained by laboratory goals, a laboratory preparation of intentional behavior. Thus, the signature of variation in the laboratory performance is the dynamical signature of intentional behavior.

Measurement of Intrinsic Dynamics

Many demonstrations of positively correlated noise already exist. We introduce the experiments below in terms of previous response-time demonstrations, and we later list other demonstrations. What remains to be settled is how to interpret all these demonstrations. The first experiment is a simple reaction-time task, and the second experiment is a word-naming task. These particular tasks speak to particular questions of interpretation. They close gaps in the existing inventory of demonstrations and narrow the field of possible interpretations. The tasks may also help illuminate methodological concerns for measurement of intrinsic dynamics. One concern is how perspective of observation limits what can be observed. We discuss perspective of observation and then introduce the term *pink noise* and the issues that surround pink noise and simple reaction-time data.

Perspective of Observation

In a simple reaction-time task, the official task demands are identical from trial to trial. The same signal to respond is presented on every trial, and it always signals the same response category. However, there are always sources of external variability, even variation in the machine that presents the signal. The simple reaction protocol merely minimizes these sources. As a consequence, observed variability is to a large degree background noise. Measurement provides an objective picture of background noise in simple reaction times, but from a particular vantage point.

Dimension is partly determined by vantage point. Consider a tautly stretched piece of thread; it closely resembles a one-dimensional Euclidean object, a line. Tightly weaving the thread back and forth results in a two-dimensional object, a piece of fabric. A line can be rearranged so that it begins to occupy area. Rolling the thread onto a spool yields an object that occupies volume in three-dimensional space. If the spool of thread is viewed from a great distance, its dimension appears to collapse to zero, a point. There is no privileged place of observation. The example comes from Mandelbrot (1982). Solé and Goodwin (2001) discussed why the perspective of observation can be crucial in analyses of complex biological systems.

The process by which one measures a biological system partly determines what one discovers. The intrinsic processes of biological systems are stacked on hierarchies of timescales (Soodak & Iberall, 1987). Systematic repeated measurements of response time also define a timescale, the loosely rhythmic trial-by-trial pace of data collection. This pace sets an entry level into the body's temporal hierarchy. The pace of measurement taking divides the timescales of the body into timescales slower and faster than the pace of data collection. From this perspective, variation on the faster timescales contributes unsystematic noise that partly or wholly decorrelates the measured signal (cf. Simon, 1973).

Correlated noise on timescales slower than the trial pace of data collection contributes measurable systematic variation. Yet one cannot resolve systematic variation on timescales faster than the pace of measurement. The timescale of data collection is too sparsely paced to accurately gauge variation on faster timescales. Furthermore, response times vary from trial to trial, which contributes to a more or less irregular pace of data collection throughout. This irregular pace tracks a signal of background noise that is also irregular by nature (cf. the coastline of Britain). All these sources decorrelate the measured signal. Every vantage point inevitably yields a picture of more or less decorrelated noise.

Pink Noise

We report two experiments that examined background noise across response times. In each experiment, we observed empirical signatures of pink noise, the specific form of correlated noise predicted by self-organized criticality. Pink noise is a fractal pattern in time and is sometimes called fractal time.

Background noise is analyzed using two analyses, spectral analysis and relative dispersion analysis. In a graph of simple reaction times, connected data points trace a complex irregular waveform (Figure 1A). A spectral analysis approximates the complex waveform as a composite of simple regular waves spanning a range of frequencies, similar to Fourier analysis. Pink noise appears as an inverse relation between the frequency of the composite waves and their amplitude (power) on log scales. Slowly meandering lower frequencies are associated with greater amplitudes, intermediate frequencies are associated with intermediate amplitudes, and jittery high frequencies are associated with smaller amplitudes in a statistically self-similar fractal pattern.

Pink noise has been observed previously in cognitive performance (see Gilden, 2001, for a review). Early reports found the pattern in residual variance. Residual variance is the variability that remains after factor means are subtracted out trial by trial—as though component-dominant dynamics separate factorial effects from background noise. However, this procedure itself decorrelates the signal of pink noise. A treatment mean is usually a poor summary of a response-time effect compared with a distribution of response times (see, e.g., Andrews & Heathcote, 2001; Balota & Spieler, 1999; Heathcote, Popiel, & Mewhort, 1991; Holden, 2002). In any case, the actual effect in each trial differs unsystematically from the mean. If factor means are nevertheless subtracted out trial by trial, then another unsystematic contribution to variability is introduced. This source combines with other sources of irregular variation

that decorrelate the measured signal. This nicely illustrates how analytic practices based on assuming component-dominant dynamics can distort or obscure a strongly nonlinear phenomenon.

Below, we describe experiments that revealed pink noise in simple reaction times and word-naming times. Both experiments are important insofar as pink noise may imply self-organization in human performance. The word-naming experiment is important in its own right because it generalized pink noise to a cognitive task that is widely assumed to elicit *automatic cognitive processing*. Previous demonstrations of pink noise in cognitive performance used tasks that required judgments and decisions, *controlled cognitive processing*. The simple reaction-time study is important for resolving a discrepancy in the literature that we discuss next.

Correlated Noise in Simple Reaction Times

Gilden (2001) has proposed that pink noise originates in an encapsulated memory process, "mechanisms of thought that lead to discrimination and choice" (p. 33). Inside the memory capsule are interaction-dominant dynamics. Encapsulated interaction-dominant dynamics are the source of pink noise. Yet the capsule itself interacts with the rest of the body in component-dominant dynamics. A single subtractive contrast supports the memory capsule hypothesis: Background noise in simple reaction times has been subtracted from background noise in discrimination and choice tasks to isolate the memory capsule (Gilden, Thornton, & Mallon, 1995). Since Donders (1868/1969), it has been widely assumed that subtractive contrasts can isolate central decision processes. Bub (2000), Pachella (1974), Sternberg (1969), Uttal (2001), Van Orden and Paap (1997), Van Orden, Pennington, and Stone (2001), and others have explained why subtractive methods cannot be trusted to isolate component processes.

In the tradition of Donders (1868/1969), residual variability in the decision times (pink noise + white noise) minus variability in simple reaction times (white noise) equals pink noise. Both tasks required motor coordination, and both produced white noise, but only the discrimination and choice tasks produced pink noise. Pink noise concerns the formation of mental representations, and white noise concerns motor components. The mental representations control the motor components. Loosely speaking, pink noise refers to the puppeteer, and white noise refers to the puppet. However, this characterization of motor components and motor noise has been contradicted (see K. M. Newell & Slifkin, 1998; Riley & Turvey, 2002). Tapping studies and other motor studies have also found pink noise in background noise (see, e.g., Chen, Ding, & Kelso, 1997, 2001). Motor-coordination tasks like tapping would seem to provide the more detailed and reliable picture of motor noise, which warrants a critical look at the reaction-time protocol.

The method of Gilden et al.'s (1995) reaction-time study built in an unintentional external source of white noise. The term external is defined with respect to the measurement procedure, from considering how a laboratory protocol may function as a gauge of intrinsic dynamics. Factors that can be manipulated or randomized by an experimenter are external sources of variability. The design of the simple reaction-time study inserted random intervals of time between each response and the next signal to respond. There was a special concern with the simple reaction-time task that participants should not anticipate the signal to respond. Random intervals made the signal to respond unpredictable.

Random intervals exaggerate irregularity in the pace of data collection and contribute random perturbations to the coordination

of simple reactions. Random intertrial intervals decorrelate a trial series and obscure the pink-noise signal. It is crucial to minimize external sources of noise (Bassingthwaighte et al., 1994). If they predominate, then the possibility of observing intrinsic dynamics may be lost. It is also important specifically whether pink noise is found in simple reaction times. The memory capsule hypothesis depends on its absence.

Our reaction-time experiment included fixed intervals and predictable signals to respond and produced scaling relations consistent with pink noise. Fixed intervals reduce the degree to which measurement decorrelates the pink noise signal.

Method

Participants. Ten introductory psychology students received course credit in exchange for participation.

Procedure. Each participant completed 1,100 simple reaction-time trials. On each trial, a fixation signal (+++), visible for 172 ms (12 raster refresh cycles), was followed, after 200 ms, by a signal to respond (######). Each signal appeared in the center of a computer monitor controlled by a PC running DMASTR software (Forster & Forster, 1996). The signal to respond remained visible for 200 ms past when a response was recorded (up to a maximum of 972 ms). Participants responded by saying /ta/ quickly into a microphone (similar patterns of response-time variability occur with other response modes). Responses were detected using a voice key and were reliable to within 1 ms. Each response was followed by a fixed 415-ms intertrial interval. If a response was not detected, trials timed out after 4 s. Every participant completed a block of 45 practice trials and then the 1,100 experimental trials, which required about 30 min.

Details of the Spectral Analysis

Each participant's trial series of reaction times was kept in the order in which it was collected for spectral analysis. A power-spectral density was computed for each trial series—a particular kind of spectral analysis that outputs the squared amplitude of the component oscillations. We used standard techniques such as the analyses described in Gilden et al. (1995) and Chen et al. (1997).

The theory behind fractal time would lead one to expect extreme times up to the natural limits of the system. Yet a few extreme times, or simple long-term trends, could distort the outcome of the analysis. Trimming and detrending procedures brought the series of simple reaction times (the finite irregular natural object) in line with the idealized mathematics of spectral analysis. The contortion is necessary because the mathematics ultimately assume an ideal, stationary, strictly periodic process of infinite duration.

We removed simple reaction times greater than 1,000 ms, then computed the series mean and standard deviation, and removed times that fell beyond ± 3 standard deviations from the trial-series mean. The trimming criteria eliminated an average of 19.20 (1.75%) simple reaction times from each trial series ($Mdn = 18$, $SD = 10.05$, minimum = 6, maximum = 42). The trimming criteria also eliminated trials in which the voice key failed to detect the /ta/ pronunciation ($Mdn = 6$). The number of eliminated trials was unrelated to the spectral slopes or fractal dimensions of the series by either parametric or nonparametric correlation analyses or by visual inspection of scatter plots. In every case, more than 1,024 measurements remained after trimming. Subsequently, we truncated the beginning trials of the experiment until 1,024 observations remained. Trends up to a quadratic were removed, and then the series was normalized.

Figures 1A–1C step through a spectral analysis of a single participant's trial series. Figure 1A shows the trial series of reaction times after they have been trimmed, detrended, and normal-

ized. Figure 1B displays an intermediate step in which the results of the spectral decomposition are plotted on linear axes. Frequency (*x*) is plotted against power (*y*), or amplitude squared, on linear scales. Figure 1C displays the same spectral results after frequency (*x*) and power (*y*) are transformed to Base-10 logarithmic scales. Figures 1D–1F show the same steps in an analysis of a randomly ordered version of the same trial series, the surrogate trial series that approximates white noise.

Results of the Spectral Analysis

The spectral analysis estimates the slope of the line that relates amplitude of change to frequency of change on log/log scales. The negative slope of the graph (−.60) in Figure 1C illustrates the expected scaling relation. This is a power spectrum consistent with pink noise. The power spectrum of idealized pink noise aligns itself precisely along a line with a slope of −1 on the same scales as Figures 1C and 1F. Pink noise is called *1/f^α noise,* or *1/f noise,* for this reason. The exponent α is the absolute value of the line's slope that relates frequency to power, and $\alpha = 1$ for idealized pink noise. (Recall that $f^{-\alpha} = 1/f^{\alpha}$.)

Individual participant slopes are listed in Table 1. Empirical 1/*f* scaling relations produce a noisy spectrum with a slope that may vary over a range of values greater than negative one and less than zero. We found slope values that ranged from −1.0 to −0.30. The spectral slope of each intact trial series was contrasted with the spectral slope of surrogate data. Surrogates were produced by a random shuffle of trial orders in each trial series (Theiler, Eubank, Longtin, Galdrikian, & Farmer, 1992). The contrast tests whether intact series differ reliably from surrogate white noise. All 10 intact trial series yielded steeper slopes than their respective surrogate counterparts ($p < .05$ by a sign test; intact trial series: $M = -0.66$, $SD = 0.22$; surrogate trial series: $M = -0.01$, $SD = 0.06$).

Details of the Dispersion Analysis

We computed fractal dimensions using dispersion analysis. Dispersion analyses are comparably more reliable than other methods of computing fractal dimension (Bassingthwaighte et al., 1994; Caccia, Percival, Cannon, Raymond, & Bassingthwaighte, 1997; Eke et al., 2000; Eke, Hermán, Kocsis, & Kozak, 2002).[1] However, one dispersion technique is required for fractional Gaussian

noise (white and pink noise), and a different technique is required for fractional Brownian motions (brown noise). One first needs to know the noise category to choose the appropriate dispersion technique. Spectral analysis does not yield reliable fractal dimensions, but it does work to pick out the category of noise. The two analyses together choose a color from the crayon box of ideal noises (blue, white, pink, brown, black).

A dispersion analysis repeatedly resamples the data series using sampling bins of different sizes to estimate the fractal dimension of a trial series. The fractal dimension estimates the scaling relation between a variance statistic and sample size—the change in a variance statistic due to changes in bin sample sizes. It determines whether the variance statistic converges fast enough, as sample size increases, to yield a stable population parameter. If not, then the process that produced the variance is scale free. It has no characteristic scale or quantity of variance.

We adapted the standard technique of *relative dispersion analysis* to use normalized data—call this *standardized dispersion analysis* to avoid confusion. The outcomes of the two techniques are identical. The standardized dispersion analysis yields dispersion measurements in units of the standard error of the mean. Dispersion techniques typically use a relative dispersion statistic, which is expressed in terms of a ratio of the standard deviation and the mean (i.e., $RD = SD/M$; see Bassingthwaighte et al., 1994). We computed a fractal dimension statistic for each trial series after the series had been prepared for the previous spectral analysis—after each trial series was first detrended and normalized as described above. Detrending is conservative in this kind of analysis.[2]

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[1] A single fractal dimension is sufficient to characterize the signal of a *monofractal* process. Such signals have stationary scaling properties. To say a process has stationary scaling properties is to say that the fractal dimension that characterizes the process at one point in time is essentially the same at other points in time. Signals taken from *multifractal* processes are more complex. Multifractal processes may yield different local fractal dimensions at different periods of time (Ivanov et al., 2001). Although dispersion techniques are relatively robust, they do ultimately assume that the estimated scaling relation does not fluctuate appreciably as a function of time—that the measured process is an approximately stationary monofractal process (Caccia et al., 1997). It is possible that the system on which response times attend may not respect these assumptions. If so, then the present techniques would estimate the largest fractal dimension in the data series. A test to distinguish a multifractal process requires very long data series and more sophisticated statistical techniques.

[2] We mentioned already that natural fractals live within a finite range of scales. This has implications for the technique of dispersion analysis. Trial series that display self-similar patterns of fluctuation are expected to display nonstationary drift (trends) at many scales. It is difficult to distinguish simple long-term trends from nested, long-range, fractal correlations (Hausdorff et al., 1996). Simple long-term trends can bias estimates of fractal dimension. They can even overwhelm the analysis and yield a spurious fractal dimension statistic (Caccia et al., 1997). Consequently, it is prudent to remove at least linear and quadratic trends before conducting the analysis. Detrending helps protect against the false identification of scaling relations resulting from local nonstationarities or fluctuations. It eliminates variability at scales close to the size of the entire series, which works against a hypothesis of pink noise. As a general rule, if the trial series has fractal structure, progressively more liberal detrending procedures will not dramatically change fractal dimension estimates (Hausdorff et al., 1996). For the simple reaction-time trial series, we removed trends up to a quadratic, and we verified that the fractal dimension estimates were essentially the same whether we removed only linear trends or trends up to a quartic.

Table 1

Fractal Dimension and Spectral Slope Statistics for Each Participant's Trial Series of Simple Reaction Times

Fractal dimension	Slope of the power spectrum
1.34	−0.43
1.33	−1.00
1.29	−0.60
1.33	−0.53
1.28	−0.73
1.33	−0.63
1.27	−0.89
1.30	−0.66
1.18	−0.86
1.34	−0.30
$M = 1.30$	$M = -0.66$
$SD = 0.05$	$SD = 0.22$

Note. The mean and standard deviation computations include all 10 series.

Figure 2 illustrates the outcome of a dispersion analysis, a scaling relation between dispersion and sample size on log/log scales. The relation is linear on these log scales except for the last four points (the most extreme point is not pictured; it falls outside of the figure axes). The excluded points are the unfilled dots in Figure 2. They correspond to the largest sample sizes in the analysis. They are excluded because the detrending procedures have eliminated variability at these scales. Depending on the system under study, the linear scaling relation can be expected to break down at either the smallest or largest sample sizes or both (Cannon, Percival, Caccia, Raymond, & Bassingthwaighte, 1997). See Caccia et al. (1997) for additional refinements of this technique. The fractal dimension of the series is given by subtracting the negative slope of the least squares regression line from 1, the Euclidean dimension of the series.

Results of the Dispersion Analysis

Participants' fractal dimension statistics are listed in Table 1. Fractal dimensions of natural pink noise can range across an interval less than 1.5 and equal to or greater than 1.2. Fractal dimensions that cannot be distinguished statistically from 1.5 are effectively white noise. Fractal dimensions less than 1.2 could imply fractional Brownian motion (brown noise). One of our trial series yielded a fractal dimension of 1.18, which cannot be classified unambiguously as pink noise. We excluded the ambiguous case because its fractal dimension would favor our hypothesis in the contrast with surrogate data. Excluding the ambiguous case equals a more conservative test. The remaining nine trial series ranged from 1.27 to 1.34 in fractal dimension. These nine trial series all had smaller fractal dimensions than their shuffled surrogates ($p < .05$ by a sign test; intact trial series: $M = 1.31$, $SD = 0.03$; shuffled trial series: $M = 1.50$, $SD = 0.02$). All participants' fractal dimension statistics were consistent with partly decorrelated pink noise.

Correlated Noise in Word-Naming Times

All previous demonstrations of pink noise in cognitive performance used cognitive tasks that required controlled cognitive processing—participants made explicit discriminations or choices. Word naming is widely assumed to be an automatic cognitive process based on learned relations between words' spellings and their pronunciations (see Tzelgov, Henik, Sneg, & Baruch, 1996; cf. Besner & Stolz, 1999a, 1999b, who questioned whether words are processed automatically). If word naming is an automatic cognitive process, then it provides a second test of the memory capsule hypothesis. If pink noise in cognitive tasks is exclusive to controlled processing, then pink noise should not appear in a trial series of word-naming times.

Our alternative hypothesis is a bit more involved and suggests a comparison with simple reaction times. We expected to find pink noise in trial series of naming times, but the signal should have been less visible compared with simple reaction time. Both word naming and our previous study presented visual signals to respond and took spoken responses, but the

reaction-time paradigm holds signal and response constant. The word-naming procedure presented a different printed word on each trial, and each word required a different pronunciation. The words also differed unsystematically in initial phonemes that determine voice key registration and thereby affect naming time (Kessler, Treiman, & Mullennix, 2002). Moreover, the words in our experiment were presented to each participant in a different random order. Thus, word properties functioned as an external random manipulation with respect to estimating internal background noise.

Random changes in word properties affect variability in the same way as random intertrial intervals. Both decorrelate the signal of pink noise. However, word properties may not entirely obscure the signal. Gilden (1997) has previously demonstrated pink noise in a discrimination task that used word targets. Thus, we expected to find pink noise signals in naming times but weaker signals compared with simple reaction times. Weaker signals yield less steep slopes in spectral analyses and fractal dimensions closer to 1.5.

Method

Participants. Twenty additional, native English-speaking, introductory psychology students received course credit in exchange for their participation.

Stimuli. The words for the naming study were 1,100 four- and five-letter words drawn at random from 1,857 four- and five-letter words, a subset of words used by Spieler and Balota (1997). Words ranged in frequency from 10,601 to 1 per million ($M = 86.81$, $SD = 458.28$) and otherwise included an uncontrolled mix of word properties.

Procedure. Each trial began with a fixation signal ($+++$) visible for 172 ms (12 raster refresh cycles) followed by a word after 200 ms. Participants were instructed to name the word quickly and accurately into a microphone. Each word appeared in the center of a computer monitor controlled by DMASTR software running on a PC (Forster & Forster, 1996).

A word target remained on the screen 200 ms after a response was recorded, up to a maximum of 972 ms. If no response was recorded, trials timed out after 4 s. Responses were detected using a voice key reliable to within 1 ms. The experimenter sat quietly, well behind a participant, and recorded pronunciation errors. Each response was followed by a fixed 629-ms intertrial interval. Every participant completed 45 practice trials and then the 1,100 experimental trials, which required about 45 minutes.

Results and Discussion

The mean error rate was 2.12% ($SD = 1.48\%$), and the largest error rate was 5.18%. Timed-out trials ($Mdn = 1$) were eliminated, but the small portion of naming times that came from pronunciation errors were included to better preserve the trial-by-trial continuity of each trial series (cf. Gilden, 1997). In addition, we removed naming times less than 200 ms and greater than 1,500 ms, then computed the series mean and standard deviation, and removed times that fell beyond ± 3 standard deviations from the mean. The trimming criteria eliminated an average of 24.40 (2.22%) naming times from each trial-series ($Mdn = 21$, $SD = 10.33$, minimum $= 14$, maximum $= 57$). The number of times eliminated was unrelated to the spectral slopes or fractal dimensions of the series. In every case, more than 1,024 measurements remained after trimming. Subsequently, we trun-

cated the beginning trials until 1,024 observations remained. Trends up to a quadratic were removed, and then, the series was normalized.
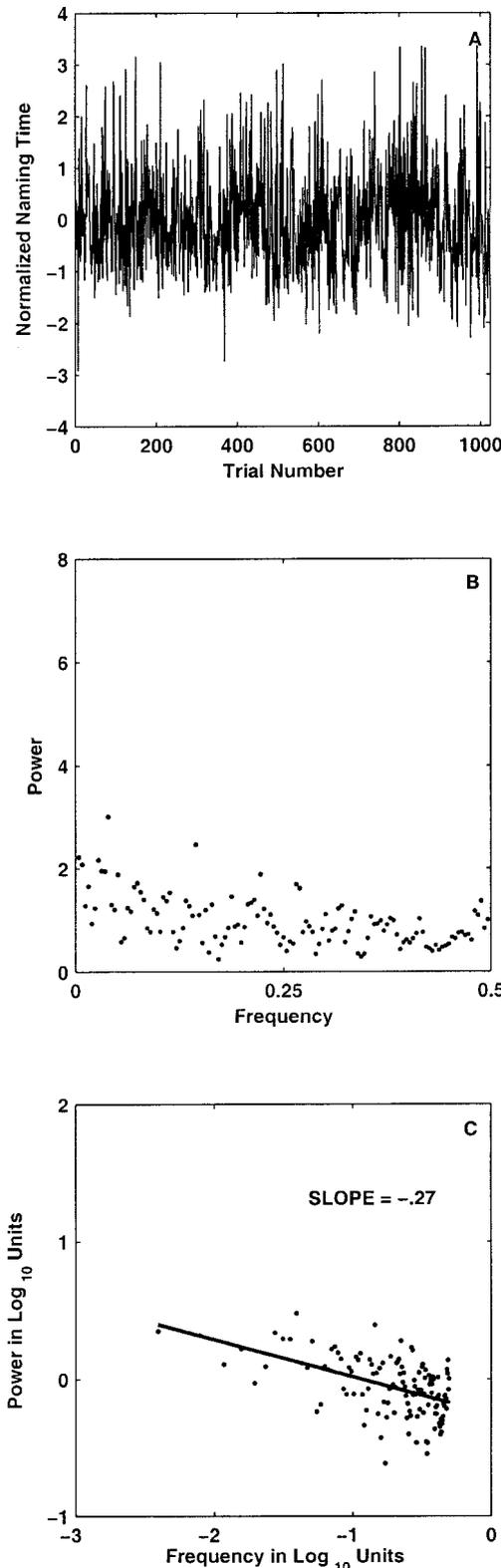

Figure 3. Figures A–C (A: Naming Time Trial Series; B: Naming Time Power Spectrum; C: Power Spectrum on Log-Log Scales) step through a spectral analysis of one participant's naming trial series. Figure A shows the trial series of naming times after they have been trimmed, detrended, and normalized. Figure B displays an intermediate step in which the results of the spectral decomposition are plotted on linear axes. Frequency (x) is plotted against power (y), or amplitude squared, on linear scales. Frequency and amplitude range from low (near the origin) to high (away from the origin). Low frequency is associated with high amplitude and high frequency with low amplitude. Figure C displays the spectral results after the frequency (x) and power (y) axes have been transformed to Base-10 logarithmic scales. Lower frequencies have higher amplitude in the form of a scaling relation between frequency and amplitude.

Table 2

Fractal Dimension and Spectral Slope Statistics for Each Participant's Trial Series of Word-Naming Times

Fractal dimension	Slope of the power spectrum
1.47	−0.16
1.33	−0.38
1.37	−0.22
1.51	−0.22
1.41	−0.21
1.35	−0.35
1.33	−0.40
1.52	−0.20
1.44	−0.28
1.40	−0.27
1.42	−0.25
1.43	−0.14
1.41	−0.41
1.45	−0.22
1.40	−0.19
1.33	−0.40
1.35	−0.28
1.40	−0.29
1.30	−0.49
1.34	−0.40
$M = 1.40$	$M = -0.29$
$SD = 0.06$	$SD = 0.10$

We are again interested in the slope of the line that relates amplitude and frequency in the spectral analysis plus the fractal dimension of the trial series. Each participant's trial series of naming times was subjected to a spectral analysis. Figure 3 portrays the outcome of a single participant's spectral analysis. The y-axis in the figure indicates the amplitude of change (power), and the x-axis indexes the frequency of change. The negative slope of the graph ($-.27$) indicates the expected relation between power and frequency and is a power spectrum consistent with partly decorrelated pink noise. The fractal dimension of the trial series is 1.40.

Table 2 presents the spectral slope and the fractal dimension of each participant's trial series. The naming slopes ranged from a minimum of -0.49 to a maximum of -0.14. As before, the spectral slope of each intact trial series was compared with the spectral slope of a randomly shuffled surrogate series. All 20 intact trial series yielded steeper slopes than their surrogate counterparts ($p < .05$ by a sign test; intact trial series: $M = -0.29$, $SD = 0.01$; surrogate trial series: $M = -0.01$, $SD = 0.04$). Fractal dimensions

ranged from 1.30 to 1.52 across participants. Eighteen of the 20 intact trial series yielded smaller fractal dimensions than their surrogate counterparts ($p < .05$ by a sign test; intact trial series: $M = 1.40$, $SD = 0.06$; surrogate trial series: $M = 1.50$, $SD = 0.03$).

Variation across response times from both simple reaction time and word naming is consistent with partly decorrelated pink noise. Naming yielded larger fractal dimension statistics than simple reactions (nonparametric Mann-Whitney U test: $Z_U = -3.39$, $p < .05$). The pink-noise signal was less prominent in naming times. The more whitened signal is sensibly understood as due to random word properties that further decorrelate the pink noise signal.

What Kind of System Do We Confront?

We now have sufficient evidence to broach the question, What kind of dynamics are indicated by background noise in response times? We begin by summarizing what we and others have learned using spectral and dispersion analyses. After that, we review hypotheses that have already been offered to explain pink noise in human performance. Finally, we discuss the implications of pink noise as we see them.

Our experiments have demonstrated the pattern of pink noise in trial series of simple reaction times and word-naming times. These demonstrations are significant because they fill significant gaps in this literature. One previous article reported a failure to observe pink noise in simple reaction times.[3] So far as we know, the question of pink noise in word naming or other automatic cognitive performances has been previously overlooked. The addition of our studies gives a more complete and agreeable inventory of background noise in laboratory performances, which we review after the caveat that follows.

Conventional distinctions such as controlled versus automatic were useful for organizing existing findings. Yet we do not mean to perpetuate these distinctions; we mean to call them into question. The distinctions themselves collapse in a framework of interaction-dominant dynamics as their theoretical motivation disappears. The term automatic derives from the metaphor of billiard-ball causality. A stimulus-cause triggers a ballistic effect such as the Stroop effect. The conventional distinctions between controlled and automatic (or cognitive vs. motor) assume component-dominant dynamics between components of the mind or brain and between the mind and body. Otherwise, the distinctions make no sense. Replacing billiard-ball causality with circular causality and component-dominant dynamics with interaction-dominant dynamics eliminates the conventional meaning of the term automatic (Van Orden & Holden, 2002). Keeping this caveat in mind, we list examples of where correlated noise has been previously observed.

Correlated noise has been observed in perceptual learning (Wagman, Dahle, & Schmidt, 2002), postural sway (Riley, Wong, Mitra, & Turvey, 1997), and the timing of perceptual reversals of reversible Necker cubes (Aks & Sprott, 2003). It has been found in motor performances such as spacing and timing of rhythmic movement (Rhodes & Schmidt, 2002) and the phase relation between rhythmic movements (Schmidt, Beek, Treffner, & Turvey, 1991). It has been found in tapping (Chen et al., 1997, 2001; Ding, Chen, & Kelso, 2002), human gait (Hausdorff et al., 1996; Hausdorff, Zemany, Peng, & Goldberger, 1999), and simple reaction time (Table 1; Wagenmakers et al., in press; Ward & Richard, 2001).

Correlated noise has been found in controlled cognitive performances including mental rotation, lexical decision, visual search, repeated production of a spatial interval, repeated judgments of an elapsed time, and simple classifications (Aks, Zelinsky, & Sprott, 2002; Clayton & Frey, 1997; Gilden, 1997; Gilden et al., 1995; Kelly, Heathcote, Heath, & Longstaff, 2001). The word-naming experiment demonstrated correlated noise in the background noise of an automatic cognitive performance (Table 2). Background noise is correlated noise in all these laboratory performances, and the correlated noise is virtually always pink noise. Pink noise implies interaction-dominant dynamics and self-organized criticality. Pink noise is the natural prediction given the current understanding of self-organized criticality. Ubiquitous pink noise is not sufficient evidence for self-organized criticality; it is simply a necessary consequence. "A mathematical theory never guarantees any property of empirical process; what it says is that if certain assumptions are true, then certain results will follow" (Green & Swets, 1988, p. 11).

Next, we review several different explanations of pink noise. All encapsulate control of one kind or another inside the mind or brain. We discuss each hypothesis in turn to clarify why none succeeds. No evidence exists that is sufficient to encapsulate control or pink noise inside the mind or brain. No evidence exists to contradict global emergence.

The Memory Capsule Hypothesis

Self-organizing systems that exhibit pink noise come in two general forms. A single process extends to multiple timescales, or multiple processes are linked across multiple timescales. We introduced the memory capsule hypothesis above: Processes of discrimination and choice are linked across multiple timescales within the memory capsule (Gilden, 2001). Pink noise is localized in a specialized component of the mind.

The memory capsule hypothesis requires that pink noise be localized in a particular kind of performance. Tasks that require discrimination and choice should yield pink noise; tasks that do not should not. The actual state of affairs contradicts the memory capsule hypothesis. So-called automatic word naming, simple reactions, and other motor performances all yield scaling relations consistent with pink noise. Conventionally, none of these performances require controlled cognitive processing. Consequently, they contradict the hypothesis that pink noise originates in a memory capsule associated with controlled cognitive processing.

Encapsulated Subsystems

Ward and colleagues proposed an alternative to Gilden's (2001) memory capsule: They described a three-subsystems account en-

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[3] After we had submitted the present findings for publication, we were made aware of two other studies, then unpublished, that had also found pink noise in simple reaction times (Wagenmakers, Farrell, & Ratcliff, in press; Ward & Richard, 2001). Of note, Wagenmakers et al. observed a shallow spectral slope, different from white noise, in conditions like those of Gilden et al. (1995) that had previously been interpreted as white noise. Although Gilden et al. did not highlight the shallow spectral slope in their simple reaction-time data, it is nevertheless there and in exactly the same magnitude as reported by Wagenmakers et al. (D. L. Gilden, personal communication, January 27, 2003).

capsulated inside the brain (Greenwood & Ward, 2001; Ward, 2002; Ward & Richard, 2001). The central nervous system is not a single process but a complex of processes that extend across multiple timescales (on that we can agree; cf. Koch & Laurent, 1999). The number three simply comes from the minimum number of relaxation equations that can be combined to mimic a pink-noise spectrum across three decades of frequency (e.g., 100 Hz, 10 Hz, and 1 Hz). Greenwood and Ward did not limit themselves to a three-subsystems account; they also considered coupled processes in the spirit of our proposal (Greenwood & Ward, 2003).

The three subsystems live on three different timescales. One timescale is equated with a preconscious subsystem, another with an unconscious subsystem, and the third with a consciousness subsystem—the basis of conscious experience. Each of the three subsystems includes its own source of white noise, with a separate parameter to modulate the amount of white noise from that component. The apparent pink noise in macro-level measurements is simply the sum of noises from the three subsystems. However, no existing data reliably dissociate preconscious, unconscious, or conscious components or any other cognitive components (Chalmers, 1996; Farah, 1994; Fodor, 2000; Uttal, 2001; Velmans, 2000).

All attempts to dissociate cognitive components rely on conventional laboratory methods. Most rely on logically flawed subtractive and dissociative methods, which require a roadmap of cognitive processes before the fact to interpret dissociations after the fact (Shallice, 1988; Van Orden et al., 2001). All standard factorial analyses share the assumptions of homogeneous variability, independent measurements, and component-dominant dynamics, the very assumptions that pink noise brings into question. Pink noise implies heterogeneous variability, interdependent measurements, and interaction-dominant dynamics.

Another three-subsystems account equates its three timescales with different mental functions (Wagenmakers et al., in press). Yet the shared assumption of three timescales is too limiting, too easily overwhelmed. Consider that a full session in either of our experiments took less than one hour. Now compare with Delignières, Fortes, and Ninot (2002), who observed pink noise in estimates of self-esteem taken twice a day for 512 days. Roughly speaking, the full range of timescales that we observed within the timeframe of one hour is contained within one data point in Delignières et al.'s data series. Their results require another, different, linear model on top of the model that is already proposed—a six-subsystems account. Three-subsystems accounts are found wanting each time correlated noise is demonstrated outside their range of timescales. Again, our working hypothesis anticipates correlated noise at all scales to the limits of the system.

The timescales of linear accounts are carefully chosen and precisely tuned to approximate the coincidence of the scaling relation. Yet this ignores the inherent order of the scaling relation. How do intrinsic dynamics align power and frequency in such a coherent fashion? In linear accounts, the implied coincidence of the scaling relation becomes an extraordinary hypothesis that would itself require extraordinary evidence. No such evidence exists. Clearly, piecemeal accounts bear a burden of proof. They must corroborate the assumption of linearity. Otherwise, "it is not clear how much sense it makes to develop models and theories of strongly correlated processes and then to describe them as a linear superposition of independent events" (Jensen, 1998, p. 10).

Given our concerns, we frankly question the motivation for linear accounts. A component-dominant approximation of an ap-parent interaction-dominant phenomenon perpetuates an unintended linear imperialism. Covert imperialism assigns a logical priority to linearity as when linearity is assigned the favored status of default hypothesis (Wagenmakers et al., in press). This is simply incredible; linearity cannot be given the benefit of the doubt. The assumption of linearity is not sufficiently trustworthy. It is too often a specious assumption about complexity in nature, especially the complex behavior of living beings (Rosen, 2000; West & Deering, 1995).

All linear accounts parse scaling relations into pieces and add them up again. However, a linear partition supplies a statistical artifact, not a theoretical model. Piecemeal artifacts produce overly regular features in a simulated data series. For example, an account proposed by Wagenmakers et al. (in press) exhibits "terraces" in simulated data series, which are never seen in behavioral data (D. L. Gilden, personal communication, September 6, 2002). Piecemeal artifacts do not fully accommodate the irregularity in the natural data series, and residual irregularity cannot be simply equated with random events (Mandelbrot, 1982, 1998). In nature, there is no guarantee that signal and noise are causally distinct or superposed (Abraham, 1983). Actual fractal noise is a coherent whole extended in time. Actual pink noise does not come apart as a linear partition of power among frequencies.

Encapsulated Cognitive Demands

Chen and colleagues (2001) proposed a different brain hypothesis. They focused on cognitive demands and the presence of pink noise. Briefly, the presence of pink noise is modulated by encapsulated cognitive demands, and the locus of cognitive demands is "in the multiple timescale activities . . . in the human brain" (Chen et al., 2001, p. 7; see also Ding et al., 2002).

Encapsulated cognitive demands were motivated by data from tapping tasks, by dissociation studies of brain-damaged individuals, and by neuroimaging studies (Chen et al., 2001). We focus on the tapping data exclusively. Dissociation studies and neuroimaging both require specific a priori knowledge of the components in question before reliable conclusions can be drawn, as we have already noted. This point is not contentious. Scientists must first know that there are units of behavior and what they are before looking for their counterparts in the nervous system. The tapping data have priority.

The tapping data consisted of timing errors compared with the metronome that set the pace for tapping. The timing errors were subjected to spectral analysis. Different power spectra were observed for syncopated versus synchronized tapping. Syncopated tapping between the beats of a metronome yielded a steeper spectral slope than synchronized tapping on the beat. Chen et al. (2001) attributed the steeper slope to the increased task difficulty of tapping between the beats. They then used linked intuitions to encapsulate the effect. They equated an increase in task difficulty with an increase in cognitive demands, and they assumed that cognitive demands are encapsulated inside the brain. Thus, the change to a more pink pattern of background noise is encapsulated within the brain.

The trigger assumption of Chen et al.'s (2001) logic is challenged by the present findings and by other studies. More difficult tasks do not usually produce more pink signals; one almost always sees the opposite. Gilden (2001) noted that pink noise is usually most pronounced in simple tasks that repeat identical trials, and we

saw the clearest signal of pink noise in what is arguably our least difficult task, simple reaction time. Ward and Richard (2001) conducted a more careful study of task difficulty that they equated with decision load, "the number of stimulus and response alternatives" (Ward, 2002, p. 141). Like us, they found more pronounced signals of pink noise in less difficult task conditions (see also Clayton & Frey, 1997). Yet Chen et al. found the more pronounced signal in the more difficult condition.

Recall again that external manipulations of task demands are external sources of white noise. More difficult task demands amplify unsystematic variability in response measures, which creates a more irregular sampling pattern and decorrelates the signal of pink noise. Task difficulty equals more unsystematic variability equals less pink, whiter signals. If this were true for tapping, then one should see the opposite of what was found. Again, Chen et al. (2001) found the more pink signal in the more difficult condition.

So how is one to understand the contradiction? To begin with, one must quit calling syncopated tapping more pink. This way of talking assigns a particular direction to the effect, from synchronized to syncopated. It takes synchronized tapping as a sort of baseline, which leads us to ask how syncopated tapping differs from synchronized tapping. Why not call the results from synchronized tapping less pink? Why not take the condition of the visible pink-noise signal to be the baseline? This change realigns the conditions within the logic of internal versus external sources of noise as it reverses their logical priority.

If syncopated tapping is taken as the baseline, then we are led to ask how synchronized tapping differs from syncopated tapping in which a healthy pink-noise signal is observed. We are led to ask what it is about synchronized tapping that whitens the pink-noise signal. Apparently, the change from syncopated to synchronized tapping reduces the sensitivity of the tapping protocol for gauging intrinsic dynamics. The task conditions of the synchronized condition allow a more stable entrainment of internal dynamics to the metronome beat. Each tap is on the beat. This coordination cedes more control to the external driving force of the metronome, which blunts the sensitivity of the laboratory protocol as a gauge of internal dynamics. The example simply illustrates again how changes in task demands are external factors that affect the capacity to measure pink noise.

Is Control Ever Encapsulated Inside the Brain?

We continue our discussion of hypotheses in which control is partly or wholly encapsulated in a brain, however brains are conceptualized. Both brain hypotheses that we have considered equate changes in task demands with brain functions. However, if task demands are merely intuitively brainified, so to speak, then we leave ourselves at risk of logical fallacy: If task demands are exclusively cognitive demands and effects of cognitive demands are encapsulated inside the brain, then effects of task demands would be so encapsulated. Effects of task demands are observed, therefore encapsulated brain effects are observed. This misleading logic begs the question of encapsulated control. Nevertheless, task demand = cognitive demand = brain function is the usual intuition. So, we must look closely at the burden of proof that this intuition carries.

Brain hypotheses require evidence sufficient to motivate component-dominant dynamics between brain and body if they are to make sense as scientific hypotheses. No doubt, micro-level fluctuations in the central nervous system are necessary for cognitive activity. That is not at issue, only whether the control of cognitive activity can be encapsulated in the brain. Such brain hypotheses require specific reliable corroboration for encapsulated control. However, this is a weighty burden of proof, and no such evidence exists.

For instance, it would not be sufficient to observe correlated noise in brain activity to establish the intuition. Corroboration of a brain hypothesis requires evidence sufficient to encapsulate correlated noise in the brain, not simply to establish that it can be observed (likewise for other behavioral phenomena). Correlated noise is observed in many physiological systems (see, e.g., Bassingthwaighte et al., 1994; Goldberger, 1997; Solé & Goodwin, 2001), including the central nervous system (see, e.g., Georgelin, Poupard, Sartène, & Wallet, 1999; Poupard, Sartène, & Wallet, 2001). Yet one presently confronts correlated noise in measurements taken at a macro-level—the level of a person acting as a whole being.

Neither is it enough to observe online correlations between (nonlinear) behavioral dynamics and (nonlinear) brain dynamics, as have been observed (Kelso, 1995). As with any correlation, this simply establishes a relation between dynamics in the nervous system and behavioral dynamics—a relation that could just as well imply interaction-dominant dynamics that extend at least to the periphery of the body.

If pink noise can be equated with the intrinsic dynamics of the body, then the intrinsic dynamics of the body entail global emergence. Among other things, isolation of causal powers in component-dominant dynamics requires behavioral measures with characteristic scales. Yet characteristic scales are precisely what pink noise contradicts. The reviewed findings bring into question whether human performance ever reduces to causal loci in the mind, brain, or body.

Let us summarize the discussion to this point: Pink-noise scaling relations are not exclusive to any particular kind of task (see also Wagenmakers et al., in press). Pink noise cannot be encapsulated; it is not the product of a particular component of the mind or body. It appears to illustrate something general about human behavior. Pink noise could signal states of self-organized criticality, and self-organized criticality is a useful metaphor for understanding the actions of intentional beings, which simply restates Juarrero's conjecture. Pink noise should not be equated with intentional contents. Strictly speaking, pink noise may imply criticality and interaction-dominant dynamics and provide a basis in evidence for Juarrero's conjecture. The entailed ideas of circular causality and emergent properties accommodate intentional contents. Circular causality perpetuates globally emergent, ordered, dynamic states in positive feedback processes. Circular causality sustains intentional contents in time.

Global Emergence

Intentional acts emerge out of situated intentional contents. Intentional contents live within the hierarchy of constraints expressed in human activity. Different purposes entail different constraints that organize the body into different functional devices. Put differently, the body comprises processes that take on their functional character within an act, not prior to an act. The functional device that responds in a laboratory task is constructed in the act. Laboratory performances cannot be assigned to or reduced to

specialized material devices in the body or brain. "Explicit material processes [are] relegated to abstractions of enfolded coordination dynamics" (Turvey, 2002). In global emergence, the microbehaviors of parts take on meaning with respect to the global macroactivities in which they participate. Within the constraints of task instructions and inside a simple reaction trial, the participant's mind and body create together a simple reaction device, in word naming, a word-naming device.

Compare the previous claim with the following fact from conventional cognitive psychology: Trivial differences between cognitive tasks require distinct cognitive devices. Even simple judgments about when an event starts or where an object is located "vary with task requirements in ways indicating the use of multiple distinct mechanisms with different characteristics in different tasks" (Durgin & Sternberg, 2002, p. 288). A Noah's ark of devices supplies a never-ending zoo of purposes.

If cognitive activity does not reduce to specialized cognitive devices and scientists continue the pursuit, they will perpetuate irreconcilable quarrels. Lacking confirmation of additivity, scientists lack proper tools to discover which behaviors go with what devices. Untethered, cognitive scientists choose devices intuitively (Shallice, 1988), but they cannot reach agreement on whose intuitions to trust (Van Orden et al., 2001; Watkins, 1990).

Juarrero's conjecture looks attractive by comparison. Human bodies are flexibly coupled across many timescales to the changing circumstances in which people find themselves. Behavior self-organizes in a principled manner within the boundary conditions that circumstances supply. Intentional contents themselves emerge out of historical circumstances, and they enfold the perpetually oncoming flow of changing circumstances. Together, previous and oncoming circumstances bring novel purposive behaviors into existence.

These, then, are the alternatives: either theorists build in unexpected circumstances a priori as component causes and special devices or they equate circumstances with constraints on interaction-dominant dynamics. Either theorists content themselves with ad hoc explanation or they seriously consider Juarrero's conjecture.

Direct Perception

For now, global emergence may seem a fairly unconventional suggestion. Nevertheless, there are ideas in circulation that follow naturally from assuming global emergence and interaction-dominant dynamics. Interaction-dominant dynamics motivate several ongoing research programs. This section and the next illustrate this for *direct perception* and *embodiment*. These examples demonstrate the wider implications of Juarrero's conjecture. It is not a narrow claim about background noise; it reinforces reliable general hypotheses about perception, action, and cognition. One example is direct perception.

William James (1912/1976) proposed direct perception within his radical empiricism. James stipulated that relations among perceptual objects and between a perceiver and perceptual objects are real and are directly perceived. Relations are intrinsic to experience and have the same ontological status as objects and perceivers. Relations provide the order in experience, and perception of order is immediate, direct, unmediated. James Gibson inherited this ontological stance via his graduate mentor, Edwin B. Holt, a student of James (Heft, 2001). However, Gibson enriched the term direct perception. He referred to an unmediated relation between perception and action, which recurs as a cycle: Action makes possible perception, perception specifies the possibilities for action, action makes possible perception, perception specifies action, and so on (Michaels & Carello, 1981).

Direct perception can seem counterintuitive. Even the superficial fact of time passing between stimulus and response appears to contradict direct perception. Surely in-line causal factors must fill up the gap in time between stimulus and response. If so, then researchers should discover these factors. This intuition was widely trusted at the end of the 19th century, and it is widely trusted today. Yet the intuition is impracticable because behavior cannot be neatly carved at stimulus–response joints. Others have pointed this out concerning molar behaviors that are extended in time (Hineline & Wanchisen, 1989). The insight is justly extended to all behavior. Global emergence bars scientists from dividing purposive activity among causal factors. It necessitates *methodological direct perception*, as we explain.

We described above how the pace of data collection sets an entry level into the body's temporal hierarchy. The trial pace of measurement taking divides the temporal scales of the body into timescales slower and faster than this pace. The trial pace also sets up an artifactual cycle of perception and action. On each trial, the signal to respond is perceived and acted on, which ends the trial and starts the next cycle of perception and action. The pattern of variation across trial measurements reveals the intrinsic dynamics of perception and action, which is seen as the scaling relation of pink noise.

The scaling relation concerns bodily changes on timescales slower than the artifactual trial pace. Pink noise implies interdependence among changes on these slow timescales, which implies interdependence among cycles of perception and action. Instead of discrete responses, one finds a continuous, intertwined flow of activity. This fact has consequences for how researchers study perception and action. Manipulations of human activity may perturb or redirect the flow of activity—that researchers can do—but they cannot partition the flow among individual response trials. If they cannot partition data among effects, then they cannot discover causes between perception and action. No empirical basis exists to discover causal factors (cf. Watkins, 1990).

In sum, interdependence implies irreducible relations among signals to respond, responses themselves, and the data scientists collect. Task instructions and measurement protocols alter the flow of activity (Van Orden, Holden, Podgornik, & Aitchison, 1999). Scientists change behavior as they measure it, as each measurement changes the potential for perception and action on subsequent trials. Consequently, cycles of perception and action cannot be causally segregated. Clearly, research tools designed to partition measurements among effects and to reduce effects to causes are inappropriate for the job at hand (Rosen, 2000). Researchers require the right kind of tools to study globally emergent phenomena. Methodological direct perception means simply that the tools scientists use should be the right tools for the job.

Embodiment

Juarrero's conjecture also concerns how the body figures in cognitive activity. Traditional cognitive science has explicitly rejected the body as a basis for control of cognitive activity. Its well-publicized objective is the architecture of a disembodied

mind. Interaction-dominant dynamics combine body and mind in cognitive activity. Human beings are "creatures whose design principles do not respect the intuitive boundaries between cognition, body, and world" (Clark, 1999, p. 98). Take poetry, an undeniably cognitive activity. Poetry was once viewed as an arbitrary product of creative expression. Figurative poetic meanings were assumed to be unstructured. Only literal meanings were systematic. However, this view is incorrect. Figurative and literal expressions come out of the same sources of systematic use, constraints on human experience that come from being a body in the world (Gibbs, 1994).

For example, the meanings of the word *stand* are constrained by human posture. Human bodies stand erect, and figurative meanings reflect this fact as in *stand your ground*, *outstanding*, and *standoffish*. These patterns of word use reflect dimensions of posture such as verticality, balance, force, and resistance to force. These embodied constraints come from upright stance in a gravitational field (Lakoff, 1987). The case of *stand* is deceptively transparent of embodiment. One can easily overlook the profound subtleties of the insight, but figurative expression is one of many examples of embodied cognition (Gibbs, 1994; Johnson, 1987; Lakoff, 1987; Lakoff & Johnson, 1999; Varela, Thompson, & Rosch, 1991; Wilson, 2002).

Notably, embodiment refers to heterogeneous processes stacked on a hierarchy of timescales. Being human with respect to timescales of human evolution constrains the patterns of language and thought that emerge on timescales of cultural change—the body constrains language and thought. In turn, cultural patterns of language and thought constrain cognitive propensities on faster timescales of human discourse—culture constrains the cognitive activities of the mind and body. In the next turn, cognitive constraints that emerge in human discourse are continually available to control motor coordination. Cognitive factors supply subtle, measurable structure to the rapidly changing kinematics of bodily movements (Abrams & Balota, 1991; Balota & Abrams, 1995; Gentilucci, Benuzzi, Bertolani, Daprati, & Gangitano, 2000; Kawamoto, Kello, Higareda, & Vu, 1999; Zelinsky & Murphy, 2000).

In another example, neural processes develop to fit the geometry of actions. Bodily activities shape the topography of neural processes—the body constrains the brain (compare Purves, 1988). In still other instances, long-term bodily limits such as range of motion, plus the current configuration of the body, constrain cognitive judgments—the body constrains the mind (see, e.g., Glenberg, 1997; Glenberg & Kaschak, 2002; Klatzky, Pelligrino, McCloskey, & Doherty, 1989). Imagination, including imagined movements that never occur, is likewise constrained (Parsons, 1994). Imagination unfolds along lines of recurring embodied activity (Gibbs & Berg, 2002).

In summary, interaction-dominant dynamics necessitate a research program of situated embodied cognition. No causal distinction is made between the mind and body, so being a body comes with constraints for cognitive activity. Timescales of embodiment compose a hierarchy ranging from glacial scales of evolution to online kinematics. In hindsight, embodiment would appear to have required interaction-dominant dynamics. In what other form could formal a priori motivation appear? Picture toe-tapping proponents of embodied cognition, arms folded, waiting impatiently for Juarrero's conjecture and the justification it supplies.

Conclusions

The most reliable implications of new science are often what it can say about old science—that scientists should question the assumption of component-dominant dynamics and the Newtonian metaphor of cause and effect. The contrast with interaction-dominant dynamics and self-organized criticality has been the engine of change in this regard. The story that these assumptions tell is necessary to understand the significance of ubiquitous correlated noise. As in any critical contrast, the confirmed hypothesis becomes more credible. It is therefore more credible that intentional acts originate in states of self-organized criticality, that they express general principles of pattern formation in thermodynamic systems.

Self-organized criticality supplies the first plausible metaphor for self-control. Near critical points, interaction-dominant dynamics coordinate activity across the multiple timescales of embodied fluctuations. Context sensitivity near critical points situates behavior within the flow of circumstances. An actor situated in this sense reflects previous and oncoming circumstances directly as purposive behavior. These conclusions are supported by widespread evidence of pink background noise that we have described. They find another kind of support in the widely held belief that human beings are intentional beings. People interpret each other's actions as intentional in all domains of human discourse (Gibbs, 1999). Scientists do the same when they seek a participant's cooperation, give careful instructions on how to perform, or discard an uncooperative person's data.

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Call for Nominations: *Rehabilitation Psychology*

The APA Publications and Communications (P&C) Board has opened nominations for the editorship of *Rehabilitation Psychology* for the years 2006–2011. Bruce Caplan, PhD, is the incumbent editor.

Candidates should be members of APA and should be available to start receiving manuscripts in early 2005 to prepare for issues published in 2006. Please note that the P&C Board encourages participation by members of underrepresented groups in the publication process and would particularly welcome such nominees. Self-nominations are also encouraged.

Rehabilitation Psychology will transition from a division publication to an "all APA" journal in 2006, and the successful candidate will be involved in making suggestions to the P&C Board and APA Journals staff about the transition process.

Gary R. VandenBos, PhD, and Mark Appelbaum, PhD, have been appointed as cochairs for this search.

To nominate candidates, prepare a statement of one page or less in support of each candidate. Address all nominations to

> *Rehabilitation Psychology* Search Committee
> Karen Sellman, Search Liaison
> Room 2004
> American Psychological Association
> 750 First Street, NE
> Washington, DC 20002-4242

The first review of nominations will begin December 8, 2003. The deadline for accepting nominations is **December 15, 2003**.