Attractor Networks

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Artificial neural networks (*ANNs*), sometimes referred to as *connectionist networks*, are computational models based loosely on the neural architecture of the brain. Over the past twenty years, ANNs have proven to be a fruitful framework for modeling many aspects of cognition, including perception, attention, learning and memory, language, and executive control. A particular type of ANN, called an *attractor network*, is central to computational theories of consciousness, because attractor networks can be analyzed in terms of properties—such as temporal stability, and strength, quality, and discreteness of representation—that have been ascribed to conscious states. Some theories have gone so far as to posit that attractor nets are the computational substrate from which conscious states arise.

ANNs consist of a large number of simple, highly interconnected neuron-like processing units. Each processing unit conveys an *activation level*, a scalar that is usually thought to correspond to the rate of neural spiking. Typically, activation levels are scaled to range between 0 (no spiking) to 1 (maximal spiking), and might represent the absence or presence of a visual feature, or the strength of belief in some hypothesis. For example, if the processing units—*units* for short—are part of a model of visual information processing, activity of a particular unit might denote the presence of the color red at some location in the visual field. If the units are part of a model of memory, activity of individual units might instead denote semantic features of an item to be recalled.

Each unit receives input activation from a large number of other units, and produces output—its activation level—that is a function of its inputs. A typical function yields an output that grows monotonically with the weighted sum of the inputs. The weights, or strength of connectivity, can be thought of as reflecting the relationship among features or hypotheses. If the presence of feature A implies the presence of feature B, then the weight from A to B should be positive, and activation of A will tend to result in activation of B; if A implies the absence of B, the weight from A to B should be negative.

Units in an ANN can be interconnected to form two basic architectures: *feedforward* and *recurrent*. In a feedforward architecture (Figure 1a), activity flows in one direction, from input to output, as indicated by the arrows. A feedforward network performs associative mappings, and might be used, for instance, to map visual representations to semantic representations. In a recurrent architecture (Figure 1b), units are connected such that activity flows bidirectionally, allowing the output activity of a unit at one point in time to influence its activity at a subsequent point in time. Recurrent networks are often used to implement *content-addressible memories*. The network is first trained on a set of items, and then when it is presented with a partial featural description of one item, network dynamics fill in the missing features. Both feedforward and recurrent networks can perform cued retrieval, but recurrent networks are more flexible in that they allow any subset of features to serve as a cue for the remaining features.

The activation *state* of a network with n units can be characterized as a point in an n-dimensional space, and temporal dynamics of a recurrent network can be described as a time-varying trajectory through this

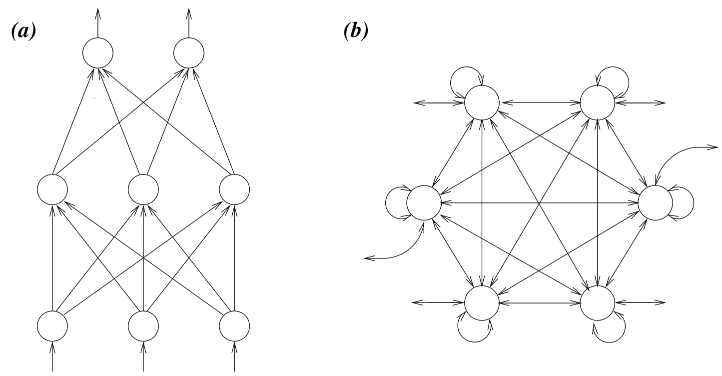

Figure 1. (a) A feedforward architecture in which activity flows from the bottom layer of units to the top layer; (b) A recurrent architecture in which activity flows in cycles

state space (Figure 2a). An *attractor network* is a recurrent ANN whose dynamics cause the network state to converge to a fixed point. That is, given an input—which might represent a stimulus to be processed, or the output of another ANN—the dynamics of the network will cause the state to evolve over time to a stable value, away from which the state will not wander. The states to which the net might evolve are called *attractors.* The attractors are typically sparse in the state space. (Technically, attractors can also be limit cycles—nonstatic, periodic trajectories—but attractor net dynamics ordinarily produce only point attractors.)

The state space of an attractor net can be carved up into *attractor basins*, regions of the state space in which all starting points converge to the same attractor. Figure 2b depicts a state space with three attractor basins whose boundaries are marked by dotted lines, and some trajectories that might be attained within each attractor basin.

Attractor dynamics are achieved by many neural network architectures, including Hopfield networks, Harmony networks, Boltzmann Machines, adaptive resonance networks, and recurrent back propagation networks. To ensure attractor dynamics, these popular architectures require symmetry of connectivity: the connection weight from processing unit *A* to unit *B* must be the same as the weight from *B* to *A*. Given this restriction, the dynamics of the networks can be characterized as performing local optimization—minimizing *energy*, or equivalently, maximizing *harmony.* Consider the attractor state space of Figure 2b, and add an additional dimension representing harmony, a measure of the goodness of a state, as shown in Figure 2c.

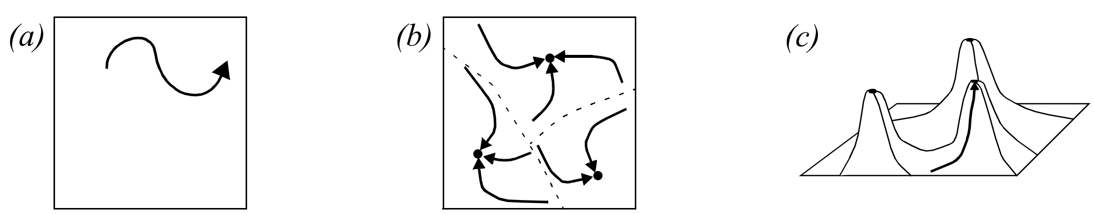

Figure 2. (a) The activation state of a two-unit recurrent network can be depicted as a point in a two-dimensional space. If activation is bounded, e.g., to lie between 0 and 1, then the state lies within a box. The solid curve depicts the time-varying trajectory of the state, where the arrow represents the forward flow of time. (b) A state space with three attractors carved into attractor basins (dotted lines). (c) A harmony landscape over the state space with three attractors

The attractors are at points of maximum harmony, and the network dynamics ensure that harmony is non-decreasing. Because the net is climbing uphill in harmony, it is guaranteed to converge to a local optimum of harmony. The input to an attractor net can either specify the initial state of the net, or it can provide *biases*—fixed input—to each unit; in the latter case, the biases reshape the landscape such that the best-matching attractor has maximum harmony, and is likely to be found for a wide range of initial network states.

The connection strengths (including biases) in the network determine the harmony landscape, which in turn determines the attractors and the shape of the attractor basins. When a set of attractor patterns are stored in a net, *gang effects* are typically observed: the shapes of attractor basins are influenced by the proximity of attractors to one another (Zemel & Mozer, 2001).

In traditional attractor nets, the knowledge about each attractor is *distributed* over the connectivity pattern of the entire network. As a result, sculpting the attractor landscape is tricky, and often leads to spurious (undesired) attractors and ill-conditions (e.g., very narrow) attractor basins. To overcome these limitations, a *localist* attractor net has been formulated (Zemel & Mozer, 2001) that consists of a set of state units and a set of attractor units, one per attractor. Each attractor unit draws the state toward its attractor, with the attractors closer to the state having a greater influence. The localist attractor net is easily configured to obtain a desired set of attractors. The dynamics of a localist attractor net, like its distributed counterpart, can be interpreted as climbing uphill in harmony.

Attractor nets can also be conceptualized from a probabilistic perspective. If the net has intrinsically stochastic dynamics (e.g., Boltzmann machines, or back propagation networks with added noise), each point in the state space can be characterized in terms of the probability of reaching each attractor from that point—a discrete probability distribution over attractors. The points far from any attractor have a nearly uniform distribution (maximum entropy), whereas the attractors themselves are represented by a distribution with probability 1.0 for the attractor and probability 0.0 for any other attractor (minimum entropy). This conceptualization allows for one to abstract away from neural net representations and dynamics, and to characterize the dynamics as entropy minimization (Colagrosso & Mozer, 2005).

Relationship between attractor states and conscious states

Theorists have identified certain properties that are claimed to be prerequisites or characteristics of conscious mental states. Attractors share these properties, as we elaborate here.

Conscious perceptual states have been conceived of as *interpretations* of noisy or ambiguous sensory input (Marcel, 1983). For example, the Necker cube admits two possible interpretations, and perceptual awareness flips between these interpretations. Searle (1992) focuses on interpretation in terms of preexisting categories. One can conceive of attractors as interpretations or learned categories, and the dynamics of an attractor net as mapping a noisy or partial input to the most appropriate interpretation. Attractor dynamics are highly nonlinear: two similar initial states may lead to distant attractors. This type of nonlinearity allows two similar inputs to yield distinct interpretations. The Necker cube is an extreme case in which a single input—lying on the boundary between two attractor basins—can lead to two different interpretations. (Many attractor nets assume intrinsic noise to break symmetry for ambiguous inputs.)

Conscious states have been characterized as *high quality* representations (Farah, 1994; Munakata, 2001). The notion of quality is ill defined, but essentially, a high quality representation should be capable of triggering the correct representations and responses further along the processing stream; in the terminology of the consciousness literature, such a representation is *accessible*. Quality is not an intrinsic property of a representation, but comes about by virtue of how that representation affects subsequent processing stages, which in turn is dependent on whether past learning has associated the representation with the appropriate effects. From this definition, attractors are high quality. Attractors come into existence because they correspond to states the system has learned about in the past. An attractor net cleans up a noisy input, yielding a pattern that corresponds to a previously experienced state. Because of this past experience, later stages of processing receiving input from the attractor net are likely to have learned how to produce appropriate responses to attractor states. When cognitive operations involve multiple steps, the quality of a representation is critical: without the sort of clean-up operation performed by an attractor net, representations degrade further at each step (Mathis & Mozer, 1995).

Temporal stability of neural states is often associated with consciousness (e.g., Taylor, 1998). Attractors have the property of temporal stability. Once the dynamics of the attractor net lead to an attractor, the state the state of the network persists until the network is reset or is perturbed by a different input.

Conscious states are generally considered to be *explicit* (e.g., Baars, 1989; Dehaene & Naccache, 2001), meaning that they are instantiated as patterns of neural activity, in contrast to implicit representations, which are patterns of connectivity. An attractor net encodes its attractors implicitly, but the current attractor state is explicit.

Conscious states might arise at the interface between subsymbolic and symbolic processing (Cleeremans & Jiménez, 2002; Smolensky, 1988). From a connectionist perspective, perceptual processes are intrinsically subsymbolic, but yield representations of object identities and categories that subserve subsequent symbolic processing. This view fits in well with the fact that attractor nets typically map a continuous activation space to a *discrete* set of alternatives (Figure 2b), which can be viewed as a mapping from subsymbolic to symbolic representations. If conscious states are indeed symbolic, then they should be all-or-none. Studies have indeed suggested discrete, all-or-none states of consciousness (Sergent & Dehaene, 2004), although others consider consciousness to be a graded phenomenon (Cleeremans & Jiménez, 2002; Farah, 1994; Munakata, 2001).

Attractor networks and theories of consciousness

Grossberg's adaptive resonance theory, proposed in 1976, describes an attractor network that achieves resonant states between bottom-up information from the world and top-down expectations. Grossberg (1999) subsequently made the claim that conscious states are a subset of resonant (attractor) states. From neuroimaging data, evidence is also consistent with the notion that conscious states arise from resonant circuits linking temporal, parietal, and prefrotal cortical areas (Lumer & Rees, 1999).

Many computational theories of consciousness have argued that attractors have the right functional characteristics to serve as the computational correlate of consciousness. Rumelhart, Smolensky, McClelland, and Hinton (1986) and Smolensky (1988) first proposed that conscious mental states may correspond to stable states of an attractor network. Like subsequent theorists, they envision an attractor net defined over multiple cortical regions thereby able to capture global cortical coherence. Farah, O'Reilly, and Vecera (1993) describe attractor nets as allowing stimuli to be integrated into a global information-processing state which corresponds with consciousness. Other theorists are less explicit in describing attractor nets, yet focus on key properties of attractor nets, such as self-sustaining activation patterns (Dehaene & Naccache, 2001), dynamic competitions among coalitions of neurons (Crick & Koch, 2003), and nonlinear bifurcations in neural activity (Sergent & Dehaene, 2004). Although many theories simply postulate that stable, high-quality representations—such as attractors—are associated with awareness, some models to show that accessibility and reportability is an emergent property of such representations (Colagrosso & Mozer, 2004; Mathis & Mozer, 1996).

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