TOPICS
TOPICS IN COGNITIVE SCIENCE

Topics in Cognitive Science 4 (2012) 87–93

ISSN: 1756-8757 print / 1756-8765 online
DOI: 10.1111/j.1756-8765.2011.01164.x

Abstract Concepts Require Concrete Models: Why Cognitive Scientists Have Not Yet Embraced Nonlinearly Coupled, Dynamical, Self-Organized Critical, Synergistic, Scale-Free, Exquisitely Context-Sensitive, Interaction-Dominant, Multifractal, Interdependent Brain-Body-Niche Systems

Eric-Jan Wagenmakers,[a] Han L. J. van der Maas,[a] Simon Farrell[b]

[a]*Department of Psychology, University of Amsterdam*
[b]*School of Experimental Psychology, University of Bristol*

Received 3 March 2011; accepted 3 March 2011

Abstract

After more than 15 years of study, the 1/*f* noise or complex-systems approach to cognitive science has delivered promises of progress, colorful verbiage, and statistical analyses of phenomena whose relevance for cognition remains unclear. What the complex-systems approach has arguably failed to deliver are concrete insights about how people perceive, think, decide, and act. Without formal models that implement the proposed abstract concepts, the complex-systems approach to cognitive science runs the danger of becoming a philosophical exercise in futility. The complex-systems approach can be informative and innovative, but only if it is implemented as a formal model that allows concrete prediction, falsification, and comparison against more traditional approaches.

Keywords: Nonlinear dynamical systems; Formal model; 1/*f* noise

Ever since its introduction (Gilden, Thornton, & Mallon, 1995), the precise contribution of the complex-systems approach to the study of cognition has been shrouded in mystery. It is not entirely clear, for example, what exactly we will have learned about the mind when psychological time series contain ‘‘1/*f* noise,’’ that is, long-range correlations in observed performance.

The mystery deepens when we consider the four topiCS articles that promote a complex-systems approach to cognitive science (Dixon, Holden, Mirman, & Stephen, in

Correspondence should be sent to Eric-Jan Wagenmakers, Department of Psychology, University of Amsterdam, Weesperplein 4, 1018 XA Amsterdam, The Netherlands. E-mail: ej.wagenmakers@gmail.com

press; Gibbs & Van Orden, in press; Riley, Shockley, & Van Orden, in press; Silberstein & Chemero, in press). At their core, these four articles advance the following three-step argument: (a) there is 1/*f* noise in psychological time series; (b) 1/*f* noise is a signature of systems that are nonlinearly coupled, dynamical, self-organized critical, synergistic, scale-free, exquisitely context-sensitive, interaction-dominant, multifractal, and interdependent; (c) hence, the presence of 1/*f* noise demonstrates that the brain is an interaction-dominant system that should be studied using techniques from dynamical systems theory. Moreover, traditional component-dominant theories and models should be abandoned. We aim to show that this line of reasoning is counterproductive, potentially misleading, and a way to avoid the difficult but necessary mathematical modeling that has gone hand in glove with the complex-systems approach in physics (see also van der Maas, 1995).

To be fair, the complex-systems approach does have a lot of potential. It is inherently multidisciplinary as it draws heavily on concepts first developed in physics and economics; it promotes the study of intraindividual variability, a topic that is currently understudied; it advances a new perspective on human performance and cognition; it can improve our understanding of clinical disorders (Gilden & Hancock, 2007; Gottschalk, Bauer, & Whybrow, 1995); it tries to account for phenomena that have been ignored by more traditional approaches; and it could yield insights that change the way we model cognition, as many current approaches such as ACT-R (Anderson, Fincham, Qin, & Stocco, 2008; Borst, Taatgen, Stocco, & van Rijn, 2010) are explicitly modular (''component-dominant''). However, the complex-systems approach has harbored this potential for over 15 years. At some point, that potential needs to be transformed to tangible benefits: new insights, new models, and new predictions. In our opinion, this has happened in the movement sciences (e.g., Torre & Wagenmakers, 2009) but much less so in cognitive science.

1. Analysis of the three-step argument

There are some problems with the three-step line of reasoning as it is used in the complex-systems approach to the study of human cognition. We expect many of these problems will disappear once the complex-systems approach develops concrete models for the phenomenon under study.

1.1. Step 1: Detect 1/f noise in time series of human performance

This is the least controversial step in the argument, and it nonetheless continues to be the topic of a heated methodological debate (Craigmile, Peruggia, & Van Zandt, 2010; Delignières, Ramdani, Lemoine, Torre, Fortes, & Ninot, 2006; Farrell, Wagenmakers, & Ratcliff, 2006; Gilden, 2009; Ihlen & Vereijken, 2010; Thornton & Gilden, 2005; Torre, Delignières, & Lemoine, 2007; Wagenmakers, Farrell, & Ratcliff, 2004). To show that a time series contains 1/*f* noise or long-range correlations, one needs to rule out that the observed correlations are short-range; short-range correlations are automatically generated by run-of-the-mill autoregressive moving average processes. This means that one needs to propose one set of statistical models for long-range correlation and another, competing set of models for short-range correlations—subsequently, the models can be compared on how well they fit the observed data, after appropriately correcting for differences in model complexity. In addition, one needs to take into account that the data could be nonstationary, for instance, because of slow changes in mean or variance. Wagenmakers, Farrell, and Ratcliff (2005) and Farrell et al. (2006) showed that many psychological times series most likely did not contain 1/*f* noise, a conclusion contested by Thornton and Gilden (2005) and Gilden (2009). In the movement sciences, the evidence for 1/*f* noise appears to be much stronger than it is in cognitive science (e.g., Torre, 2008).

1.2. Step 2: Conclude that the presence of 1/f noise shows the system is interaction-dominant

This is a crucial step that goes at the heart of what it means to observe 1/*f* noise. As summarized by Wagenmakers et al. (2005), 1/*f* noise is not a unique property of interaction-dominant systems. For instance, Granger (1980) has shown that the aggregation of many short-range processes can yield a long-range process. Such aggregation is plausible in economics and also in the neurosciences. More important, the physics literature shows that the phenomenon of 1/*f* noise is acutely sensitive to specific details of the system under study. To observe 1/*f* noise and label the system ‘‘interaction-dominant‘‘ is to ignore the more interesting question of why and under what circumstances the system generates 1/*f* noise.

As an example, consider systems that display self-organized criticality (SOC; Bak, 1996; Jensen, 1998; Sornette, 2000). One often-studied system that displays SOC is a pile of rice on a table (Fig. 1A; e.g., Wagenmakers et al., 2005; see Jensen, 1998 for details). Grains of rice are dropped onto the pile one by one. When the local slope of the rice pile is sufficiently steep, this causes an avalanche that transports grains downhill. A rice pile that is in a critical state features many local slopes near threshold, such that adding a single grain of rice can trigger a cascade of avalanches. Thus, by continually adding grains the rice pile self-organizes to a critical state in which the size of avalanches follows a power-law distribution or 1/*f* noise (see also Lörincz, 2008). Grains of rice exit the system when they fall off the table.

Now consider Fig. 1B, showing a pile of salt.[1] Under exactly the same circumstances as the pile of rice, the pile of salt does not display 1/*f* noise. Fig. 1C shows a different pile of salt. This pile is bounded by two orthogonal walls on the corner of the table, and it is driven by dropping grains along the edges of the walls. This particular pile of salt does display 1/*f* noise. Finally, Fig. 1D shows the same situation as in Fig. 1C, but now the grains are added to random positions on the interior of the pile. Surprisingly, this pile of salt does not display 1/*f* noise (Jensen, 1998, pp. 30–42).

This example highlights the fact that SOC systems generate 1/*f* noise under very specific circumstances. When these circumstances are ignored—the shape of the grains that make up the pile, the way in which the pile is driven to threshold—one cannot truly understand why

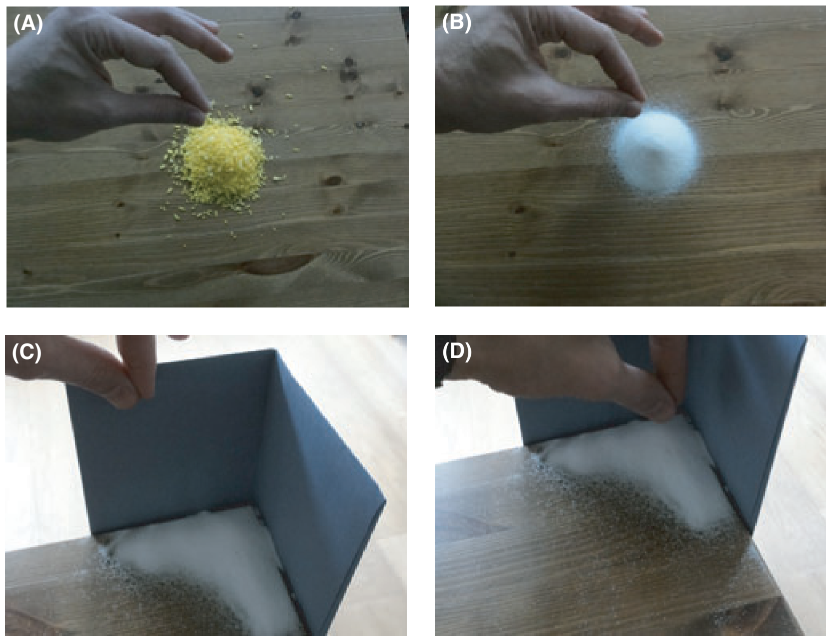

Fig. 1. Piles of rice and salt illustrate the sensitivity of SOC to design details. (A) A pile of rice exhibits 1/*f* noise; (B) a pile of salt does not exhibit 1/*f* noise; (C) when driven by adding grains along the edges of two orthogonal walls, the bounded pile of salt exhibits 1/*f* noise; (D) when driven by adding grains to random positions on the interior, the bounded pile of salt does not exhibit 1/*f* noise. For details, see Jensen (1998).

some piles show 1/*f* noise and others do not. Regardless, we expect that many cognitive scientists feel that the comparison of human cognition to a pile of rice is not compelling; what we need instead is a concrete model for the phenomenon of interest (van der Maas, 1995). In the study of human performance, we need a model of the task requirements and the mental processes involved. The idea that the complex-systems approach does not require such concrete modeling is mistaken. As already pointed out by Jensen (1998, p. 6), verbal descriptions and metaphors of SOC in the absence of concrete models constitute ‘‘rather abstract, heuristic wishful thinking.’’

1.3. Step 3: Conclude that cognition is interaction-dominant and traditional approaches should be abandoned

The final step is to conclude that cognition is ‘‘interaction-dominant‘‘ and that the new tools of complex-systems theory should replace the old science of component-dominant dynamics. However, from the perspective of a cognitive scientist the tools of complex-systems theory may appear to be limited (i.e., they mostly involve the detection of 1/*f* noise), superficial (i.e., they deal with the observed data instead of latent cognitive processes), and overly general (i.e., they ignore the details of the task and the participant). Moreover, old science seems to be doing rather well and can boast an arsenal of useful models of how people think, decide, reason, learn, recall, attend, perceive, and act. These models allow us to go beyond the observed data and infer something about the underlying cognitive processes or architecture, something that the complex-systems approach only admits in the most general sense.

The deeper problem is whether cognitive scientists really care whether cognition is ‘‘interaction-dominant’’ or not. Many people already intuit that the human brain is a pretty complex entity, something substantially more complex than a pile of rice. If the goal is to convince cognitive scientists that particular paradoxes can be resolved only in a complex-systems framework, then one needs to construct a formal complex-systems model that succeeds where a standard model fails (van der Maas, 1995).

It should also be noted that standard models of human cognition are sometimes special cases of nonlinear systems with many interacting components. For instance, Bogacz, Brown, Moehlis, Holmes, and Cohen (2006) discussed models for optimal decision making in neural networks, and they demonstrated that the standard drift diffusion model (Ratcliff, 1978) can be considered a simplification of a highly interactive ‘‘pooled inhibition‘‘ model proposed by Wang (2002). In this case a standard mathematical model in psychology is fully justified from a complex-systems perspective. We conjecture that this applies to many existing models in psychology. The tension between old science versus the complex-systems approach may therefore be more apparent than real.

Currently, the complex-systems approach proceeds by identifying a mysterious phenomenon (i.e., 1/*f* noise) and explaining this phenomenon by verbal reference to a series of other mysterious phenomena (e.g., SOC), without ever making contact with latent cognitive processes. This is unfortunate because latent cognitive processes are exactly what cognitive scientists are interested in (Kaplan & Bechtel, in press).

2. Concrete alternative approaches

We wish to avoid the impression that we dislike almost everything about complex-systems theory. In fact, the opposite is true, and we have worked on several collaborative projects that involve complex systems: Dutilh, Wagenmakers, Visser, and van der Maas (in press) proposed a cusp catastrophe model of the speed-accuracy tradeoff (see also Ploeger, van der Maas, & Hartelman, 2002; van der Maas & Molenaar, 1992) and Torre and Wagenmakers (2009) demonstrated how a mechanistic model of 1/*f* noise can be successfully integrated with currently established models for rhythmic self-paced, synchronized, and bimanual tapping. We also like the work by Usher, Stemmler, and Olami (1995), who developed a model of 1/*f* noise in spike trains of neural populations.

Another relatively recent trend in cognitive science is that of quantum cognition. The verdict on quantum cognition is still out, but its proponents have at least developed concrete models to account for phenomena that normative models have had difficulty explaining (e.g., Aerts, 2009; Bruza, Busemeyer, & Gabor, 2009; Pothos & Busemeyer, 2009).

3. Conclusion

The complex-systems approach provides an exciting new perspective on human cognition. However, we believe it is vital that the approach matures to include concrete models for the cognitive phenomena under study. Currently, the complex-systems approach does itself a disservice by eschewing formal models in favor of verbal generalities. As a result, we fear that many cognitive scientists might judge the four current topiCS articles (Dixon et al., in press; Gibbs & Van Orden, in press; Riley et al., in press; Silberstein & Chemero, in press) to be mostly speculation, wrapped in jargon, inside wishful thinking.

Note

1. The standard example concerns a pile of sand. For convenience, we assume here that grains of sand behave identically to grains of salt.

Acknowledgement

This research was supported by a Vidi grant from the Dutch Organization for Scientific Research (NWO).

References

Aerts, D. (2009). Quantum structure in cognition. *Journal of Mathematical Psychology*, *53*, 314–348.

Anderson, J. R., Fincham, J. M., Qin, Y., & Stocco, A. (2008). A central circuit of the mind. *Trends in Cognitive Sciences*, *12*, 136–143.

Bak, P. (1996). *How nature works: The science of self–organized criticality*. New York: Springer Verlag.

Bogacz, R., Brown, E., Moehlis, J., Holmes, P., & Cohen, J. D. (2006). The physics of optimal decision making: A formal analysis of models of performance in two–alternative forced choice tasks. *Psychological Review*, *113*, 700–765.

Borst, J. P., Taatgen, N. A., Stocco, A., & van Rijn, H. (2010). The neural correlates of problem states: Testing fMRI predictions of a computational model of multitasking. *PLoS ONE*, *5*, e12966. doi:10.1371/journal.pone.0012966.

Bruza, P., Busemeyer, J. R., & Gabor, L. (2009). Introduction to the special issue on quantum cognition. *Journal of Mathematical Psychology*, *53*, 303–305.

Craigmile, P. F., Peruggia, M., & Van Zandt, T. (2010). Hierarchical Bayes models for response time data. *Psychometrika*, *75*, 613–632.

Delignières, D., Ramdani, S., Lemoine, L., Torre, K., Fortes, M., & Ninot, G. (2006). Fractal analyses for 'short' time series: A re-assessment of classical methods. *Journal of Mathematical Psychology*, *50*, 525–544.

Dixon, J. A., Holden, J. G., Mirman, D., & Stephen, D. G. (in press). Multifractal dynamics in the emergence of cognitive structure. *topiCS*.

Dutilh, G., Wagenmakers, E.-J., Visser, I., & van der Maas, H. L. J. (in press). A phase transition model for the speed–accuracy trade–off in response time experiments. *Cognitive Science*.

Farrell, S., Wagenmakers, E.-J., & Ratcliff, R. (2006). 1/*f* noise in human cognition: Is it ubiquitous, and what does it mean? *Psychonomic Bulletin & Review 13*, 737–741.

Gibbs, R., & Van Orden, G. (in press). Pragmatic choice in conversation. *topiCS*.

Gilden, D. L. (2009). Global model analysis of cognitive variability. *Cognitive Science*, *33*, 1441–1467.

Gilden, D. L., & Hancock, H. (2007). Response variability in attention-deficit disorders. *Psychological Science*, *18*, 796–802.

Gilden, D. L., Thornton, T., & Mallon, M. W. (1995). 1/*f* noise in human cognition. *Science*, *267*, 1837–1839.

Gottschalk, A., Bauer, M. S., & Whybrow, P. C. (1995). Evidence of chaotic mood variation in bipolar disorder. *Archives of General Psychiatry*, *52*, 947–959.

Granger, C. W. J. (1980). Long memory relationships and the aggregation of dynamic models. *Journal of Econometrics*, *14*, 227–238.

Ihlen, E. A. F., & Vereijken, B. (2010). Interaction-dominant dynamics in human cognition: Beyond $1/f^{\alpha}$ fluctuation. *Journal of Experimental Psychology: General*, *139*, 436–463.

Jensen, H. J. (1998). *Self–organized criticality*. Cambridge, England: Cambridge University Press.

Kaplan, D. M., & Bechtel, W. (in press). Dynamical models: An alternative or complement to mechanistic explanations? *topiCS*.

Lörincz, K.-A. (2008). *Avalanche dynamics in a three-dimensional pile of rice*. Unpublished doctoral dissertation, Vrije Universiteit.

van der Maas, H. L. J. (1995). Beyond the metaphor? *Cognitive Development*, *10*, 621–642.

van der Maas, H. L. J., & Molenaar, P. C. M. (1992). Stagewise cognitive development: An application of catastrophe theory. *Psychological Review*, *99*, 395–417.

Ploeger, A., van der Maas, H. L. J., & Hartelman, P. A. I. (2002). Stochastic catastrophe analysis of switches in the perception of apparent motion. *Psychonomic Bulletin & Review*, *9*, 26–42.

Pothos, E. M., & Busemeyer, J. R. (2009). A quantum probability explanation for violations of 'rational' decision theory. *Proceedings of the Royal Society Series B: Biological Sciences*, *276*, 2171–2178.

Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review*, *85*, 59–108.

Riley, M. A., Shockley, K., & Van Orden, G. (in press). Learning from the body about the mind. *topiCS*.

Silberstein, M., & Chemero, A. (in press). Complexity and extended phenomenological-cognitive systems. *topiCS*.

Sornette, D. (2000). *Critical phenomena in natural sciences*. Berlin: Springer Verlag.

Thornton, T. L., & Gilden, D. L. (2005). Provenance of correlations in psychological data. *Psychonomic Bulletin & Review*, *12*, 409–441.

Torre, K. (2008). *Absolute and relative timing in bimanual coordination: Contribution of serial correlation analysis and implications for modeling*. Unpublished doctoral dissertation, University of Montpellier.

Torre, K., & Wagenmakers, E.-J. (2009). Theories and models for $1/f^{\beta}$ noise in human movement science. *Human Movement Science*, *28*, 297–318.

Torre, K., Deligniéres, D., & Lemoine, L. (2007). Detection of long-range dependence and estimation of fractal exponents through ARFIMA modelling. *British Journal of Mathematical and Statistical Psychology*, *60*, 85–106.

Usher, M., Stemmler, M., & Olami, Z. (1995). Dynamic pattern formation leads to 1/*f* noise in neural populations. *Physical Review Letters*, *74*, 326–329.

Wagenmakers, E.-J., Farrell, S., & Ratcliff, R. (2004). Estimation and interpretation of $1/f^{\alpha}$ noise in human cognition. *Psychonomic Bulletin & Review*, *11*, 579–615.

Wagenmakers, E.-J., Farrell, S., & Ratcliff, R. (2005). Human cognition and a pile of sand: A discussion on serial correlations and self–organized criticality. *Journal of Experimental Psychology: General*, *134*, 108–116.

Wang, X.-J. (2002). Probabilistic decision making by slow reverberation in cortical circuits. *Neuron*, *36*, 955–968.