# Today's dynamical systems are too simple

## Commentary to Tim van Gelder's "The Dynamical Hypothesis in Cognitive Science"

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### Abstract

Cognitive systems are wilder than today's dynamical systems theory can handle. While cognitive systems might be tamed in principle, it seems that the very notion of a dynamical system will change in the process.

### Commentary

Van Gelder stresses the power of recent mathematical insights into dynamical systems. Indeed, today we have profound insight into the qualitative phenomenology (attractors, bifurcations, stability) of low-dimensional, input-free systems; have a working familiarity with chaos; know something about high-dimensional, collective dynamics; and have inklings of spatial and non-stationary systems.

Dynamical-systems oriented investigations into cognitive systems make use of what is today mathematically possible. Typically, a cognitive system is measured or simulated in a approximately stationary mode, i.e. with input that most of the time changes much slower than on the system's own timescale. The time series thus obtained are then either *described* as resulting from a certain class of dynamical laws (like in the DFT model cited by van Gelder), or they are mathematically *explained* as resulting from universal laws concerning attractors, bifurcations, and chaos-related phenomena (as in the HKB model reported by van Gelder).

The systems thus studied are typically anatomical or functional subsystems of complete agents. When complete agents are investigated (e.g. Beer 1995b: walking insects; Smithers 1995: maneuvering robots), only a minute fraction of their behavioral repertoire is ever assessed.

Arguably, complete cognitive systems have the following properties: (i) they are driven by stochastic input which varies on the system's own characteristic timescales, (ii) they are high-dimensional, with many variables developing according to different laws in different subsystems, (iii) and they are non-stationary. Non-stationarity is here understood as resulting from a non-parametric change in the dynamical law itself, as occasioned e.g. by topological restructuring of neural connectivity, by evolutionary processes, or by growth.

I will call systems having properties (i)-(iii), *wild* systems.

Wild systems cannot be caught by today's mathematicians. Even basic concepts like attractors or bifurcations cease to be of much help in systems driven by fast, stochastic input. High-dimensional systems currently can only be approached with respect to some kind of collective parameters , like in synergetic systems or mean-field approaches. Finally, with non-stationarity of the hard kind meant in (iii) we are simply lost.

In my view, cognition can only be rightfully understood as a property of complete, situated agents. This is also the view of the interdisciplinary strand of research variously referred to as, e.g., "situated action", "behavior-based robotics", or "new AI" (Pfeifer & Scheier 1998).

Therefore, given the premises:

- cognition is irreducibly a property of complete, situated agents,
- complete, situated agents are wild systems,
- current dynamical systems theory cannot catch wild systems,

it follows that

- current dynamical systems theory cannot catch cognitive systems.

One remedy is to bring in CH again, and pursue "hybrid" models of cognition. Examples abound, especially in mobile robotics. While most of these hybrid architectures amout to an addition of dynamical and computational-symbolical modules, some aim at a true marriage of

DH with CH (e.g. Jaeger 1994, Tsotsos 1997, Hertzberg et al. 1998). This leads to richer notions of dynamical systems than those contained in van Gelder's table 1.

Another remedy is to further dynamical systems theory. Unfortunately, progress is slow, since dynamical systems theory is mostly being developed by pure mathematicians and theoretical physicists who have little interest in wild systems. The only exception I am aware of is Casdagli's (1992) generalization of chaos to input-driven systems (but of course there must be others).

I think more hope rests on control theorists, who combine a mathematical inclination with a professional interest in wild systems. However, most control theorists prefer to domesticize wild systems by linearization, rather than to embark on wild mathematics. In my opinion, the principal advance afforded by control theory is that a notion of optimal behavior and hence ofgoal-directedness is integrated into dynamical systems theory. To me it seems obvious that some notion of goal-directedness must be included into any satisfactory model of cognitive systems. Again, van Gelder's table 1 would have to be expanded.

I take the opportunity to mention a recent progress in hunting wild systems, namely, the "observable operator models" (OOMs) (Jaeger 1997). OOMs can model any stationary stochastic system driven by stochastic input. They come equipped with a constructive learning algorithm which is faster by orders of magnitude than current state-of-the-art hillclimbing procedures (cf. Bengio 1996).

The surprising powers of OOMs arise from a re-interpretation of what a dynamical system is. Classically, temporal development is seen as a *succession of states* in some state space. By contrast, an OOM trajectory is a *succession of operators* (hence, "observable operators"). Intuitively, OOMs model temporal development as actions which bring forth new actions. This nicely allows to model thoughts (concepts, propositions, mental images, associations...) as bringing forth successive thoughts. No mechanism or "law" would be needed besides the thoughts themselves. Again, van Gelder's table 1 would have to grow.

Tim van Gelder, being a scrupulous philosopher, forwards DH as a *hypothesis*. Personally I believe DH is true. But I also believe we don't understand what DH means. Our notions are too narrow when dynamical systems get as wild as true cognition. I feel most grateful toward Tim van Gelder for rowing us out into clear waters, but we still have to learn how to lift sails.

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