Figure 2a. Three-dimensional state space defined by the values for brain activation (A), input source and strength (I), and mode of processing (M). It is theoretically possible for the system to be at any point in the state space, and an infinite number of state conditions is conceivable. In practice the system is normally constrained to a boomerang-like path from the back upper right in waking (high A, I, and M), through the center in NREM (intermediate A, I, and M) to the front lower right in REM sleep (high A, low I, and M).

Figure 2b. (A) Movement through the state space during the sleep cycle. (B) Segments of the state space associated with some normal, pathological, and artificial conditions of the brain.

See also CONSCIOUSNESS; CONSCIOUSNESS, NEUROBIOLOGY OF; LIMBIC SYSTEM; NEUROTRANSMITTERS

—*J. Allan Hobson*

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Dynamic Approaches to Cognition

The dynamical approach to cognition is a confederation of research efforts bound together by the idea that natural cognition is a dynamical phenomenon and best understood in dynamical terms. This contrasts with the "law of qualitative structure" (Newell and Simon 1976) governing orthodox or "classical" cognitive science, which holds that cognition is a form of digital COMPUTATION.

The idea of mind as dynamical can be traced as far back as David HUME, and it permeates the work of psychologists such as Lewin and Tolman. The contemporary dynamical approach, however, is conveniently dated from the early cybernetics era (e.g., Ashby 1952). In subsequent decades dynamical work was carried out within programs as diverse as ECOLOGICAL PSYCHOLOGY, synergetics, morphodynamics, and neural net research. In the 1980s, three factors—growing dissatisfaction with the classical approach, developments in the pure mathematics of nonlinear dynamics, and increasing availability of computer hardware and software for simulation—contributed to a flowering of dynamical research, particularly in connectionist form (Smolensky 1988). By the 1990s, it was apparent that the dynamical approach has sufficient power, scope, and cohesion to count as a research paradigm in its own right (Port and van Gelder 1995).

In the prototypical case, the dynamicist focuses on some particular aspect of cognition and proposes an abstract dynamical system as a model of the processes involved. The behavior of the model is investigated using dynamical systems theory, often aided by simulation on digital computers. A close match between the behavior of the model and empirical data on the target phenomenon confirms the hypothesis that the target is itself dynamical in nature, and that it can be understood in the same dynamical terms.

Consider, for example, how we make decisions. One possibility is that in our heads there are symbols representing various options and the probabilities and values of their outcomes; our brains then crank through an ALGORITHM for determining a choice (see RATIONAL DECISION-MAKING). But this classical approach has difficulty

accounting for the empirical data, partly because it cannot accommodate temporal issues and other relevant factors such as affect and context. Dynamical models treat the process of DECISION-MAKING as one in which numerical variables evolve interactively over time. Such models, it is claimed, can explain a wider range of data and do so more accurately (see, e.g., Busemeyer and Townsend 1993; Leven and Levine 1996).

A better understanding of dynamical work can be gained by highlighting some of its many differences with classical cognitive science. Most obviously, dynamicists take cognitive agents to be dynamical systems as opposed to digital computers. A dynamical system for current purposes is a set of quantitative variables changing continually, concurrently, and interdependently over quantitative time in accordance with dynamical laws described by some set of equations. Hand in hand with this first commitment goes the belief that dynamics provides the right tools for understanding cognitive processes. Dynamics in this sense includes the traditional practice of dynamical modeling, in which scientists attempt to understand natural phenomena via abstract dynamical models; such modeling makes heavy use of calculus and differential or difference equations. It also includes dynamical systems theory, a set of concepts, proofs, and methods for understanding the behavior of systems in general and dynamical systems in particular. A central insight of dynamical systems theory is that behavior can be understood geometrically, that is, as a matter of position and change of position in a space of possible overall states of the system. The behavior can then be described in terms of attractors, transients, stability, coupling, bifurcations, chaos, and so forth—features largely invisible from a classical perspective.

Dynamicists and classicists also diverge over the general nature of cognition and cognitive agents. The pivotal issue here is probably the role of time. Although all cognitive scientists understand cognition as something that happens *over* time, dynamicists see cognition as being *in* time, that is, as an essentially temporal phenomenon. This is manifested in many ways. The time variable in dynamical models is not a mere discrete order, but a quantitative, sometimes continuous approximation to the real time of natural events. Details of timing (durations, rates, synchronies, etc.) are taken to be essential to cognition itself rather than incidental details. Cognition is seen not as having a sequential cyclic (sense-think-act) structure, but rather as a matter of continuous and continual coevolution. The subtlety and complexity of cognition is found not *at* a time in elaborate static structures, but rather *in* time in the flux of change itself.

Dynamicists also emphasize SITUATEDNESS/EMBEDDEDNESS. Natural cognition is always environmentally embedded, corporeally embodied, and neurally "embrained." Classicists typically set such considerations aside (Clark 1997). Dynamicists, by contrast, tend to see cognitive processes as collective achievements of brains in bodies in contexts. Their language—dynamics—can be used to describe change in the environment, bodily movements, and neurobiological processes (e.g., Bingham 1995; Wright and Liley 1996). This enables them to offer integrated accounts of cognition as a dynamical phenomenon in a dynamical world.

In classical cognitive science, symbolic representations and their algorithmic manipulations are the basic building blocks. Dynamical models usually also incorporate representations, but reconceive them as dynamical entities (e.g., system states, or trajectories shaped by attractor landscapes). Representations tend to be seen as transient, context-dependent stabilities in the midst of change, rather than as static, context-free, permanent units. Interestingly, some dynamicists claim to have developed wholly representation-free models, and they conjecture that representation will turn out to play much less of a role in cognition than has traditionally been supposed (e.g., Skarda 1986; Wheeler forthcoming).

The differences between the dynamical and classical approaches should not be exaggerated. The dynamical approach stands opposed to what John Haugeland has called "Good Old Fashioned AI" (Haugeland 1985). However, dynamical systems may well be performing computation in some other sense (e.g., analog computation or "real" computation; Blum, Shub, and Smale 1989; Siegelmann and Sontag 1994). Also, dynamical systems are generally effectively computable. (Note that something can be *computable* without being a digital *computer.*) Thus, there is considerable middle ground between pure GOFAI and an equally extreme dynamicism (van Gelder forthcoming).

How does the dynamical approach relate to connectionism? In a word, they overlap. Connectionist networks are generally dynamical systems, and much of the best dynamical research is connectionist in form (e.g., Beer 1995). However, the way many connectionists structure and interpret their systems is dominated by broadly computational preconceptions (e.g., Rosenberg and Sejnowski 1987). Conversely, many dynamical models of cognition are not connectionist networks. Connectionism is best seen as straddling a more fundamental opposition between dynamical and classical cognitive science.

Chaotic systems are a special sort of dynamical system, and chaos theory is just one branch of dynamics. So far, only a small proportion of work in dynamical cognitive science has made any serious use of chaos theory. Therefore the dynamical approach should not be identified with the use of chaos theory or related notions such as fractals. Still, chaotic dynamics surely represents a frontier of fascinating possibilities for cognitive science (Garson 1996).

The dynamical approach stands or falls on its ability to deliver the best models of particular aspects of cognition. In any given case its ability to do this is a matter for debate among the relevant specialists. Currently, many aspects of cognition—e.g., story comprehension—are well beyond the reach of dynamical treatment. Nevertheless, a provisional consensus seems to be emerging that some significant range of cognitive phenomena will turn out to be dynamical, and that a dynamical perspective enriches our understanding of cognition more generally.

See also COGNITIVE MODELING, CONNECTIONIST; COMPUTATION AND THE BRAIN; COMPUTATIONAL THEORY OF MIND; CONNECTIONIST APPROACHES TO LANGUAGE; NEURAL NETWORKS; RULES AND REPRESENTATIONS

—*Tim Van Gelder*

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Dynamic Programming

Some problems can be structured into a collection of small problems, each of which can be solved on the basis of the solution of some of the others. The process of working a solution back through the subproblems in order to reach a final answer is called dynamic programming. This general algorithmic technique is applied in a wide variety of areas, from optimizing airline schedules to allocating cell-phone bandwidth to justifying typeset text. Its most common and relevant use, however, is for PLANNING optimal paths through state-space graphs, in order, for example, to find the best routes between cities in a map.

In the simplest case, consider a directed, weighted graph $< S, A, T, L>$, where S is the set of nodes or "states" of the graph, and A is a set of arcs or "actions" that may be taken from each state. The state that is reached by taking action a in state s is described as $T(s,a)$; the positive length of the a arc from state s is written $L(s,a)$. Let $g \in S$ be a desired goal state. Given such a structure, we might want to find the shortest path from a particular state to the goal state, or even to find the shortest paths from each of the states to the goal.

In order to make it easy to follow shortest paths, we will use dynamic programming to compute a distance function, $D(s)$, that gives the distance from each state to the goal state. The ALGORITHM is as follows:

```
D(s): = large
D(g): = 0
Loop |S| times
    Loop for s in S
        D(s): = min_a ɪ_A L(s,a) + D(T(s,a))
    end loop
end loop
```

We start by initializing $D(s) = large$ to be an overestimate of the distance between s and g (except in the case of $D(g)$, for which it is exact). Now, we want to improve iteratively the estimates of $D(s)$. The inner loop updates the value for each state s to be the minimum over the outgoing arcs of $L(s,a) + D(T(s,a))$; the first term is the known distance of the first arc and the second term is the estimated distance from the resulting state to the goal. The outer loop is executed as many times as there are states.

The character of this algorithm is as follows: Initially, only $D(g)$ is correct. After the first iteration, $D(s)$ is correct for all states whose shortest path to the goal is one step long. After $|S|$ iterations, it is correct for all states. Note that if L was uniformly 1, then all the states that are i steps from the goal would have correct D values after the ith iteration; however, it may be possible for some state s to be one step