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The Computational Brain.  
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## 1 INTRODUCTION

What is computation? In virtue of what is something a computer? Why do we say a slide rule is a computer but an egg beater is not? These are, in a way, the philosophical questions of computer science, inasmuch as they query foundational issues that are typically glossed over as researchers get on with their projects.<sup>1</sup> Like the philosophical questions of other disciplines (What is the nature of life? [Biology] What is the nature of substance and change? [Physics and Chemistry]), the answers become more convincing, meaningful, and interconnected as the empirical discipline matures and gives more ballast to the theory. In advance of understanding that there are atoms, how atoms link together, and what their properties are, one simply cannot say a whole lot about the nature of substance and change. It is not, however, that one must say *nothing*—in that event, one could not get the science started. The point rather is that the theory outlining the elementary ideas of the discipline gradually bootstraps itself up, using empirical discoveries as support, and kicking away old misconceptions in the haul.

The definition of computation is no more *given* to us than were the definitions of light, temperature, or force field. While some rough-hewn things can, of course, be said, and usefully said, at this stage, precision and completeness cannot be expected. And that is essentially because there is a lot we do not yet know about computation. Notice in particular that once we understand more about what sort of computers *nervous systems* are, and how they do whatever it is they do, we shall have an enlarged and deeper understanding of what it is to compute and represent. Notice also that we are not starting from ground zero. Earlier work, especially by Turing (1937, 1950), von Neumann (1951, 1952), Rosenblatt (1961), and McCulloch and Pitts (1943), made important advances in the theory and science of computation. The technological development of serial, digital computers and clever software to run on them was accompanied by productive theoretical inquiry into what sort of business computation is.<sup>2</sup>

Agreeing that precise definitions are not forthcoming, can we nonetheless give rough and ready answers to the opening questions? First, although we may be guided by the example of a serial digital computer, the notion of “computer” is broader than that. Identifying computers with *serial digital* com-

puters is neither justified nor edifying, and a more insightful strategy will be to see the conventional digital computer as only a special instance, not as the defining archetype. Second, in the most general sense, we can consider a physical system as a computational system when its physical states can be seen as representing states of some other systems, where transitions between its states can be explained as operations on the representations. The simplest way to think of this is in terms of a mapping between the system's states and the states of whatever is represented. That is, the physical system is a computational system just in case there is an appropriate (revealing) mapping between the system's physical states and the elements of the function computed. This "simple" proposal needs quite a lot of unpacking.

### Functions: Computable or Noncomputable, Linear or Nonlinear

Since this hypothesis concerning what makes a physical system a computational system may not be self-evident, let us approach the issue more gradually by first introducing several key but simple mathematical concepts, including "function," and the distinction between *computable* and *noncomputable* functions. To begin, what is a function? A function in the mathematical sense is essentially just a mapping, either 1 : 1 or many : 1, between the elements of one set, called the "domain," and the elements of another, usually referred to as the "range"<sup>3</sup> (figure 3.1). Consequently, a function is a set of ordered pairs, where the first member of the pair is drawn from the domain, and the second element is drawn from the range. A computable function then is a mapping that can be specified in terms of some *rule* or other, and is generally characterized in terms of what you have to do to the first element to get the second. For example, multiply the first by 2,  $\{(1, 2), (2, 4), (3, 6)\}$ , expressible algebraically as  $y = 2x$ ; multiply the element from the domain by itself  $\{(6.2, 38.44), (9.6, 92.16)\}$ , expressible algebraically as  $y = x^2$ , and so on.

What then is a noncomputable function? It is an infinite set of ordered pairs for which no rule can be provided, not only now, but in principle. Hence its specification consists simply and exactly in the list of ordered pairs. For example, if the elements are randomly associated, then no rule exists to specify the mapping between elements of the domain and elements of the range. Outside of mathematics, people quite reasonably tend to equate "function" with "computable function," and hence to consider a nonrule mapping to be no function at all. But this is not in fact how mathematicians use the terms, and for good reason, since it is useful to have the notion of a noncomputable function to describe certain mappings. Moreover, it is useful for the issue at hand because it is an empirical question whether brain activity can really be characterized by a computable function or only to a first approximation, or perhaps whether some of its activities cannot be characterized at all in terms of computable functions (Penrose 1989).

What is a *linear* function? Intuitively, it is one where the plot of the elements of the ordered pair yields a straight line. A *nonlinear* function is one where the plot does not yield a straight line (figure 3.2). Thus when brain function is

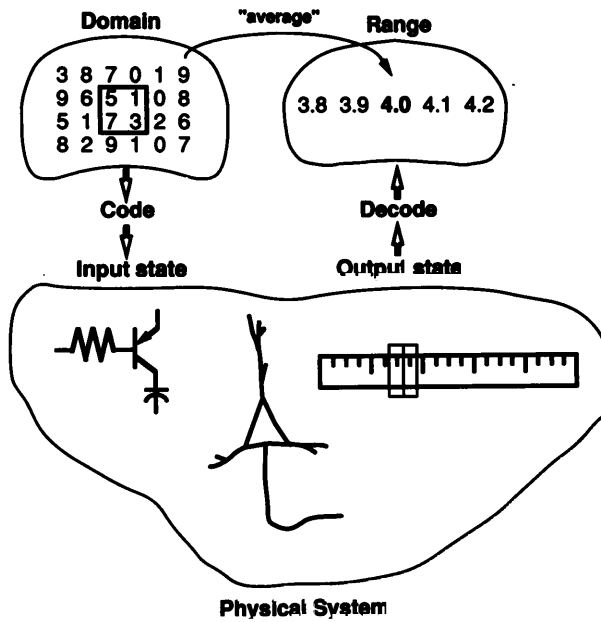


Figure 3.1 Mapping between a domain and a range can be accomplished by a variety of physical systems. There are three steps: (1) The input data is coded into a form appropriate for the physical system (electrical signal in an electrical circuit, chemical concentration in neuron, position of a slider in a slide rule). (2) The physical system shifts into a new state. (3) The output state of the physical system is decoded to produce the result of the mapping. The example shown here is the "average" map that takes four values and produces their average. Such a mapping might be useful as part of a visual system. Mappings could also be made from the domain of temporal sequences, and the range could be a sequence of output values.

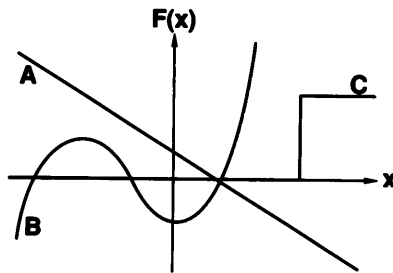


Figure 3.2 Examples of functions  $F(x)$ , plotted along the vertical axis, of one variable,  $x$ , plotted along the horizontal axis. Function  $A$  is a linear function. Function  $B$  is a nonlinear function. Function  $C$  is a discontinuous function.

described as “nonlinear,” what this means is that (a) the activity is characterized by a computable function, and (b) that function is nonlinear. Notice also that the space in which functions are plotted may be a two-dimensional space (the  $x$  and  $y$  axes), but it may, of course, have more than two dimensions (e.g., an  $x$  axis,  $y$  axis, and also  $w$ ,  $v$ ,  $z$ , etc. axes).

Because the notion of a *vector* simplifies discussion enormously, we introduce it here. A vector is just an ordered set of numbers. For example, the set of incomes for 1990 of three vice-presidents in a corporation can be represented by the vector  $\langle \$30, \$10, \$10 \rangle$ ; the eggs laid per week by five hens as  $\langle 4, 6, 1, 0, 7 \rangle$ ; the spiking frequency of four neurons/sec as  $\langle 10, 55, 44, 6 \rangle$ . By contrast, a scalar is a single value rather than a many-valued set. The *order* in the set matters when we want to operate on the values in the set according to an order-sensitive rule. Systems, including the nervous system, execute functions that perform vector-to-vector mapping. For example, from the stretch receptors’ values to the muscle contraction values, or from the head velocity values to eye velocity values.

A geometric articulation of these concepts compounds their value. Any coordinate system defines a state space, and the number of axes will be a function of the number of dimensions included. A state space is the set of all possible vectors. For example, a patient’s body temperature and diastolic blood pressure can be represented as a position in a 2-D state space. Or, if a network has three units, each unit may be considered to define an axis in a 3-D space. The activity of a unit at a time is a point along its axis, so that the global activation of all the units in the net is specified by a point in that 3-D space (figure 3.3). More generally, if a network has  $n$  units, then it defines an  $n$ -dimensional activation space, and an activation vector can be represented as a point in that state space. A sequence of vectors can be represented as a trajectory in the state space.<sup>4</sup> Thus the patient’s body temperature and blood pres-

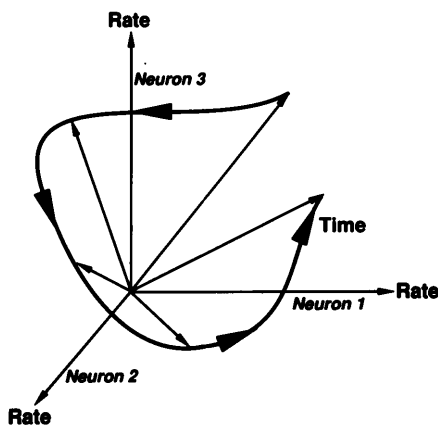


Figure 3.3 Schematic diagram of the trajectory of a three-neuron system through state space. The state of the system is a 3-D vector whose components are the firing rates of the three neurons. As the firing rates change with time, the tip of the vector traces out a trajectory (thick line). For more neurons the state space will have a higher dimension.

sure followed through time results in a trajectory in a 2-space. A function maps a point in one state space to a point in another state space—for example, from a point in stretch-receptor activation space to a point in muscle spindle activation space.

These notions—“vector” and “state space”—are part of linear algebra, and they are really the core of the mathematics needed to understand model networks. They are mercifully simple conceptually, and they are rather intuitively extendable from easily visualizable 2-D cases to very complex,  $n$ -D cases, where  $n$  may be thousands or millions. Although volumes more can be written on the topic of linear algebra, this is perhaps enough to ease the entry into the discussion of model neural networks.<sup>5</sup>

### **Computers, Pseudocomputers, and Cryptocomputers**

The mathematical interlude was intended to provide a common vocabulary so that we might return to the question of characterizing, albeit roughly, what about a physical system makes it a computer. To pick up the thread left hanging during the mathematical interlude, let us hypothesize that a physical system computes some function  $f$  when (1) there is a systematic mapping from states of the system onto the arguments and values of  $f$ , and (2) the sequence of intermediate states executes an algorithm for the function.<sup>6</sup> Informally, an algorithm is a finite, deterministic procedure, e.g., a recipe for making gingerbread or a rule for finding the square root.

We count something as a computer because, and only when, its inputs and outputs can usefully and systematically be interpreted as representing the ordered pairs of some function that interests us. Thus there are two components to this criterion: (1) the objective matter of what function(s) describe the behavior of the system, and (2) the subjective and practical matter of whether we care what the function is. This means that delimiting the class of computers is not a sheerly empirical matter, and hence that “computer” is not a natural kind, in the way that, for example, “electron” or “protein” or “mammal” is a natural kind. For categories that do delimit natural kinds, experiments are relevant in deciding whether an item really belongs to the category. Moreover, there are generalizations and laws (natural laws) about the items in the categories and there are theories interleaving the laws. Nonnatural kinds differ in all these respects, and typically have an interest-relative dimension.

“Bee,” for example, is a natural kind, but “gem” and “weed” are not. Objects are considered gems depending on whether some social group puts special value on them, typically as status symbols. Plants are considered weeds depending on whether gardeners (serious gardeners?) in the region happen to like having them in the garden. Some gardeners cultivate baby’s breath as a desirable plant; other gardeners fight it as a weed. There is no experiment that will determine whether baby’s breath is really a weed or not, because there is no fact of the matter—only social or idiosyncratic conventions.<sup>7</sup> Similarly, we suggest, there is no intrinsic property necessary and sufficient for all computers, just the interest-relative property that someone sees value in interpreting

a system's states as representing states of some other system, and the properties of the system support such an interpretation. Desk-top von Neumann machines exist precisely because we are keenly interested in the functions we build and program them to execute, so the interest-relative component is dyed in the wool. For this reason, and because these machines are so common, they are the prototypical computers, just as dandelions are prototypical weeds. These prototypes should not, however, be mistaken for the category itself.

It may be suggested as a criticism of this very general characterization of computation that it is *too* general. For in this very wide sense, even a sieve or a threshing machine could be considered a computer, since they sort their inputs into types, and if one wanted to spend the time at it, one could discover a function that describes the input–output behavior. While this observation is correct, it is not so much a criticism as an apt appreciation of the breadth of the notion. It is rather like a lawn-growing perfectionist incredulously pointing out that on our understanding of “weed,” even dandelions might be nonweeds relative to some clime and some tribe of growers. And so, indeed, they might be some farmer's cash crop. Nor is this idle fancy. Cultivated dandelion greens now appear as a delicacy in the specialty section of the greengrocery.

Conceivably, sieves and threshing machines could be construed as computers if anyone has reason to care about the specific function reflected in their input–output behavior, though it is hard to see what those reasons might be (figure 3.4). Unlike desktop computers that are engineered precisely for their computational prowess, sieves and threshing machines are constructed for other reasons, namely their sheerly mechanical prowess in the sorting of objects according to size and shape. Not too much emphasis should be placed on the link between purposeful design and use as a computer, however, for a fortuitously shaped rock can be used as a sundial. This is a truly simple computer-trouvé, but we do have reason to care about the temporal states that its shadow-casting states can be interpreted as representing.

There is perhaps a correct intuition behind the criticism nonetheless. Finding a device sufficiently interesting to warrant the description “computer” probably also entails that its input–output function is rather complex and inobvious, so that discovering the function reveals something important and perhaps unexpected about the real nature of the device and how it works. Thus finding out what is computed by a sieve is probably not very interesting and will not teach us much we did not already know. How a sieve works is dead simple. In contrast, finding out what is computed by the cerebellum will teach us a lot about the nature of the tissue and how it works.

A computer is a physical device with physical states and causal interactions resulting in transitions between those states. Basically, certain of its physical states are arranged such that they represent something, and its state transitions can be interpreted as computational operations on those representations. A slide rule is taken to compute—for example, (Mult 2, 7) to give 14 as the output—by dint of the fact that its physical regularities are set up in such a way as to honor the abstract regularities in the domain of numbers; the system of Aubrey holes at Stonehenge computes eclipses of the sun by dint of the fact

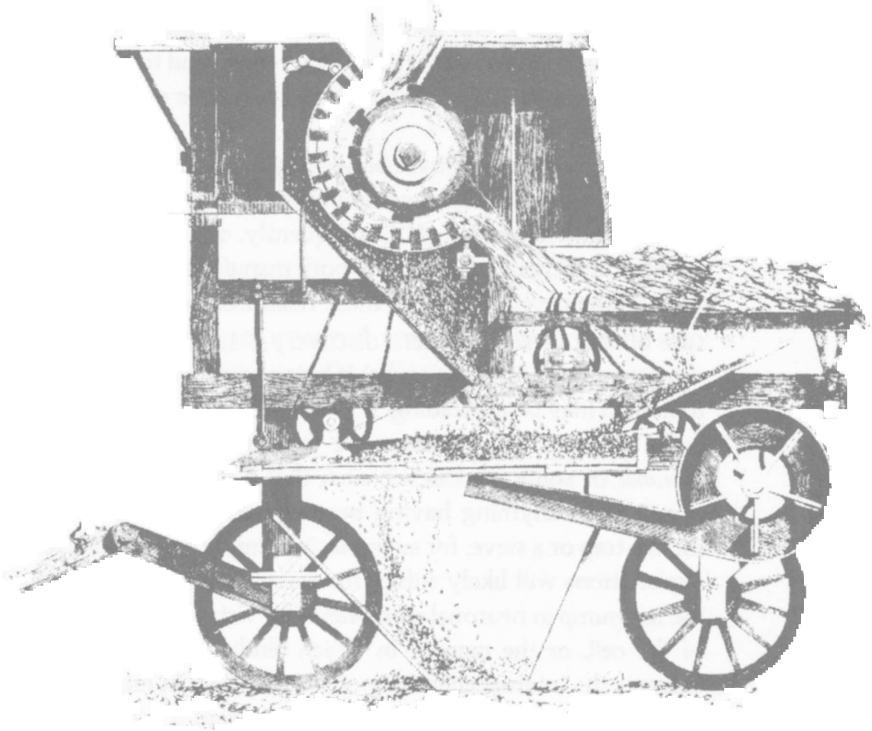


Figure 3.4 Garrett's improved threshing machine, 1851. The wheat was fed in from above, and the grain was removed by the rubbing action of the beater bars on the drum as it rotated inside the fixed concave. The grain fell onto a sieve below and the chaff was blown away by the fan system on the right. (From *The Illustrated Science and Invention Encyclopedia*. Westport, CT: H. S. Stuttman, 1983.)

that its physical organization and state transitions are set up so that the sun stone, moon stone, and nodal stone land in the same hole exactly when an eclipse of the sun occurs. Notice that this would be so even in the highly unlikely event that Stonehenge was the fortuitous product of landslides and flooding rather than human contrivance.

Nervous systems are also physical devices with causal interactions that constitute state transitions. Through slow evolution, rather than miraculous chance or intelligent design, they are configured so that their states *represent*—the external world, the body they inhabit, and in some instances, parts of the nervous system itself—and their physical state transitions execute computations. A circuit in mammalian brain stem evolved to compute the next position of the eyeball based on the angular velocity of the head. Briefly, the neuronal activity originating in the semicircular canals represents head velocity, and the interneurons, motor neurons and eyeball muscles are physically arranged such that for head velocity of a certain amount, the neurons causally interact so that the muscles of eyeball change tension by exactly the amount needed to compensate for the head movement. (For more on this circuit and its computation, see chapter 6). Loosely speaking, this organization evolved “for”



this task; a little more strictly speaking, this circuit came to be the way it is by random mutations and natural selection; in standard epigenetic circumstances and relative to the ancestor's nervous system and to the system's other components, this organization enhances somewhat the organism's chances of surviving and reproducing.

There is a major contrast between manufactured and biological computers. Since we construct digital computers ourselves, we build the appropriate relationship into their design. Consequently, we tend to take this mapping for granted in computers generally, both manufactured and evolved. But for structures in the nervous system, these relationships have to be discovered. In the case of biological computers, discovery may turn out to be very difficult since we typically do not know what is being computed by a structure, and intuitive folk ideas may be misleading.

By contrast with systems we conventionally call computers, the *modus operandi* of some devices are such that a purely causal explanation, without reference to anything having been computed or represented, will suffice. A mouse-trap or a sieve, for example, is a simple mechanical device. Purely causal explanations will likely suffice for some aspects of brain activity too, such as the ion pump in neuronal membranes by virtue of which sodium is pumped out of the cell, or the manner in which binding of neurochemicals to receptors changes the internal chemistry of the cell. Bear in mind, however, that even at this level, an ion, such as  $\text{Na}^+$ , *could* represent a variable like velocity. At this stage, no one is really convinced that this is in fact so, but the possibility is not ruled out simply because ions are very low-level entities. Effects at higher levels of organization appear to require explanations in terms of computations and representations. Here a purely causal story, even if the line is still fairly clean, would give only a very unsatisfying explanation. For example, a purely causal or mechanical explanation of the integration of signals by dendrites is unenlightening with respect to what information the cell is getting and what it does with it. We need to know what this interaction means in terms of what the patterns of activity represent and what the system is computing.

Consider, for example, the neurons in parietal cortex whose behavior can be explained as computing head-centered coordinates, taking positions of the stimulus on the retina and position of the eyeball in the head as input (Zipser and Andersen 1988). Knowing that some neurons have a response profile that causes other neurons to respond in a certain way may be useful, especially in testing the computational hypothesis, but on its own it does not tell us anything much about the role of those neurons in the animal's visual capacity. We need additionally to know what the various states of neurons represent, and how such representations can be transformed by neural interactions into other representations. At the network level, there are examples where the details of connectivity and physiology of the neurons in the network still leave many of the whys and wherefores dangling, while a computational approach that incorporates the physiological details may make contact with the broader brain-scape of tasks, solutions, environmental niche, and evolutionary history.<sup>8</sup>

There is a nonmathematical sense of “function,” according to which the job performed by something is said to be its function. In this sense, the heart is said to function as a pump, rather, than say as a noisemaker to soothe babies on their mother’s breast. Though making a “ka-thump” sound is something the heart does, and though babies appear to be soothed by it, this surely is not the heart’s *function*, meaning, roughly, its “primary job.” Functional assignments can reasonably be made in the context of evolutionary development, what the animal needs to survive and reproduce, its environmental niche, and what would make sense given the assignment of function to related structures. In this “job” sense of function, the function of some part of the nervous system is to compute some function (in the mathematical sense), such as position for the eyeball given head velocity.

There is nothing mystical about characterizing a biological structure as having a specific function, even though neither god nor man designed the structure with a purpose in mind.<sup>9</sup> The teleological trappings are only that, and the teleology is eliminable or reducible without remainder in an evolutionary framework. To assign a computational role to a circuit is to specify a job of that circuit—detecting head velocity, for example. Consequently, the considerations that bear on determining the job of an organ such as the liver bear also on the assignment of computational role to neuronal structures. That the nervous system evolved, and that maladaptive structures tend to be weeded out in the evolutionary contest, restricts many functional hypotheses—in both senses of “functional”—that are logically possible but just not biologically reasonable. The crux of the matter is that many biologically irrelevant computational hypotheses can be culled out by a general functional truth about nervous systems, namely that *inter alia* they serve to help the animal move adaptively in the world.<sup>10</sup>

In this chapter we shall characterize a range of computational principles that may be useful when addressing the question of computation in nervous systems. As we shall see, moreover, the computational perspective will allow us to ask questions of biological systems that might not otherwise have been asked. The computational principles introduced here will be applied first to a number of examples chosen for their pedagogical value rather than for immediate biological salience. They allow us to introduce the basic ideas in a simple fashion, and this is their single, overriding virtue. They are not meant to be hypotheses concerning the mechanisms underlying the computational properties of real nervous systems. In chapters 4 to 6 neurobiological realism will be of paramount concern, but an understanding of the basic concepts is the entry ticket to these chapters.

## 2 LOOKING UP THE ANSWER

Conceptually, the simplest computational principle is “look up the answer.” A look-up table is simply some physical arrangement in which answers to specific questions are stored. The engineering trick is to rig the table so that access to answers is fast and efficient, for if it is slow and clumsy, calculating the answers

*de novo* might be preferable. Inasmuch as look-up tables are really repositories of precomputed answers rather than devices for working out the answer on the spot, it may be suggested that they are not genuine computers at all. For the purist, however, accepting this semantic refinement promotes confusion. A look-up table does after all effect a mapping, it instantiates a rule, and its states represent various things. That, given our groundfloor criteria, qualifies it as a computer. Call it unglamorous, call it humdrum, but a look-up table embedded in a mechanism for delivering answers can as properly be called a computer.

The easiest way to think of a look-up table is simply as an array of boxes each of which says, in effect, "if  $x$  is your problem, then  $y$  is your answer," for specific  $x$  and  $y$ . In other words, it does a matching job. For example, the truth table for exclusive "or" looks like this:

P	Q	XOR
T	T	F
T	F	T
F	T	T
F	F	F

This mode of representing the truth conditions happens to be very convenient, though many other, less convenient arrangements are easily imagined. And as students are usually told, it requires no significant intelligence to use this look-up table: just ask your question (e.g., what is the value when  $P$  is true and  $Q$  is false?), go to that row, and scan the answer.

A second but more powerful look-up table is the slide rule. Actually it is a multiplexed look-up table, since it stores answers not only for multiplication tasks, but also for finding sines, cosines and logarithms. When the task is multiplication, one enters the question (what is  $3 \times 7$ ?) by sliding the center piece and cursor, and scanning the answer at the cursor. Moreover, while the truth table can handle only discrete functions, a slide rule can do continuous functions. To accommodate the variety of arithmetic questions and answers on two pieces of wood, the look-up table is metrically deformed (figure 3.5). As before, there are other ways of physically structuring a look-up table to perform exactly these tasks, but the flat, pocketable slide rule is in fact a wonderfully convenient and efficient way to do so.

Extending the idea a bit further, consider the Tinkertoy look-up table constructed in 1975 by a group of MIT undergraduates to play the game of tic-tac-toe<sup>11</sup> (figure 3.6). Making the "table" part of this device consists in storing a set of ordered pairs, where the first element is a possible game position, and the second element is the correct move, given that game position. In operating, the machine looks for a match between its current position and one of the possible positions sitting in storage. Finding the match will automatically divulge what to do next.

The first step in building the Tinkertoy look-up table was to decide on a representation for the state of the board using just the resources of Tinkertoy pieces. The second step was to use rotation and reflection symmetries to reduce the total number of game positions in the table, since the more entries



Figure 3.5 The object in the center is an oversized slide rule. The authors are on either side.

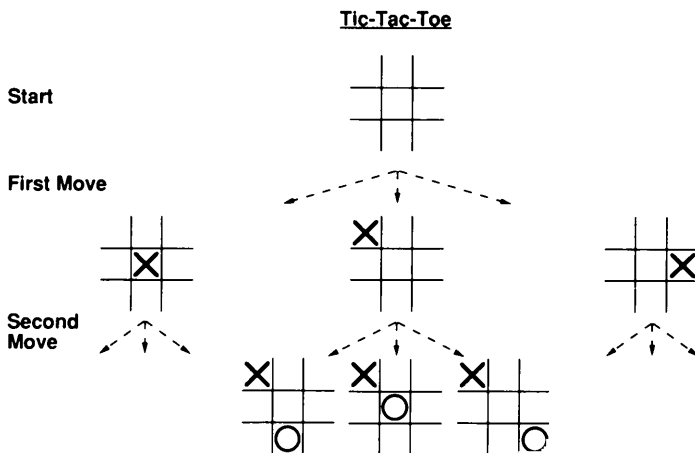


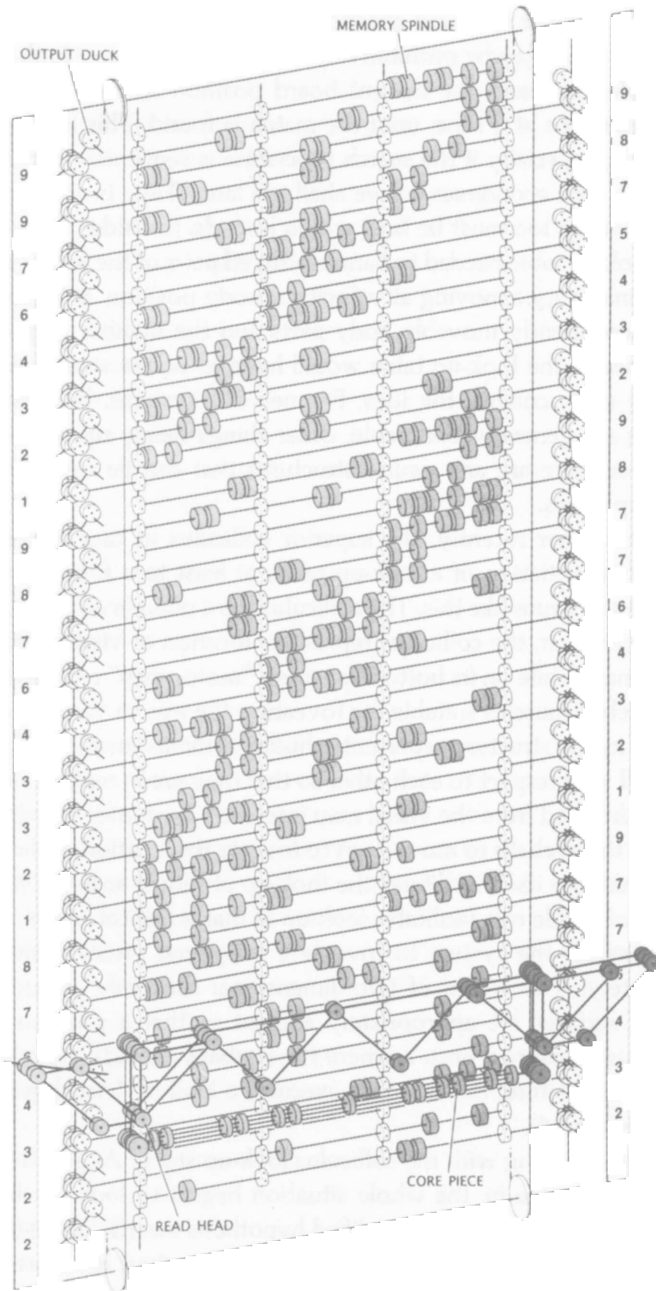
Figure 3.6 The first three levels of the game tree for tic-tac-toe. The  $3 \times 3$  board at starting position is in the center, and the first move must be in one of three board positions (arrows) irreducible by mirror and reflection symmetries. The next level gives several possible replies by the opponent.

the larger the storage and the longer the time to search for a match. Thus a board with nothing but an X (or an O) in the upper right corner can be dealt with in the same way as a board with nothing but an X (or an O) in any of the other corners, and this consequently reduces the number of stored first positions by six, a substantial savings. These economies are important in reducing the number of entries in the look-up table to a manageable number—in this case from 300,000 to 48. The next step was to design a mechanical system that could match a position on the board with one of the 48 irreducible positions, and to retrieve the correct move (figure 3.7).

Although the tic-tac-toe example may at first seem frivolous, it clearly illustrates a number of points relevant to computational neuroscience. First, look-up tables can be constructed from unorthodox materials but still come up with the same answer as do conventional electronic circuits. Second, the Tinkertoy computer is not a general-purpose computer; rather, it was built to solve one specific problem. So far as nervous systems are concerned, the analogy is that the genes probably wire up some neural circuits on the look-up table blueprint with the consequence that the animal is prepared at birth to do such things as snuffle around for a warm spot and then suck at whatever soft, mouth-sized thing sticks out. Circuits that yield sucking behavior in rats are probably not general-purpose devices, but are dedicated more or less exclusively to sucking.

The theoretical lesson is that if a problem is conceptually reducible to a look-up table problem, then, cost and efficiency aside, it could in principle be implemented by look-up table mechanisms. Cost is rarely irrelevant, however. It is especially pertinent here, since precomputing the answers for each problem requires a substantial, and sometimes exorbitant, investment in the construction of the machine. From an evolutionary point of view, it might be too costly or too difficult to precompute certain tasks, such as semantics or place-in-the-social-scheme or dinner-whereabouts, and hence many things must be learned by the infant organism.

How practical really is the look-up table approach? The answer depends on a number of factors, including the complexity of the problem to be solved, the architectural pliancy of the available materials, and the size limits of the look-up table. Chess, unlike tic-tac-toe, appears to be a poor candidate for the look-up table solution. There are approximately  $10^{40}$  game positions—far more than the capacity of any existing machine.<sup>12</sup> The complexity factor can be reduced considerably using the economy described above; namely, take advantage of the underlying symmetries and position similarities in the problem to reduce the number of entries. Given this possibility, it remains to be seen whether the look-up strategy is indeed utterly unrealistic for chess. For many real-world problems, as in the problem of visually recognizing an object, advantage can be taken of translation, rotation, and scaling invariances, as well as smoothness and continuity constraints, to reduce the number of stored categories. The possibility to consider is that look-up craftsmanship may be seen at various stages in nervous system processing, even if it is not ubiquitous.



**Figure 3.7** Tinkertoy computer for playing the game of tic-tac-toe. Each memory spindle encodes a possible game position, along with the optimal response. The read head, loaded with the current game position in the core piece, moves down the memory spindles, one by one, until there is a match. This activates the output duck, which drives the correct move. Compare this special-purpose computer with the general mapping scheme in figure 3.1. (From Dewdney [1989] *Computer recreations: a Tinkertoy computer that plays tic-tac-toe*. Copyright © 1989 *Scientific American*.)

If the number of stored question–answer pairs is large, then the search-for-a-match time may be prohibitively long. The Tinkertoy look-up machine, for example, compares the current board position to each of the stored board positions, one at a time, until the match is found. This is a rather ponderous business, especially if the search procedure is sequential. Parallel search could provide time economies, as we shall see later. Time is not the only consideration; wiring too must be kept within bounds. Consider, for example, the size of a look-up table needed to handle ordered pairs of the form  $\langle \text{edible goodie at coordinates } x, y, z \text{ moving at velocity } v / \text{body position } \neq \rangle$ . Given the number of independently movable body parts and the number of possible locations and speeds, the look-up table would have to be massive, at a minimum. The wiring cost scotches the idea. For nervous systems, brief times and sparse wiring are generally preferable, other things being equal, so the question is whether there are any neural structures that can be usefully understood as look-up tables.

Until rather recently, the superior colliculus in cats suggested itself as a neural instantiation of a look-up table, at least to a first approximation. The simple story runs like this. The colliculus has a number of layers, or laminae. On its upper layer, the colliculus represents location of visual stimuli on a retinotopic map, while on its bottom layer is a “motor map” representing position of the eyeball muscles suitable for foveating the eye to various locations. Other layers in the structure represent whisker-stimulus location. The maps are deformed with respect to each other so that they are in register. The effect is that a line dropped from the visual map intersects the motor map in a location that causes the eyeballs to move so as to foveate the location of the visual stimulus. The anatomy itself facilitates the look-up of motor answers, just as the “anatomy” of a slide rule facilitates look-up of mathematical answers. The organization enables the system to foveate a peripheral visual stimulus quickly and accurately. It is a kind of two-dimensional slide rule, where the visual and motor surfaces are appropriately aligned so that a position of a peripheral stimulus is mapped onto a where-the-eyeballs-should-be position. According to this conjecture, the anatomy executes a kind of “visual grasp” transformation (figure 3.8).

What is wrong with the colliculus look-up story? As so often in biology, as more data come in, the whole situation begins to look much more complex than the unencumbered, unqualified hypothesis asserts. To begin with, the relation between the visual input and the motor output is not as straightforward as simple “visual grasp”; there are descending fibers from the cortex that affect collicular output, and attentional processes play an important if poorly understood role in collicular function. Although there do exist ostensible “drop line” connections between mapped layers, it is not yet known exactly what these connections do. In particular, the long time delay between the signal entering the sensory layer and a signal reaching the lower motor layer undermines the hypothesis that these connections straightforwardly execute “visual grasp.” So withal, the colliculus cannot be taken as an unproblematic case of a neural look-up table.

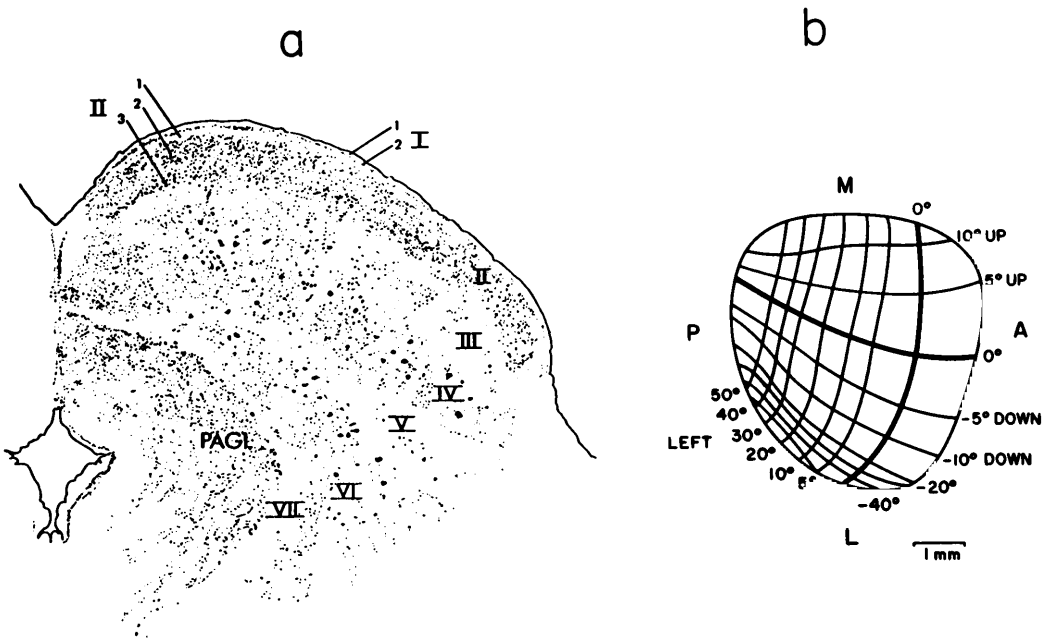


Figure 3.8 Organization of the cat superior colliculus. (a) Cross section through the colliculus showing cell bodies of neurons in each lamina (numbered). (b) Map of the eye movements produced by stimulating the deep layers of the colliculus with an electrode. The coordinates refer to the deviation of the eye from its center of gaze that is produced by electrical stimulation. M, medial; L, lateral; A, anterior; P, posterior (Adapted from Schiller 1984.)

The example is instructive nonetheless, for the discrepancies between the pure look-up configuration and the complicated anatomy and physiology of the colliculus suggest that it well behooves evolution to fancy up a true-blue look-up table into something that can do rather more complicated things. Consider first that the colliculus needs also to take head position into account, since the eyes move relative to the head, and hence relative to the ears and the whiskers. In addition to its “in register” drop lines, the system may find it can make good use of connections to other areas of the map, and to the whisker and ear-position maps interleaved in the neural stack, noting that whiskers and ears too can move relative to the head (in some mammals) but with their proprietary degrees of freedom. But if the colliculus takes these other matters into account, pure look-up conforming to the slide-rule style is not what is going on. Were the eyes stuck fast in the head, and were “foveation” to whisker and auditory stimuli absent, the colliculus might approximate more closely a look-up table. As it is, the complexities of the colliculus suggest that even if evolution had fashioned a pure look-up table, it would soon evolve to master these complex and interrelated operations. That is, neurons would have to perform additional computational steps between input and output.

To return to the matter of computer design, one means for reducing storage space consists in allowing the structures doing the transformations to adjust



themselves to existing conditions. Thrift bids the system to store only vectors (game positions) it actually uses rather than all possible vectors, and this requires that the system learn which vectors these are. What is the cost of this flexibility? If the system is to adapt, the adaptation should be in the *correct* direction. Alas, we cannot very well have a look-up table for the question “is my modification in the right direction?” without going hog-wild over the space limitations. So adaptation pulls the system even further away from the slide-rule paradigm.

But if nervous systems are not using pure look-up tables, what are they doing? The fast answer, to which the rest of the book is an extended elaboration, is this: they are computing with nets. As we shall see later in this chapter, neural nets may have certain properties akin to look-up tables. Consequently, this look-up table prologue is not merely a “first-we-crawl!” exercise, but a foundation that will help us understand what actual neural nets are doing. Before moving to a discussion of how nets compute, one further preliminary point must be laid on the board.

Might a close but imperfect match sometimes suffice? For many tasks, especially recognition and categorization tasks, the answer is “yes, close is close enough.” Accordingly, an additional modification to the true-blue look-up table consists in storing not every possible entry, but rather storing prototypes or exemplars of the categories. With this stratagem, we trade off a degree of precision for a saving of space, but the system must now take some computational steps to determine similarity to stored vectors. Eventually we shall want a net that avails itself of both economies: it stores prototypes, and it has the plasticity to learn prototypes.

To embody prototypes in a computer, related items are clustered near or less near to an exemplar, according to their degree of similarity. Items stored in this manner define a similarity space in the machine, and distance from the prototype defines a similarity metric. This is known as a *nearest-neighbor* configuration, and there are many possible architectures for realizing it and many possible ways to style nearest-neighbor algorithms to exploit the organization for computational purposes. If a conventional digital machine is chosen for the implementation, then the machine will have to be spatially prodigal to accomplish complex tasks, for it has to store all the entries, make the distance measures, find the match, and deliver the answer. Clever ways to store data in hierarchical trees have been devised, but even these bog down when the going gets realistic. This gloomy prospectus may be sufficiently discouraging to downgrade the look-up idea to nothing more than a charming curiosity, rather like an ornithopter<sup>13</sup>—conceivable perhaps, but practical, probably not. On the other hand, though a digital machine may be impractical in this sphere, there is an architecturally very simple organization that will do the job, and do it cheaply, efficiently, and in satisfyingly few steps. That is a net. In the next several sections, we shall look at a number of types of networks, starting with very simple examples and moving on to networks of greater power and sophistication.

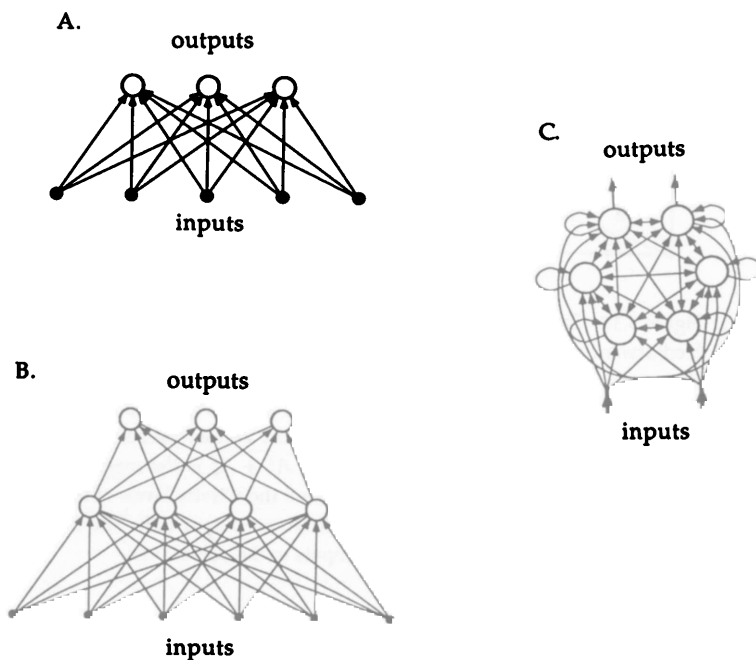


Figure 3.9 Three types of networks. (A) Feedforward network with one layer of weights connecting the input units to the output units. (B) Feedforward network with two layers of weights and one layer of hidden units between the input and the output units. (C) Recurrent network with reciprocal connections between units. (Adapted from Hertz et al. 1991.)

### 3 LINEAR ASSOCIATORS

What is a net? The architecture of the canonical net consists of units, loosely based on neurons, connections (generously speaking, axons) between the units, and weights (generously speaking, synapses) on the connections (figure 3.9). Some units receive external input, some deliver the output, and some may do neither. Because there is more than one input unit and more than one output unit, the ingoing and outgoing representations are vectors, meaning ordered sets of values (e.g.,  $\langle 3.2, 668.9, 0 \rangle$ ) rather than single values (scalars, e.g., 668.9). Signals with various magnitudes are passed between units. That is the nub of a net. How can a net compute anything? The abstract explanation is reassuringly simple: the weights on the units are set in such a way that when the input units are given certain values, the output units are activated appropriately. This means that a mapping is achieved and hence that a function is executed. Now to follow the recipe for making a net in a concrete case, we have to decide how to set the weights, whether they are modifiable and if so how, what range of activity values a unit may take and how they are determined, how to represent the input vectors, and the nature of the connectivity between units (network topology). Obviously this means that the canonical description carves out a vast area of computational space, within which specific nets occupy small regions. The canonical description thus stands to a running

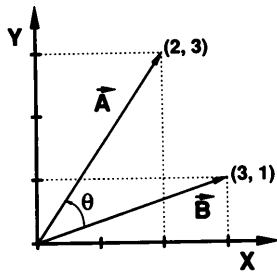


Figure 3.10 Computing the inner product between two vectors is a fundamental operation in a feedforward associative network. The example given here is for two-dimensional vectors, but the same relationships apply to vectors with more components. The inner product is defined as  $A \cdot B = A_x B_x + A_y B_y = 2 \times 3 + 3 \times 1 = 9$ , where  $A_x$  is the x component and  $A_y$  is the y component of vector A. The angle  $\theta$  between the vectors can be computed from the relationship  $\cos \theta = (A \cdot B) / (\|A\| \cdot \|B\|)$ , where  $\|A\| = \sqrt{A_x^2 + A_y^2}$  is the magnitude of A. In the network shown in figure 3.9a, vector A might represent the activity levels of the input units and vector B could be the weights from the input units to an output unit. The inner product can then be interpreted as the sum of the weighted inputs to the output unit.

neural network model like a dictionary definition of an airplane stands to a veritable machine itself.

In the 1970s, more or less independently, a number of people were developing associative nets, including Leon Cooper, James Anderson, Teuvo Kohonen, Gunther Palm, Christopher Longuet-Higgins, and David Willshaw.<sup>14</sup> How do associative nets work? In a nutshell, they associate an input vector with an output vector, essentially following the “parallel architecture/similarity-measure/look-up table” format outlined above. The key mathematical task that networks can perform is computing inner products; that is, taking two vectors and multiplying them component by component and then adding up the products. So if one vector represents the input from a set of units and the other vector is a stored prototype, then the inner product yields a measure of the overlap between them, and hence of their similarity. Geometrically, the inner product is proportional to the cosine of the angle between the vectors, so when there is perfect congruence of the vectors, the angle would be zero (figure 3.10). This is a readily manipulable measure of vector similarity. How are the vectors (prototypes) stored? They are stored in the weights connecting the input units to an individual output unit. This means that each component in the prototype vector is assigned to one weight, and these weights are attached to a summing unit, which adds up all the products of these two vectors (weight vector and input vector). This summing unit is the output unit.

In the garden variety network, the output of the summing unit is proportional to the sum of the products. The output therefore is a linear transformation of the input, and the network is called a *linear associator*. For example, for a small network with three input lines and three output units, there are nine possible weights, which can be written as an array of numbers. One such  $3 \times 3$  weight matrix is:

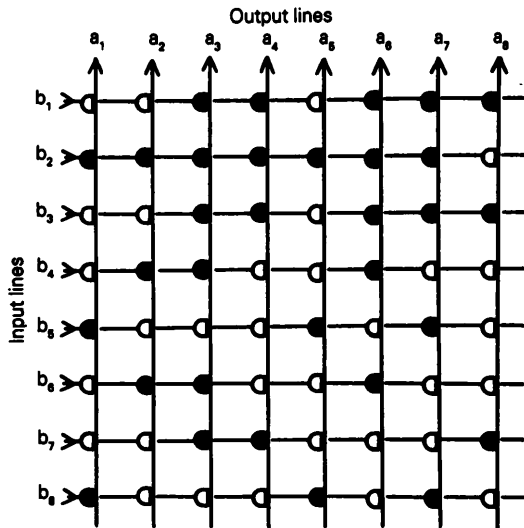


Figure 3.11 A Willshaw net showing the input lines (horizontal), the output lines (vertical), and the connections between them. The weights on the connections are binary and can be zero (open circles) or one (closed circles). Thus, the picture is a graphical representation of the weight matrix. (From Willshaw, 1989.)

$$w_{ij} = \begin{bmatrix} 0 & -1 & 2 \\ 1 & 0 & 1 \\ 2 & -1 & 0 \end{bmatrix}$$

The components of the output vector of the network are given by:

$$y_i = \sum_j w_{ij}x_j \tag{1}$$

For the input vector  $x_i = (1, 1, 1)$ , the output vector is given by  $y_i = (1, 2, 1)$ . For the input vector  $x_i = (1, 2, 3)$ , the output vector is given by  $y_i = (4, 4, 0)$ . (Multiply the first component of the vector by the first item in the top row [ $1 \times 0$ ], the second component by the second item in the top row [ $2 \times -1$ ], the third by the third [ $3 \times 2$ ]. Add the products [ $= 4$ ]. Repeat for each row.)

As you would expect, there are many variations on the simple linear associator theme, and changes are rung on whether the input and output units take on continuous or binary values, and whether the weights are continuous or binary (figure 3.11). Notice that many inner products can be computed in parallel, one for each summing unit, and the more the summing units, the bigger the net. Additionally, each of the products (weights  $\times$  inputs) can be computed in parallel. The result is that only one step is required to produce an output vector that is associated with the input vector. What is described here is the paradigmatic net for matching a sample to a stored prototype. This is evidently a classification task: for each category a representative example must be provided, and this is encoded as a vector. As a rule, the less overlap between the prototype vectors the better, since it is preferable that an input unambiguously match a prototype.

The explanation so far shows how to get a mapping from input to output, but it has not addressed how to set the values of the weights in order to get the *correct* mapping from input to output—to get the net to give the correct answer when it is asked a question. This is obviously of the essence if the net is to be of any use. The method by which the prototype vector is encoded matters enormously to the success and efficiency of the net, and different coding strategies will variously ease or gum up the operations. It is not in general known how to go about organizing the preprocessing for nervous system tasks such as vision and speech recognition, but some information is available for simpler processes such as visual tracking during head movement (chapter 6). As we discuss later, if one wants to get some insight into the characteristics of the preprocessing for good matching of input to stored vectors, then the brain will be a valuable source of ideas. The general point about preprocessing is this: at the level of sensory input, the vectors can look very different because there are many possible patterns of, say, a dog. The preprocessing has to be done in a such a way that if the many different patterns all trigger the output vector “dog,” they must be mapped onto the weights so this happens. In other words, the system needs a many:1 mapping. Exactly how to set this up varies from case to case, and more discussion of this topic follows.

A slight modification of the paradigm net yields a network that performs *autoassociative content-addressable memory*. This means that the net can produce an output that is as close as possible to a prestored vector given only part of the vector as input. This is a vector completion task, in other words. To do this, you need as many output units as input units, so that the weight matrix is square. The weights  $w_{ij}$  from unit  $j$  to unit  $i$  are constructed from an outer product of the stored vectors

$$w_{ij} = \sum_{\alpha} x_i^{\alpha} x_j^{\alpha} \quad (2)$$

where  $x_i^{\alpha}$  is the  $i$ th component of the  $\alpha$ -th stored vector. For example, if one of the stored vectors is (1, 5, 2), then its contribution to the square weight matrix is

$$w_{ij} = \begin{bmatrix} 1 & 5 & 2 \\ 5 & 25 & 10 \\ 2 & 10 & 4 \end{bmatrix}$$

These input vectors could be presented to the network one at a time, and the weights could be computed incrementally by adding each contribution to produce the sum. This is perhaps the simplest and best known of all learning rules, the Hebb rule, so-called because it reflects Hebb’s hunch that connection weights between two units should strengthen as a function of the correlated activity of the connected units. Note that the weight is built up from the product of input activities and desired output activities.

The Hebb rule is loosely speaking a “get-similar” rule. It says, “Make the output vector the same as the one you saw before which it most closely resembles.” Consider what will happen, then, when an incomplete or noisy version of an input vector  $x_i$  is presented to the network with a weight matrix

configured according to eq. (2). If we substitute the weights in eq. (2) into eq. (1), then the output can be rewritten as:

$$y_i = \sum_{\alpha} x_i^{\alpha} \left[ \sum_j (x_j^{\alpha} x_j) \right] \quad (3)$$

Roughly speaking, this means the output vector is composed from a linear combination of the stored vectors,  $x_i^{\alpha}$ , where each vector is weighted by the term in the square brackets, representing the inner product, or overlap, between the input vector and the stored vector. In the *auto*associative network the desired output vector is the closest stored input vector; at best, the output vector will be identical to the stored input vector. Such a network can perform vector completion or vector correction, but it cannot associate two different vectors. The basic *auto*associative net can be modified quite simply to handle *hetero*associations. Whereas the *auto*associative net stored the outer product of  $(x_i^{\alpha}, x_j^{\alpha})$ , the *hetero*associative net needs to store the outer product of two nonidentical vectors,  $(z_i^{\alpha}, x_j^{\alpha})$ . Once trained, the *hetero*associative network will produce an output proportional to  $z_i^{\alpha}$ , when  $x_j^{\alpha}$  is present in the input vector.

What happens if the noisy vector matches more than one stored vector? Then the output will be a weighted sum of the stored vectors (i.e., ambiguous inputs will produce hybrids of the nearest matching vectors). As more and more vectors are stored according to the Hebb rule, there will be more and more ambiguities and the performance of the network will correspondingly degrade. Indeed, an important fact about all such matrix associators is that they work very well so long as only a small number of patterns are stored, but their capacity is limited and they do get filled up surprisingly quickly. To meet this storage room problem, modifications of the Hebb rule have been proposed that increase a little the capacity of the network.

The first strategy is to use only a small subset of units to represent any given item. This is also known as making the vectors sparse (Willshaw 1981). If there are  $n$  units, Willshaw found that optimal storage occurred when  $\log n$  units are used to represent each item. The advantage of making the vectors sparse is that there is less overlap between representations, and hence a given network can store a greater number of representations.<sup>15</sup>

A second way to economize on space is to normalize the incoming activation by inhibitory connections, assuming that all the input connections are excitatory. In a Hebb network, the number of synapses that are most highly enhanced by an input vector is proportional to the square of the number of units that the input activates. It follows that by going to a sparse representation, the number of units activated by any given pattern is reduced. Feedforward inhibition achieves this by normalizing the total activity so that all input patterns produce, on average, equal excitation. This achieves an economy because it prevents a single, highly active input vector from hogging the synapses.

A third way to increase the capacity of the network is to introduce a non-linear threshold for the output units. This means that should the summed inputs fail to reach a prescribed value, then there is no output. Thus only the

most strongly activated units produce an output. A sort of cleaning out of marginal activity is thereby achieved, making room for business that counts. While housecleaning is not to be scoffed at, what turns out to be really progressive about adding nonlinearity is that it makes the net far more powerful, permitting it to perform computations much more complex than anything a linear net can handle. In other words, a whole panoply of computable functions hitherto impossible for the net becomes within its range. Nonlinearity in the response functions of the units is the next development in the evolution of invented nets.

#### 4 CONSTRAINT SATISFACTION: HOPFIELD NETWORKS AND BOLTZMANN MACHINES

What sorts of problems demand a net with nonlinear properties? Consider the problem of recognizing an object in a visual image. The object may be in an unusual perspective, it may be partially occluded in a cluttered scene, lighting conditions may be poor, or the object may be an individual that has never been seen before. One of the first steps in visual processing separates the object from the surrounding clutter. This segregation of figure from ground has important consequences for the interpretation of an object in an image, as illustrated in figure 3.12 showing the classical vase/face reversal. Depending on which part of the image is considered the figure and which the ground, the silhouette can be interpreted as either as a vase or as two faces in profile. This also illustrates an important feature of how the visual system deals with ambiguity, namely that only one of the interpretations can be perceived at any given time. Furthermore, one can flip between the two interpretations by shifting attention. Note that this shift need not be an overt shift in gaze, but rather an internal attentional shift that at least sometimes is under conscious control. Could figure-ground segmentation be performed by a look-up table?

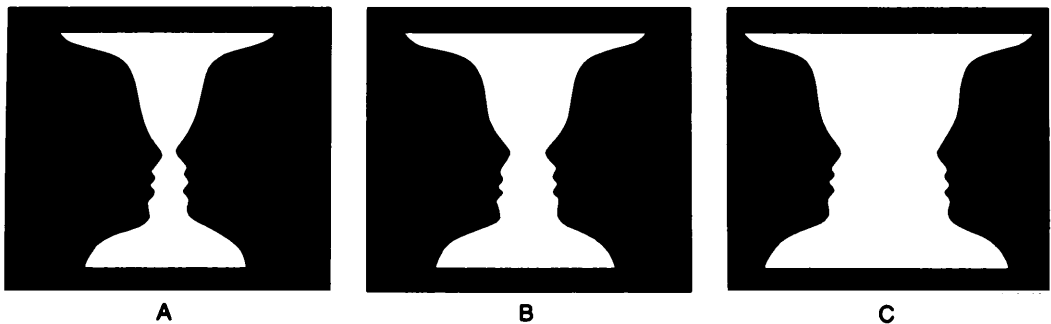


Figure 3.12 Figure-ground reversal. There are two perceptual interpretations of these images: a pair of black faces, or a white vase. The perceptual interpretation can be influenced by conscious attention and biased by features in the image. Thus, the faces interpretation is usually favored in A and the vase interpretation is favored in C. One interpretation appears to exclude the other (try to imagine a face “kissing” a vase). (With permission from Coren and Ward [1989]. *Sensation and Perception*, 3rd ed. Copyright © 1989 Harcourt Brace Jovanovich, Inc.)

The main reason to think it could not is that the solution requires the system to have a global perspective even though it does not have a "global unit." For example, the transitions between the face and the vase interpretations seem to occur coherently over the entire image. This evidently betokens a global computation, but the difficulty is that in the early stages of processing, single neurons respond only to local regions of the image. That is, early processing is local processing. The puzzle, therefore, is this: how are these local measurements integrated into a globally consistent interpretation? This type of computational problem involves the mutual satisfaction of many partial constraints, and they must be satisfied not serially, for that would lead to impossible "solutions," but simultaneously, so that a globally coherent solution is found. Consider, for example, a corner of the object. Local analysis may indicate two contiguous regions but the relationship between these two regions and regions in another corner of the object depend on constraints that link overlapping patches between these regions. Constraints such as continuity of objects and three-dimensional geometry of objects often must be incorporated into the computation to arrive at a consistent global interpretation (Ballard et al. 1983).

The Gestalt psychologists identified a number of the principles and constraints governing the interpretive process. "Gestalts" were taken to be global organizations that emerged from multiple interactions between features in an image. For example, in figure 3.13 lines that converge are seen as receding in depth. Despite identifying some of the constraints governing global interpretation, Gestalt psychologists were unable to produce a convincing mechanism for applying the constraints and resolving conflicts between constraints in achieving a consistent interpretation of the image. One of the factors that makes this a difficult problem is that the number of possible interpretations explodes combinatorially. Accordingly, a one-shot look-up table would have to have an impossibly large number of entries to accommodate all possible shapes. So for this kind of task, at least, the true-blue look-up strategy is inadequate.

In this section we shall describe a new type of computational principle that can accomplish the constraint satisfaction by a process of "relaxation." Rather than looking up a precomputed answer, a parallel system of processing

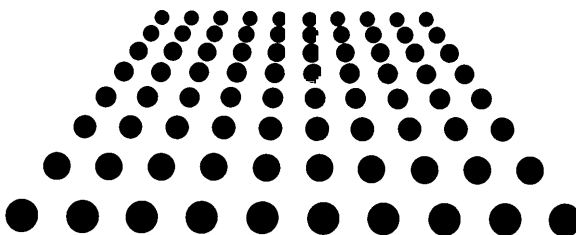


Figure 3.13 This two-dimensional array of dots evokes a strong sense of depth. Information about depth is provided by perspective (converging lines of dots) and texture (change in dot size). (From Gregory [1970]. *The Intelligent Eye*. New York: McGraw-Hill.)



units converges through local interactions to the correct global interpretation. As suggested earlier in discussion of the superior colliculus, however, this does not mean that a look-up configuration would exclude constraint satisfaction processes—there may be ways of merging the two. In addition, there is a natural way to incorporate top-down constraints from stored knowledge into the bottom-up flow of sensory data (see Chapter 5).

The linear associators described in section 3 have a feedforward topology; i.e., the information flows from input units through to output units. To do constraint satisfaction in a network, however, the topology has to be changed. In particular, it has to be changed to allow information to circulate among the output units so that the units can arrive at a mutually consistent answer. This means feedback. Feedforward nets are like a hierarchical assembly line: the basic components are made and passed on, the stage 2 components are assembled, then the stage 3 assembly is done, and the widgets pop out the delivery chute. In a feedback arrangement where there is communication between agents, there can be cross talk and plan revision, intermediate decisions can be tendered, and a mutually agreeable solution can be found. The nets featured in this section will have two new properties: feedback and nonlinearity (figure 3.14).

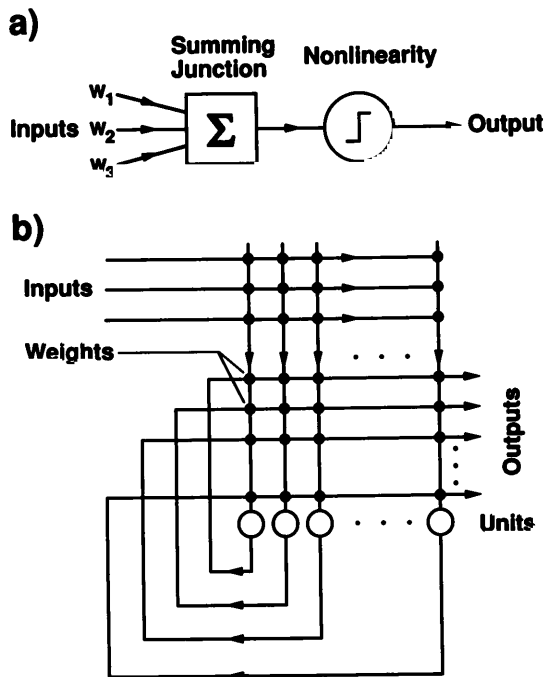


Figure 3.14 Nonlinear feedback network. (a) Each processing unit performs a nonlinear operation on the linearly weighted sum of its inputs. (b) Diagram of recurrent network. Each unit receives inputs from outside the network and feedback connections from other units in the network. Each intersection of a horizontal line with a vertical line (large filled dot) represents a weight.

Networks with feedback connections can have a wide range of dynamics, including oscillating solutions and chaotic behavior. Two difficult questions must be confronted in building nets to solve constraint satisfaction problems: (1) how can the weights be adjusted bit by bit to embody the task constraints? And (2), if the net is left to run, will it find a stable configuration that represents the desired solution? Both questions grow alarmingly complex in the case of nonlinear nets with feedback.

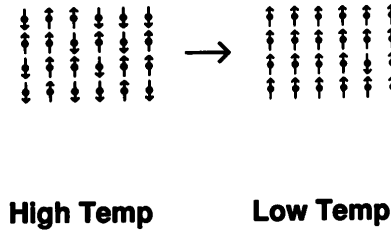
Nets, in contrast to digital computers running programs, are set running without any specification of intermediate steps. Rather, one relies on the dynamics of the net to take it to a stable state. Consequently, whether the net is a successful net depends on whether the dynamics of the units' interactions allow it to converge on the solution. But, and here is the kicker, how can one know whether it is a successful net—maybe its failure to converge so far just means it has a long and drawn-out “settling” schedule. The trouble is that the nature of the interactions between representations in nets displays no obvious orderliness, and in the early days of nets, a theory to explain and predict their behavior was essentially nonexistent. In 1982, John Hopfield showed, for a particular class of feedback networks, that their dynamics is such that convergence to a solution could be proved.<sup>16</sup> Additionally, his insights opened a line of research that eventually led to powerful solutions to the problem of how to adjust weights in a feedback net.

Hopfield's results were actually very surprising because he applied the tools and techniques of theoretical physics to the ostensibly different business of computation by nets. Hopfield's question was this: might the interactions between representations in nets that end up delivering an answer to a question be described by the same laws that describe the behavior of certain systems in physics? “Not likely” seems the first-blush answer, since there is no intuitively obvious reason to suspect that the regularities of *computational* interaction and regularities of *physical* interaction should be even formally similar. Hopfield's hunch, however, was reverse. If he was right, then network models, or at least one class of them, would be gifted with a whole parcel of powerful theory for free. Some order in the confusion might then be forthcoming.

Most physical systems do not recommend themselves as displaying behavioral regularities suitable to the computational context. To have properties analogous to computational states of a net, a system needs a richness of states comparable to that of a net. The prototypical model of a magnetic substance is a well-behaved lattice in which particles interact rather straightforwardly with their neighbors so that at a low temperature all the particles are spinning up or all are spinning down. In other words, local interactions between particles lead easily to a single global “solution.” A consequence is that a given lattice can only store one bit of information, and indeed this is the principle exploited by core memories in early digital computers. The simple lattices are, however, a poor analogy for how a network might store information, precisely because they lack a rich range of stable states.

It turns out that spin glasses are an unusual kind of substance that do have a suggestive richness, and it was from spin glasses that Hopfield drew his regu-

## Annealing



## Mean Field Approximation

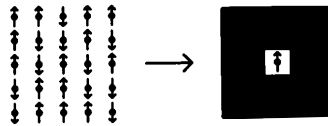


Figure 3.15 Annealing (top) and mean field approximation (bottom) in the 2-D Ising model representing states for each lattice site in a ferromagnet. The Ising model consists of a lattice of spins, each of which can be either up or down. Each spin can interact with its nearest neighbors such that the state with the lowest energy has all the spins lined up in the same direction. (Top) At a high temperature the directions of the spins are random because the thermal energy causing the fluctuations is much larger than the interaction energies, but as the temperature is reduced, the spins become aligned to the same direction. In this ground state the collection of spins behaves like a magnet. In a spin glass model the interactions can be negative as well as positive so that the ground state does not have all the spins pointing in the same direction. At intermediate temperatures the behavior of the system can be complex because of the many combinations of interactions that can occur. (Bottom) The mean field approximation replaces the sum of the local interactions with a single, average field. This approximation ignores corrections that arise from the fluctuations of the local field from its average. In a Hopfield network with binary units (only values of 0 and 1), the mean field approximation replaces the binary unit with a unit that has continuous values between 0 and 1. (Adapted from Hertz, Krogh, and Palmer [1991]. *Introduction to the Theory of Neural Computation*. Copyright © 1991 Addison-Wesley, Redwood City, CA.)

larities and equations. A spin glass is characterized by particles with spin, either up or down, in *mixtures* of attractive and repulsive interactions (figure 3.15). Suppose the spin glass starts at an excited state—at a high temperature. If the spin glass is rapidly cooled, the physics of the system are such that it “seeks” the nearest local energy minimum. Unlike a spin system in which all interactions are attractive, yielding a single energy minimum (all spins pointing in the same direction), spin glasses have many local energy minima owing to the mixture of interactions, attractive and repulsive. This property of spin glasses is called “frustration,” to reflect the inability of the system to come to a unanimous decision but rather to end up in pockets of conflicting decisions. As we outline below, inherent in the dynamics of the physical system of interacting

spins are the properties that enable it to represent and compute. The next step is to design nets that mimic spin glasses in the relevant dynamical respects, with their computing and representing properties more firmly in hand. As we show below, Hopfield's solution to the decision problem is to lay the grid of equations describing the cooling of spin glasses on the settling of networks into a stable configuration.

The units in the Hopfield net have two states, on (1) and off (0), just as the electrons can spin up or down (Amit 1989). Let  $s_i$  be the state of unit  $i$ . The connections between units are symmetrical, such that if unit  $j$  is connected to unit  $i$  with strength  $w_{ij}$ , then there is a reciprocal connection of equal strength connecting  $i$  to  $j$ . Thus:

$$w_{ij} = w_{ji} \quad (4)$$

The energy of the system, defined by analogy with that of spin glasses, is:

$$E = -\frac{1}{2} \sum_{ij} w_{ij} s_i s_j \quad (5)$$

Roughly, the energy  $E$  is simply the sum of all of the weights connecting units which happen to be on, scaled, and inverted in sign, so that the network has the same formal properties as those of a physical system.<sup>17</sup>

What does relaxation involve? The basic way to think of it is as an algorithm. "Pick any unit at random, flip it; i.e., change its 0 or 1 value. If the overall effect is to lower the energy level of the net, accept the change; otherwise refuse it. Do this again and again to arbitrarily chosen units until no single flip of a given unit will reduce the energy level of the entire net." A little more formally, suppose that the net is in some given state  $\{s_i\}$ , where each of the units is assigned a value of 0 or 1, and the corresponding energy of the net is given by  $E$  in eq. (5). If one of these units,  $s_i$ , has a current value 0, then it makes no contribution to the total energy level. If its value is now changed from 0 to 1, then  $E$  changes by  $\Delta E_i$ , which is given by the following equation:

$$\Delta E_i = -\sum_j w_{ij} s_j \quad (6)$$

If the change to the single unit should decrease energy so that  $\Delta E_i < 0$ , i.e.,

$$\text{if } \sum_j w_{ij} s_j > 0 \quad (7)$$

then this change will be accepted and the system has a new global state with an overall lower energy (figure 3.16). This is precisely the *update rule for binary threshold units in a net*. It reflects the traditional view that neurons do not spike unless their total input at a given moment exceeds some threshold. The units in a Hopfield net are updated asynchronously, one at a time. This is a deterministic update rule, but choice of the next unit to update is stochastic. If an extra term is added to the energy equation to represent the threshold  $\theta_i$  for each neuron, then:

$$E = -\frac{1}{2} \sum_{ij} w_{ij} s_i s_j + \sum_i \theta_i s_i \quad (8)$$

The term on the right adds a tilted plane to the energy landscape; that is, the

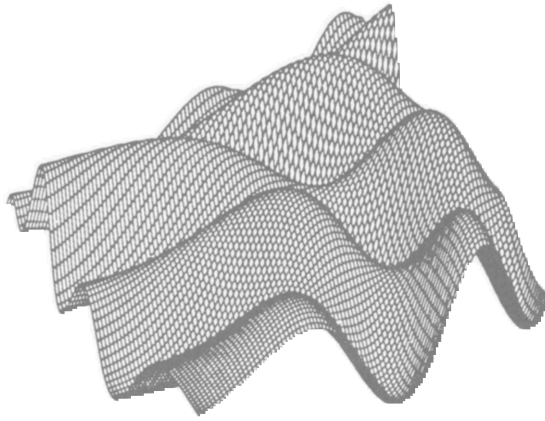


Figure 3.16 The dynamics of a Hopfield network in state space is visualized. All possible states of the network are represented by points in an  $x$ - $y$  plane, and the height of the surface is the energy of the corresponding state of the network. At each time step the state of the network moves downhill in the energy landscape. (From Hertz et al. 1991.)

energy is incremented by the values of the thresholds of all the units that are currently active. This is analogous to adding an external magnetic field to the spin glass.<sup>18</sup>

With repetition of the update procedure, picking one unit after another and changing its value from 0 or 1, the global energy state of the system continues to decrease. This cannot proceed forever, of course, because the energy has a lower bound. It therefore follows that in a finite number of steps, which typically is a handful of interactions through all the units, the network converges to a stable state. The energy of the stable state is a local energy minimum, because what “energy minimum” means is that flipping any single unit would increase the energy of the system. The minima are called “attractors” because there is a basin of states around each minimum all of which will converge to the same minimum, as shown in figure 3.17.

Hopfield saw that the local energy minima in spin glasses could be a physical embodiment of prototypes in associative memory. Thus if we make a net with the formal properties of a spin glass, and we designate attractors to be the prototype vectors, then when the network is given a vector-completion job, we know from its spin glass template that the net has the dynamics to complete the input pattern. This is a bit like saying that since we know the dynamical properties of a granite ball rolling down a hill, then a rubber ball rolling down a wooden inclined plane will have relevantly similar dynamical properties.

This formal analogy between the thermodynamics of spin glasses and the dynamics of Hopfield nets has a number of important consequences. First, we get for free the powerful theoretical framework developed by physicists for analyzing such systems. Issues concerning the capacity of the network to store prototypes and the probability of correctly retrieving the desired prototype are consequently more manageable. Second, the framework invites visualiza-

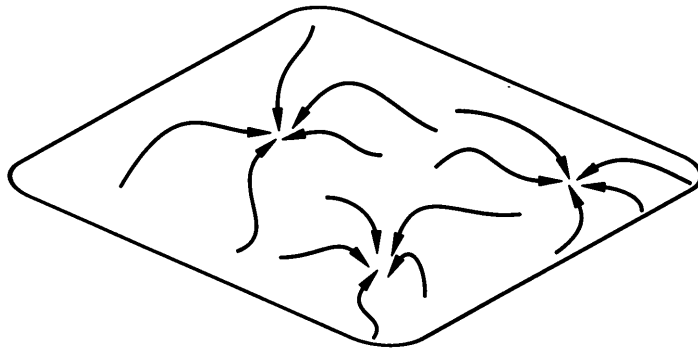


Figure 3.17 Convergence of a network to stable local minima from different starting points. Each point in the plane is a state of the network. The energy landscape has “basins” that will “attract” the state of the network, as illustrated by the trajectories. The process of reaching the stable states at the bottoms of the basins is a form of relaxation, or pattern completion through relaxation. (Adapted from Hertz et al. 1991.)

tion of the dynamics of networks as trajectories in high-dimensional landscapes. In other words, the geometric representation of the state transitions gives the visual imagination something to feed off, and invites an exploration of extensions of the basic idea. Using the dynamical framework, we can begin to bring nonlinear networks to heel; that is, to understand their capabilities, and most important, to give us insight into how best to design networks to solve particular computational problems (figure 3.18).

In the original Hopfield nets, only transitions to states of lower energy are admissible, which guarantees convergence only to a *local* minimum. How can a net be designed to find the *global* minimum? The trick, it turns out, is to permit an increase in the energy, but only in a restricted way. The best strategy for achieving this was provided by Kirkpatrick et al. (1983), who invented the technique of simulated annealing for global optimization. Crudely speaking, annealing is the process of heating a material such as a metal or glass to a high temperature, then gradually lowering the temperature. The result is that the substance forms crystals. If the annealing process is gradual enough, the material will end up at its global energy minimum. For metals, slow annealing leaves the metal ductile. In contrast, quenching the material by sudden cooling leaves the material in a local energy minimum, perhaps far from the global minimum. Typically, fast annealing produces a brittle state (e.g., steel) that may have other properties such as taking an edge.

To design a network to find the global minimum, we want the networks to copy the dynamics of annealing. So we first do the formal analog of heating it up, and then letting it slowly cool. In the informational context the analog of annealing requires a new update rule (rule for specifying what a unit’s next state is, given its current state and its input) which will prevent the network from getting stuck in a local minimum. Such a rule is:

If  $\Delta E_i$  is the energy gap as expressed in eq. (6) for state  $s_i$  of a unit  $i$ , then set  $s_i$  to 1 with the probability  $p_i$  given by

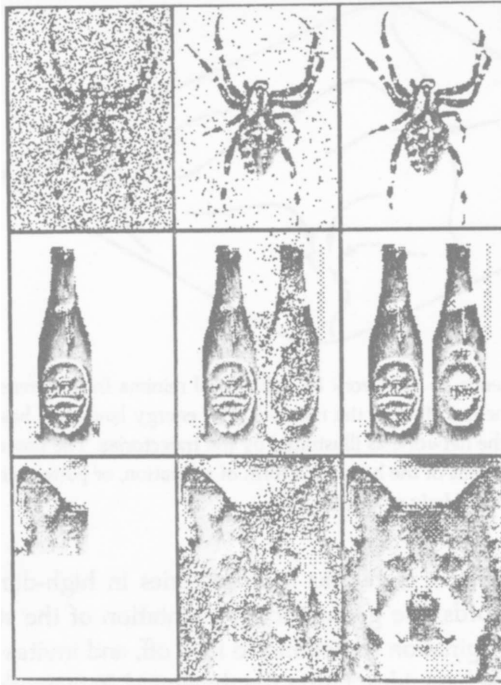


Figure 3.18 Three examples of pattern completion by a Hopfield network. Seven different images were sorted in a single network, where each unit represents a pixel in a  $130 \times 180$  array. Input patterns are the images shown in the left column, intermediate states in the middle column, and final states in the right column. In the top sequence, a spider emerges from a noisy image. In the middle sequence, a bottle in one half of the image is used to retrieve a paired bottle. In the bottom sequence, the complete image of a dog is retrieved from a small patch of its ear. (Adapted from Hertz et al. 1991.)

$$p_i = \frac{1}{1 + e^{-\Delta E_i/T}} \quad (9)$$

where  $T$  is the effective temperature of the system (figure 3.19). At very high temperatures, this probability approaches  $1/2$ , and all states in the system are equally likely. As the temperature approaches 0, the sigmoid curve for the probability gets steeper and steeper and approaches a step function which is the binary threshold rule used in the original Hopfield network. Notice, therefore, that the Hopfield network corresponds to a system that is quenched to zero temperature.

Relaxation of the net amounts to imposing a dynamics where states of the units change according to the update rule. Thus, the lower the energy of a state, the the more probable it is that the fluctuating system will be in that state. This follows as a theorem from statistical mechanics, based on the Boltzmann distribution, hence the name of the net of this configuration, the Boltzmann machine. If enough updates are performed at temperature  $T$  to reach an equilibrium (the system is fluctuating around its average energy), then the probability of a global state with energy  $E_i$  is given by:

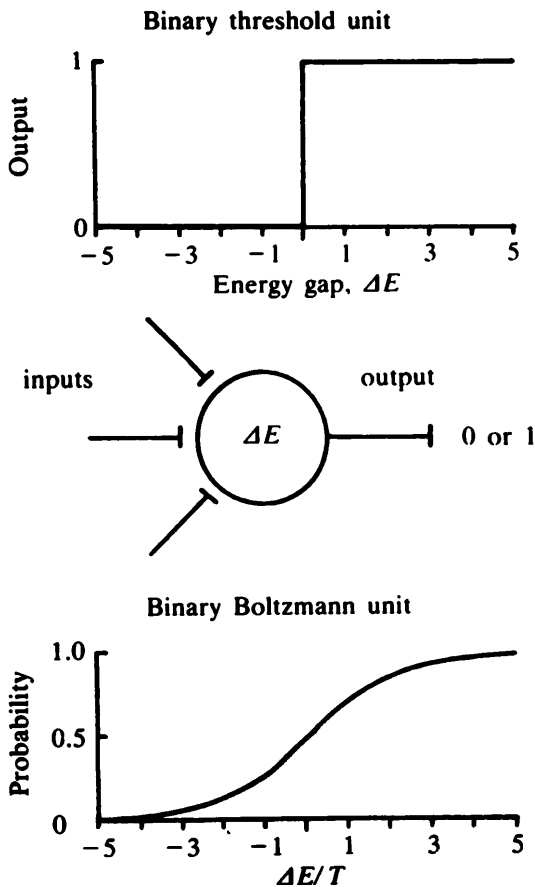


Figure 3.19 The output of a binary unit depends on its inputs and on the output rule (middle). For a unit in a Hopfield network, the output is 1 if the sum of the weights from input units that are active,  $\Delta E$ , is greater than 0, and 0 otherwise (top). This is called the binary threshold rule. For a unit in the Boltzmann machine, the output value is 1 with a probability given by a sigmoid function of  $\Delta E$  (bottom). The input is scaled by the temperature  $T$ . (From Kienker et al. [1986]. Separating figure from ground with a parallel network. *Perception* 15: 197–216.)

$$P_i \propto e^{-E_i/T} \tag{10}$$

It follows that the lowest energy state is the most probable, and that this state becomes increasingly probable as the temperature is lowered. Thus, at the end of the slow annealing process, with very high probability (approaching 1) the system will be at the global energy minimum.

This architecture was used by Hinton and Sejnowski (1983, Ackley et al. 1985, Kienker et al. 1986) to study problems in perception that require a global minimum. They called this the Boltzmann machine, reflecting formal equivalence between Ludwig Boltzmann’s contribution to statistical mechanics and the network’s dynamical properties. Independently, Hopfield and Tank (1985) developed a similar approach to optimization using continuous valued units rather than the binary units deployed in the Boltzmann machine. What is the relation between these two networks, given the choice between binary and



continuous values? At equilibrium, the units of a Boltzmann machine fluctuate on and off with a probability that depends on the average of the fluctuating input values. The mean of these fluctuations during a certain time interval represents the probability that the unit will have the value 1, and this probability is a continuous valued number between 0 and 1. Hopfield and Tank used these continuous probability values as the activation values of the units. This is the heart of the connection between the two nets. Eqs. (8)–(10) can, therefore, be solved for continuous valued units, in which case the result is called “the mean field approximation” (figure 3.15). Hopfield and Tank showed that the mean field approximation could be applied successfully to a large variety of classical optimization problems, including very difficult ones such as the traveling salesman problem and finding the minimum wire lengths for creating integrated circuits and even nervous systems.<sup>19</sup>

Now, it has been shown mathematically that finding *the* best solution to such problems is difficult in the extreme, so the pressing question is whether nets do indeed find the best solution. The answer is generally “no” for the Hopfield and Tank network. This is not as disappointing as one might surmise, however, since these networks often find *good* solutions *very rapidly*, even if they typically do not find the uniquely best solution. A Boltzmann machine, in contrast to the Hopfield and Tank network, is guaranteed to find the global minimum, so long as it is cooled slowly enough (Geman and Geman 1984).<sup>20</sup> Nevertheless, depending on the situation, it may be more efficient to cool the network at a moderate rate and go with a “just-fine” solution than to wait around for the Boltzmann machine to settle into the best. The optimal rate of cooling will be different for each network.

Using statistical mechanics to analyze a network and prove that it can find solutions to global optimization problems is a beautiful mathematical result. What good is it computationally? Given that the dynamics of a Boltzmann machine conform to the dynamics of annealing, of this much we can be certain: it will search the energy landscape and find the global energy minimum. If the network is representing an instance of an optimization problem (e.g., what is the shortest line connecting all the dots with no redundancy?) and the output values are representing the solution, *then the dynamics guarantee that the answer is forthcoming*. Since optimization problems are difficult to solve, and the more variables the more horrendous they become, this is a very useful result. As we shall see below, it is the key to developing rules for automatized weight-setting in a net and it is also the key to using model nets as a tool for analyzing real neural nets. As we shall also see, there is an additional practical matter of how long the process takes.

A brief aside: notice that in the Boltzmann machine, matters of computation, of algorithm, and of implementation are not really separable. It is the very physical configuration of the input that directly encodes the computational problem, and the algorithm is nothing other than the very process whereby the physical system settles into the solution. This contrasts rather vividly with the standard separation of hardware and algorithm in digital computers.<sup>21</sup>

How does this framework help with the weight-adjusting question raised earlier? This needs a bit of stalking, so we shall advance by going back to the problem of separating figure from ground in a visual image. Recall that the problem is to identify which parts of an image belong to the figure and which to the background. A watered-down version of this problem, suitable for the context at hand, is this: suppose the stimulus consists only of boundary lines of an object, perhaps with gaps and noise; suppose also that there is an initial bias that latches on to either the general location of the inside of the figure or the general location of the nonfigure. This version of the problem assumes that the difficult task of deciding what in the stimulus constitutes a boundary has already been solved and the remaining problem is to decide, for any given patch, whether it is figure-inside or figure-outside (ground). This residual task—the segregation task—is by no means trivial, since a decision that a local patch is figure-inside depends on the status of patches elsewhere, even patches at considerable remove. This means that a globally consistent solution is required of the net. To display its results, the net “colors in” the pixels inside the figure, leaving the area outside the figure uncolored. How can the machine figure out what pixels to color?

This is the kind of global problem that relaxation nets should be able to solve through local interactions between neighboring units. Just such a network was constructed fitting the Boltzmann machine design. Given the simplifications to the problem, there are just two variables to represent: (a) locations of boundaries, and (b)  $x$  belongs to figure (and its negation, “ $x$  does not belong to the figure,” which is equivalent to “ $x$  belongs to the ground”). The states of the machine can be displayed as a stack of two-dimensional, in-register grids, one composed of “edge” units and the other of “belongs-to-figure” units (figure 3.20). “Edge” units have a pointer to specify which direction is “in,” and they have orientation, either horizontal or vertical. “Belongs-to-figure” units fill in their space. The output is essentially a topographic map of the image, in which every pixel is either filled in or not, and for each pair of pixels, either there is a boundary or not.

The weights in the network are then chosen to reflect the relationships between the “hypotheses” specifying “edge here” or “belongs to figure.” Thus units representing two nearby patches of an image are connected with reciprocal excitatory connections, say of strength +10, thereby instantiating the property of objects to be continuous across the image. Edge units have excitatory connections with the unit it points toward (+12), with two flanking units (+10), and reciprocal inhibitory connections with the unit it points away from (−12). In addition to connections between units, there are connections from sensory inputs that bias the edge units along the boundary of the figure. There is also an attentional bias, which activates figure units near the center of the figure. This tells the net on which side of the boundary to color-fill. To switch figure–ground, the bias shifts so that the net fills the counterpart set of pixels.

The weights embody the constraints of the problem, in this case, object continuity across space, and object discontinuity at boundaries. Interactions between units are such that the final decision about whether a patch belongs to

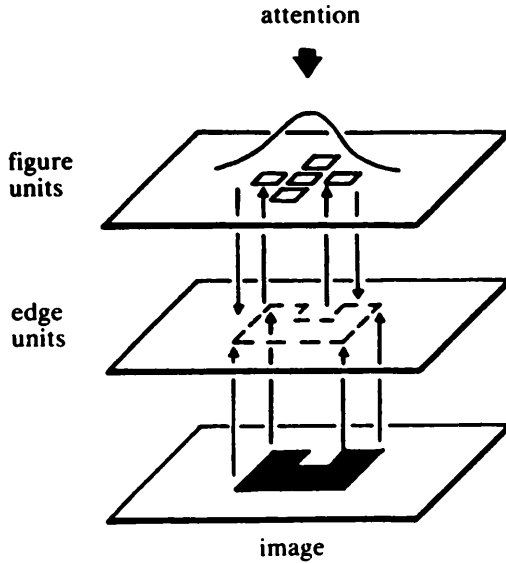


Figure 3.20 Schematic diagram of a figure-ground network using layers of binary units. Each layer is an array of units that are interconnected within and between layers. The edge units receive "bottom-up" activation at the locations of contrast boundaries in the image (shown below), and the figure units receive "top-down" activation from a Gaussian "spotlight" of attention (shown above). During the relaxation process these two inputs are maintained at constant values. (From Kienker et al. 1986.)

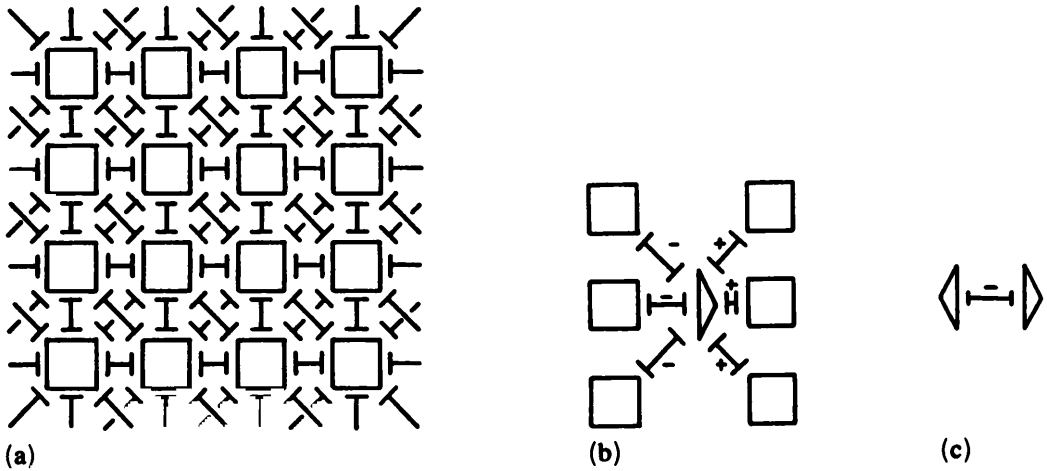


Figure 3.21 Summary of the connections and weights for the figure-ground network. (a) Each figure unit (square) is reciprocally connected to each of its eight nearest neighbors by an excitatory weight (+10). (b) Each edge unit (arrowhead) points in the direction of the figure and has excitatory connections with the figure unit it points toward (+12) and two flanking units (+10), as well as having inhibitory connections with the figure unit it points away from (-12) and the two flanking figure units (-10). (c) Two edge units that represent figures on opposite sides of the contour mutually inhibit each other (-15) to implement the constraint that the figure can be on only one side of the boundary, not both. In addition, there is excitation between adjacent edge units with the same orientation. This pattern of connectivity is repeated throughout the array. (From Kienker et al. 1986.)

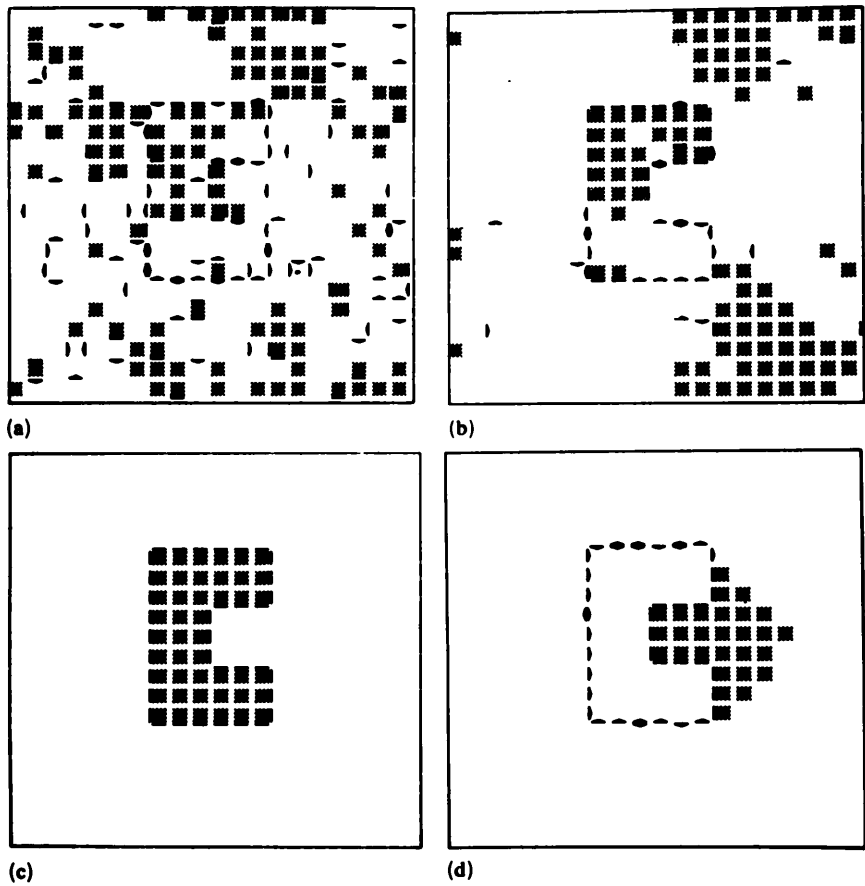


Figure 3.22 States of the figure-ground network at successive stages during simulated annealing: high temperature in (a), medium temperature in (b), and low temperatures in (c) and (d). The attention is centered on the waist of the C in (a)–(c) and is located outside the C in (d). In the final state, the figure units are uniformly filled up to the boundary, and the edge units at the boundaries are all pointing toward the figure. (From Kienker et al. 1986.)

the figure is made only after balancing all of the evidence from other units connected to it by positive and negative weights. Figure 3.21 illustrates more exactly how such a network can be constructed and the weights set.

The visual input to the network specifies the boundary of an object such as oriented cells in the cortex would be activated by luminance boundaries. The goal of the network is to decide which regions in the image should belong to the figure and which to the ground. The network starts at a high temperature, where all the figure units have a roughly equal probability of being activated. As the temperature is lowered, the figure units have a tendency to cluster together because of the excitatory weights connecting them. These clusters will dissipate unless they are stabilized by a bounding contour (figure 3.22). Whether the inside or the outside of the boundary is filled in depends on where the “spotlight of attention” biases the figure units, as shown in figure 3.22(c) and (d). This annealing procedure is successful in segmenting these simple images because the correct global configuration of figure and edge units is in



Figure 3.23 Image of a figure with an incomplete outline that may still be perceived as a familiar object. (With permission from Coren and Ward [1989]. *Sensation and Perception*, 3rd ed. Copyright © 1989 Harcourt Brace Jovanovich, Inc.)

fact the state of the network with the lowest energy. The procedure is also forgiving, in the sense that the network will fill in properly even should the input be somewhat degraded, that is, should there be a few gaps in the boundary. In this respect, it resembles human perception (figure 3.23) (Mumford et al. 1987).

This network is an instance of a more general computational approach known as “relaxation labeling” that has been applied to a variety of problems in computer vision (Waltz 1975, Hummel and Zucker 1983). In the figure-ground example of constraint satisfaction performed by a Boltzmann machine, the weights on the units were set by hand, meaning that the modeler had to figure out by rather long and laborious trial-and-error procedures what weights were needed to ensure that the global energy minimum really is the solution for any figure-ground problem. Ideally, what one would like is an automated procedure for setting weights, perhaps triggered by showing the network examples of question-answer pairs, and then letting it “figure out” what weights would do the job. How could a network do that? How could a network automatically adjust its weights appropriately?

## 5 LEARNING IN NEURAL NETS

Learning<sup>22</sup> algorithms for automated weight-setting in networks come in two basic molds: supervised and unsupervised. The basic difference concerns

whether the net infers a weight modification from a report on its behavioral performance. Supervised learning relies on three things: input, the net's internal dynamics, and an evaluation of its weight-setting job. Unsupervised learning uses only two: input, and the dynamics of the net; no external report on its behavior vis-a-vis its weight-setting progress is provided. In either case, the point of the learning algorithm is to produce a weight configuration that can be said to represent something in the world, in the sense that when activated by an input vector, the correct answer is produced. Nets using unsupervised learning can be configured such that the weights embody regularities in the stimulus domain. For example, if weights are adjusted according to a Hebb rule, then gradually, without external feedback and with only input data, the net structures itself to represent whatever systematicity it can find in the input, such as continuity in boundaries. This means that unsupervised nets are useful in creating feature detectors, and consequently unsupervised nets can be the front end of a machine whose sensory input must be encoded in some perspicuous fashion before it is sent on for use in such tasks as pattern recognition and motor control.

We emphasized that unsupervised learning has no access to external feedback, and we now take up the possibility that it nevertheless allows for internal error feedback. Because there is a confusion in the literature concerning error feedback and the convention for applying the label "supervised," we propose explicit labels for the distinction between external and internal feedback. When the feedback is external to the organism, the learning is called "*supervised*"; when there is an internal measure of error, we call the learning "*monitored*" (figure 3.24). Consider, for example, a net required to learn to predict the next input. Assume it gets no external feedback, but it does use its previous inputs to make its predictions. When the next input enters, the net may be able to use the discrepancy between the predicted input and the actual input to get a measure of error, which it can then use to improve its next prediction. This is an instance of a net whose learning is unsupervised, but monitored.<sup>23</sup> More generally, there may be internal measures of consistency or coherence that can also be internally monitored and used in improving the internal representation. The confusion in the literature is owed in part to the fact that the very same algorithms used for supervised learning can be suitably internalized for monitoring. Clarity of the semantics is especially important in discussing feedback modes in nervous systems, where certain kinds of supervised learning may be unbiological, but error detected by a monitor in one part of the nervous system is a plausible teaching signal for another part of the nervous system.

Is there a type of system that acquires organization even though it is neither supervised nor monitored? In real nervous systems, some aspects of development, such as establishing connections between nerve cells, might be considered candidates for self-organization of this kind. In models with unsupervised learning, such as competitive learning, it initially appeared that no internal objective function served as a monitor. Subsequent analysis has shown, however, that objective functions can be found for each of these models. Optimization of these implicit functions is responsible for the ability of the network to

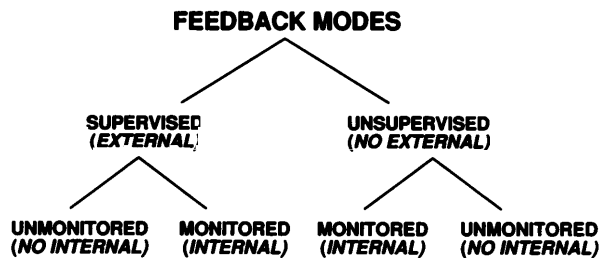


Figure 3.24 Taxonomy of learning procedures. Supervised learning occurs when there is feedback on the performance of the system from the external environment. If the feedback is a scalar reward, it is called reinforcement learning. The learning is called monitored if the system has an internal measure of error. These distinctions refer to the *system* and not the algorithms used; thus backpropagation of error, which is normally used in supervised, unmonitored (S&~M) systems, could also be used in an unsupervised, monitored (~S&M) system. For example, a feedforward net with fewer hidden units than input units can be trained to reproduce input patterns—a form of image compression (Cottrell et al. 1987). A more sophisticated example of an ~S&M net uses information-theoretic measures internal to the net to train the hidden units to predict the values of neighboring hidden units (Becker and Hinton 1989). An example of a supervised, monitored (S&M) system is the associative search network with internal predictors (Barto et al. 1981). In this system, the internal predictor learns to anticipate the reward; the difference between the predicted reward and the actual reward is used to adjust weights to hidden units. The internal monitor can be quite a sophisticated high-dimensional error signal, as in motor learning when a distal measure of performance (missing the basket) is used for adjusting a complex motor program (jump shot) (Jordan and Rumelhart 1990).

organize itself into a computationally successful state (Durbin and Willshaw 1987, Linsker 1990b). The conjecture, therefore, is that all successful self-organizing systems, including biological ones, have an implicit objective function that is optimized during the learning process (Sejnowski 1987). For an example, see section 5.9 on the development of ocular dominance columns.

Supervised learning comes in various grades as a function of the report card format. The report-card may (1) merely say “Good answer” or “Bad answer” (Sutton and Barto 1981, 1990), (2) specify a measure of the size of the error with some degrees of precision, or (3) give rich detail, saying, in effect, “You said the answer was abcd; the answer should be ahcp.” Given the range available in (2), this allows a continuum of report-card formats. Regardless of the format of the report card, the point of feedback is to give the net opportunity to reduce the error in its output.

In the original Hopfield nets, the learning rule was an update rule in the Hebbian mold. The problems given the net were, however, carefully chosen to be solvable by it. The class of problems solvable by these nets using the Hebb rule is rather narrow, embracing only first-order statistical problems. That is, problems where the question is “do feature A and feature B correlate?,” which in machine terms means “are the A-unit and the B-unit on together and off together?” Problems beyond its scope are higher-order statistical problems, e.g., “what is the correlation story for {A, B, C, D}, or for {EF, EH, GH}?” Going beyond these narrow limitations is desirable, since many problems cannot be solved using only lower-order statistics. To target high-order problems, the

basic architecture of the machine must be expanded to include units that intervene between external input and behavioral output. Called “hidden units,” they typically connect to the input units, to each other, and to output units when there are any. Adding one or more layers of hidden units allows the net to handle high-order statistics, for, crudely speaking, the extra set of connections and extra dimension of interactions is what permits the net a global perspective despite its local connectivity.

The ability of hidden layers to extract higher-order information is especially valuable when the number of input units is large, as it is, for example, in sensory systems. Suppose an input layer has  $n$  units in a two-dimensional array, as does the retina, or a one-dimensional array, as does the cochlea. If the units are binary, then the total number of possible input patterns is  $2^n$ . In fact, neurons are many valued, so the problem is really somewhat worse. Suppose all patterns (state combinations) were equally likely to occur, and suppose one hidden unit represents exactly one input pattern. This would make it possible to represent any function in the output layer by suitable connections from hidden units. The trouble arises when  $n$  is very large, e.g., a million, in which case the number of possible states is so large that no physical system could contain all the hidden units. Since not all possible input patterns are equally likely, only a very small subset of all possible input patterns need be represented by the hidden units.

Accordingly, the problem for the hidden units is to discover what combinations of features are ignorable, which features systematically occur together or are otherwise “cohered,” and among *those*, which are the combinations to “care” about and represent. The information for this last task cannot be garnered from inside the net itself, but must be provided from the outside. The division of labor in a net with hidden units looks like this: unsupervised learning is very good at finding combinations but cannot know which subset to “care” about; supervised learning can be given criteria to segregate a “useful” subset of patterns, but it is less efficient in searching out the basic combinations. So by means of unsupervised learning, a basic sorting is accomplished; by means of supervised learning, a subset of basic combinations can be extracted as the “useful” ones.

As the net runs, hidden units may be assigned states according to either a linear or a nonlinear function. If the hidden units are linear, there is an optimal solution called the *principal components*<sup>24</sup> (figure 3.25). This procedure can be used to find the subset of vectors that is the best linear approximation to the set of input vectors. (As we shall see in chapter 5, in a model devised by Miller and Stryker (1990) for development of ocular dominance columns in visual cortex, Hebbian learning finds principal components.) Principal component analysis and its extensions are useful for lower-order statistics, but many of the interesting structures in the world—the structures brains “care” about—are characterized by high-order properties. If luminance is taken as the 0th order property, then boundaries will be an example of a first-order property, and characteristics of boundaries such as occlusion and three-dimensional shape will be higher-order properties. Nonlinear hidden units are needed to represent





Input space

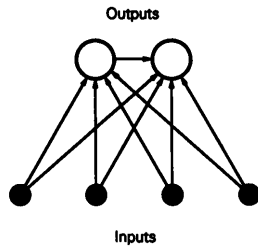


Figure 3.25 A feedforward, unsupervised network that performs principal component analysis. The input vectors, represented by dots in the plane, form two elongated clusters. The first principal component direction, along the line A, is the projection that maximizes the variance of the inputs. Discriminating along this direction is likely to be helpful in separating inputs into two or more classes. The direction of the second principal component, B, is the axis with maximum variance in the subspace orthogonal to A. These directions can be easily extracted from the inputs by the network below, which uses a modified form of the Hebbian learning rule on the feedward weights (Oja 1982) and an anti-Hebbian learning rule on the lateral connection between the output units (Rubner and Tavan 1989, Leen 1991). Following learning, the weights to each output unit correspond to the direction of a single principal component. Moreover, multi-layered networks with localized receptive fields can successively extract more complex features from the input space (Linsker 1986, Kammen and Yuille 1988). (From Hertz et al. 1991.)

these higher-order properties. If hidden units are to self-organize so that they can represent these properties, procedures more powerful than principal component analysis must be found.

How then should weights of hidden units be adjusted so that the net can do higher-order problems? Finding a suitable weight-change rule looks really tough, because not only are the units *hidden*, but they may be *nonlinear*, so trial and error is hopeless, and no decision procedure, apart from exhaustive search, exists for solving this problem in general. Moreover, any solution to the weight-adjustment problem depends critically on the architecture and dynamics of a given net. For most architectures and dynamics, the solution is simply not known.

In the specific case of the Boltzmann machine, however, a procedure whereby its nonlinear hidden units can learn to extract higher-order properties is known. The crux of the procedure depends on Boltzmann machines having an interesting property at equilibrium, namely their states have a Boltzmann distribution, eq. (10), which gives, for any global state of the system, the probability of that state occurring at equilibrium. This means that at equilibrium we

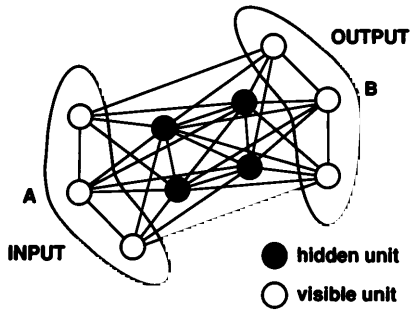


Figure 3.26 Schematic diagram of a Boltzmann machine. The units in the network have binary values and the connections between them are reciprocal. The weights on the connections can be trained by presenting patterns to the input units in the presence and the absence of output patterns and applying the Boltzmann learning rule. During the learning process, all of the weights in the network are modified, including those among the hidden units, which do not receive direct information from outside the network. The hidden units develop features that allow the network to perform complex associations between input patterns and output patterns. Hidden units give Boltzmann machines powerful internal representations not available to networks containing only visible units.

know the global consequences of any local weight change (which will change the energy). Now take the converse of this rule, and we have, for any desired global state, a simple procedure for increasing the probability of that state occurring by changing a weight locally.

It is important to emphasize that all the globally relevant information needed to update the weight is available locally. This may seem contradictory, given that units may be connected only with their immediate neighbors. It is, however, a simple consequence of the net's connectivity: a unit's neighbors are connected to its neighbors, who are in turn connected to all their neighbors, and so forth. Given the connectivity and the Boltzmann distribution at equilibrium, it is guaranteed that information from synaptically distant units is propagated throughout the net. The weight modification rule, therefore, is:

$$\Delta w_{ij} = \varepsilon [\langle s_i s_j \rangle_{\text{clamped}} - \langle s_i s_j \rangle_{\text{free}}] \quad (11)$$

where  $\varepsilon$  is the rate of learning,  $s_i$  is the binary value of the  $i$ th unit, and  $\langle \dots \rangle$  indicates that the quantity ... should be averaged over time after the network has reached equilibrium.<sup>25</sup> In the clamped condition, both the input and output units are fixed to their correct values, and in the free condition, only the inputs are so fixed (figure 3.26). This is in the supervised mode; in unsupervised mode, none of the units is fixed in the free condition.

Each application of the learning rule is a cycle with three steps: (1) clamp value of inputs, let machine come to equilibrium in the clamped condition, then compute co-occurrences of pairs of units; (2) compute co-occurrences of states in the absence of the inputs (unclamped condition and let the machine find equilibrium again); (3) subtract the two, and adjust the weight proportionally to the difference (the compare condition). Although the net is certain to learn correctly, the drawback is that it requires many, many three-step cycles to

learn one input pattern, and it must repeat this for every input pattern it is to learn.

We have seen how a Boltzmann machine could do pattern completion, in that once trained-up, if the net were given an incomplete pattern as input, it would go into a state representing the complete pattern. Can we get it to do an input-output mapping? Yes, and here is how to move from an unsupervised Boltzmann machine to a supervised Boltzmann machine without changing architecture or algorithm but only by “externalizing” the feedback. First, arbitrarily split the array of input units into two groups, A and B. The only procedural modification consists in feeding group A the same input pattern  $\#$  during *both* the clamped phase and the compare phase. The second group, B, of input units is more conventional; it is fed its pattern  $*$  only during the clamped phase. In effect, then, the hidden units are coming to associate pattern  $\#$  with pattern  $*$ . This can look like pattern completion on the part of the hidden units, but because the hidden units also have reciprocal connections to the inputs, it can look like the hidden units give output  $*$  for input  $\#$ . That is, think of the hidden-to-group-B input connection as a kind of output. Then we have the arrangement whereby in the trained-up net we can feed the net  $\#$ , and via the hidden reciprocal connection pattern  $*$  appears in group B. This means that group B is, for all intents and purposes, an external teacher, telling the net (during group B’s clamped phase) what new thing to associate with  $\#$ .

It takes only one counter-example to sunder an impossibility claim. Boltzmann learning in a net with hidden units—and even with nonlinear hidden units—was a counter-example to the received wisdom according to which the learning problem for multilayered networks was intractable (Minsky and Papert 1969). With the door open, weight-adjusting rules other than that used in the Boltzmann machine were sought. It is now clear that there are many possible solutions to the weight-adjusting problem in a net with hidden (and possibly nonlinear) units, and other solutions may draw on nets with a different architecture and with different dynamics. Thus nets may have continuous valued units, the output function for a unit may have complex nonlinearities, connections between units need not be symmetric, and the network may have more interesting dynamics, such as limit cycles and constrained trajectories. Weight-adjusting problems are really solved by an ordered triple:  $\langle$ architecture, dynamics, parameter-adjusting procedure $\rangle$ . In the final section of this chapter we shall outline a very general approach to handle all of these cases.

## 6 COMPETITIVE LEARNING

Because including a “teacher” as an adjunct to a network is informationally expensive, not to mention biologically unrealistic, it is important to explore the domain of unsupervised learning procedures. As a first pass, a rule of thumb for identifying those features in the sensory input stream that are likely to be useful in categorizing is this: the more frequently a feature occurs in various input vectors, the more likely it is to be salient in categorizing an input as belonging to a certain class. For example, if for a certain bottom creature the

presence of predators typically co-occurs with a looming darkness, then it would make sense for units in the network to extract changes in intensity at all possible locations in the visual field and represent them in its output. Extracting what is critical rather than performing all-feature coverage also has an obvious advantage for image compression where the goal is to represent an image with the fewest bits of information. Thus, if boundaries of objects are marked by discontinuities in luminance, then a network might most efficiently represent objects by allowing a single unit to represent a long length of luminance border. In short, it is cheaper to represent a stretch of border with a single unit rather than have many units representing small segments of a straight border. In this sense we get information compression.

In addition to the Boltzmann style of unsupervised learning, other kinds of interactions can self-organize so that the network embodies compressed representations.<sup>26</sup> Consider a simple two-layer network with a set of input units, and one layer of weights connecting them to a set of output units, laterally connected by mutual inhibition. This arrangement is competitive in the sense that the mutual inhibition will create a winner-take-all profile at the output level: if an input pattern happens to excite unit  $I$  to a greater degree than any of the other output units, then unit  $I$ 's consequent activity will tend to suppress the others to a greater degree than they are suppressing unit  $I$ . This is an example of relaxation of a network into a stable pattern. As with the earlier examples of relaxation, this network is guaranteed to converge to a final state in which unit  $I$  is strongly active when input pattern  $A$  is presented, while its cohort output units are suppressed. It is assumed that the activity level of the output unit is  $1$  in case it is a winner, and  $0$  otherwise. This is what permits characterization of the output unit's representation as winner-take-all.

The description so far has been confined to the net's *activities* given an input. The next matter concerns using this base to set the weights so that when pattern  $A$  is next presented, the network will go straightaway to the correct representation. Learning in this net can be accomplished by changing the weights to the winner unit  $i$  according to this rule:

$$\Delta w_{ij} = \epsilon x_j \tag{12}$$

where  $x_j$  is the  $j$ th component of the input vector, and the  $i$ th output unit is the winner. The rule is essentially Hebbian inasmuch as weights increase when pre- and postsynaptic units are concurrently active. As the label implies, in winner-take-all mode, only the winning output unit is active. Although this rule for weight adjustment should work in principle, in practice it is inadequate because the weights can grow without bound and eventually one unit will dominate the rest, and will be activated for any input pattern, thus losing the capacity to discriminate between patterns. How can we rig it so that the unit is excited when and *only when* particular input vectors are presented? Recall that the activity of an output unit is the inner product of the input vector and the weight vector. The strategy is to adjust the weights so that the weight vector for each unit becomes congruent with the input vector it specializes in. This can be accomplished without hand-setting by modifying eq. (12) as follows:

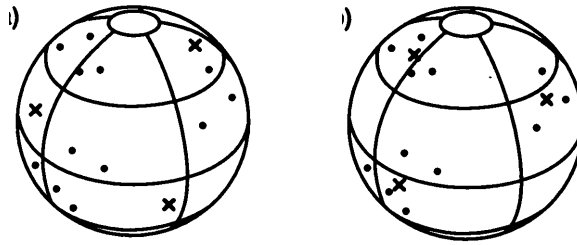


Figure 3.27 Competitive learning. The dots represent input vectors normalized to unit length, so they lie on a sphere. The weights are similarly normalized, and the input weights for the output units are indicated by crosses. (a) Organization of the network before learning. (b) After learning, each output unit has migrated to a cluster of input vectors. (From Hertz et al. 1991)

$$\Delta w_{ij} = \varepsilon(x_j - w_{ij}) \quad (13)$$

The main effect of this algorithm is to move the weight vector directly toward the input vector. Accordingly, if the weight vector and input vector are already congruent, no change will be made and the weight vector will top out.

So far we have considered the behavior of the network when it has but one pattern to represent. Suppose now that it is given many different input vectors, and hence that there are many different patterns to be represented. How will the net manage? When there are fewer output units than input vectors, each output unit will become specialized for clusters of overlapping input vectors, as illustrated in figure 3.27. In this way, the network will tend to develop output units that are sensitive to features common to its preferred input vectors, with each output specializing for a different particular feature. Consequently, what any given unit can be said to represent is a *prototype* of the range of nonidentical but overlapping vectors that turn it on.

There are three general weaknesses with networks of this type so far as adequate representation of patterns is concerned. First, sometimes critical information in a pattern may not correspond to the most frequently occurring feature, and so may fail to be represented by the net. A bottom creature who represents predators as looming shadows may thus be fooled by a predator with a thin dangling stinger, and this could be trouble if the predator is especially deadly, however rare. The second weakness is that this procedure picks out the lowest-order features, but it may be the higher-order features such as those that characterize the differences between faces that are critical for classification. Finally, relational invariances such as rotation, dilation, and translation need to be extracted before the patterns can be compared. Strategies for overcoming these drawbacks will be considered in chapter 4.

The third difficulty concerns stability of the weight configurations. The weights may shift even when the input is relatively familiar but the order of input vectors varies, and the instability problem is yet more acute should the network be given novel input vectors. In the real world, some forgetting may be advantageous, but on the other hand, it is often essential that previous learning not be wiped out by new encounters. Some provision needs to be made to retain relevant and important aspects of what has already been learned

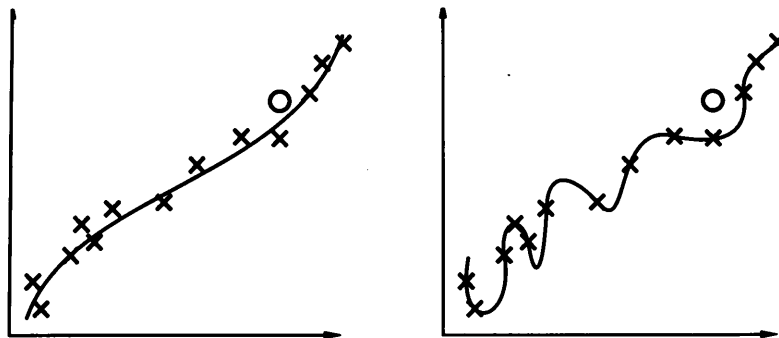


Figure 3.28 Curve fitting and overfitting. The data points are given (X) and the goal is to pass a curve through them. It is known that the data contain noise. A smooth curve (left) does a better job of predicting a new data point (O) than does a kinky curve (right). The degree of smoothing and the choice of interpolating function depend on the data and are central issues in approximation theory.

while learning new things. How nervous systems manage to do this is not understood, but one solution for artificial networks, explored by Carpenter and Grossberg (1987), is to add new units when novel inputs are encountered. There are many variations of the competitive network theme, including generalizing the basic architecture to multilayered networks (Fukushima 1975).

## 7 CURVE FITTING

The classic example of fitting parameters to a model is curve fitting, that is, fitting a host of noisy data points with a smooth function, using the least squares method (figure 3.28) (i.e., minimize squared error for the whole set). For a fit with a straight-line function, the squared error  $E$  is given by this equation:

$$E(m, b) = \frac{1}{2} \sum_i^N [mx_i + b - y_i]^2 \quad (14)$$

where  $m$  is the slope,  $b$  is the intercept with the  $y$ -axis, and there are  $N$  data points,  $(x_i, y_i)$ . When the error is at the minimum, the gradient of  $E$  with respect to the parameters ( $m$  and  $b$ ) = 0. That is,

$$\text{for } m: \quad \frac{\partial E}{\partial m} = \sum_i^N (mx_i + b - y_i)x_i = 0 \quad (15)$$

$$\text{for } b: \quad \frac{\partial E}{\partial b} = \sum_i^N (mx_i + b - y_i) = 0$$

These are two simultaneous equations with two unknowns. This is a relatively easy problem. Nevertheless, as the number of dimensions of the state space increases, and the number of parameters needed to fit the data increases, then the problem becomes much more difficult. Thus we may be looking for a curve, not in a 2-D space, but in a 10-D or 100-D or 10,000-D space. The traditional solution consists in solving the equations algebraically, which is quite manageable so long as the number of parameters and the number of data points are

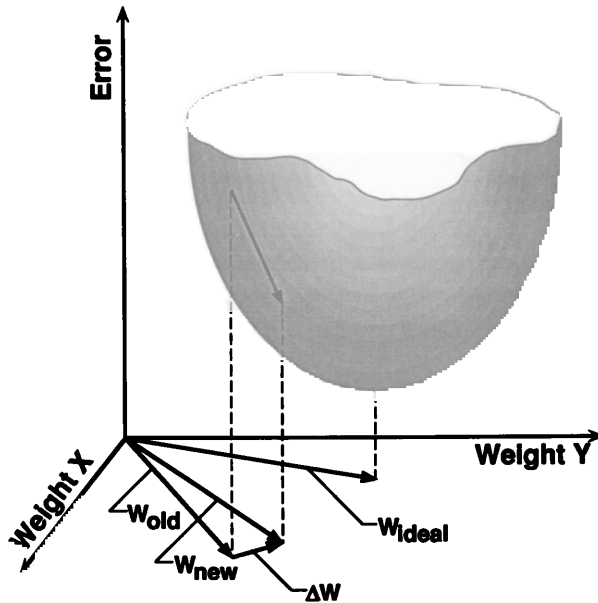


Figure 3.29 Error surface and gradient descent. The goal is to find the set of weights that gives the minimum error. For a given set of parameters (shown here for two weights plotted in the  $x$ - $y$  plane) the gradient of the error surface is computed to find the direction of steepest descent. The weights are incrementally changed by  $\Delta W$  along this direction, and the procedure is repeated until the weights reach  $W_{ideal}$ , which gives minimum error. For a nonlinear network the error surface may have many local minima.

small. As soon as either is large, then the algebraic method is nasty and unmanageable. Fortunately, there is a way, other than the traditional algebraic technique, to find the solution. This involves using knowledge of the gradients to iteratively update the estimates for the parameters.<sup>27</sup> This is essentially like iteratively updating weights in a net, and can be given geometric representation (figure 3.29). In iterative curve fitting we update according to this rule:

$$\begin{aligned} \Delta m &= -\varepsilon \frac{\partial E}{\partial m} \\ \Delta b &= -\varepsilon \frac{\partial E}{\partial b} \end{aligned} \tag{16}$$

where  $\Delta m$  is the change in  $m$ ,  $\Delta b$  is the change in  $b$ , and  $\varepsilon$  is the learning rate.

Instead of computing the exact gradient, the parameters can be adjusted after every sample, or after averaging a few samples. This speeds up convergence, which can be guaranteed if the learning rate,  $\varepsilon$ , approaches zero sufficiently slowly. This procedure is called gradient descent because at every step the parameters are changed to follow the gradient downhill, much as a skier might follow the fall line. We encountered gradient descent earlier in the context of Boltzmann learning procedures, where iterative application of the weight update rule gradually led us to better performance.<sup>28</sup>

To apply gradient descent, one must have a mathematically well-defined measure, such as mean squared error, to optimize, as well as an efficient way to calculate the gradients. Models that are dynamical and have many parameters have to be represented in a many-dimensional state space. Accordingly, the amount of computer time to perform the calculations may be astronomical, so it is essential to find efficient ways of computing. Exploring such procedures for some classes of models, such as feedforward nets and recurrent nets with linearly summing weights and nonlinear input–output functions led to important breakthroughs in the 1980s. (See section 8.)

When the curve-fitting task is fitting a *straight line*, gradient descent guarantees convergence to the global minimum of the error function. By contrast, there is no such guarantee for the general nonlinear problem, where the error surface may have many local minima, though if one is lucky, they will be close enough to the global minimum that it will not matter much if the net stops in one. For most of the problems presented in the later chapters, finding the true global minimum is unnecessary, and there are many equally good local minima. Thus if a net is started running with its initial weights randomly set to small values, it is likely to end up with one of these good solutions.

## 8 FEEDFORWARD NETS: TWO EXAMPLES

In feedforward networks the input leads directly to an output without feedback. Because feedforward nets have significant advantages in speed and simplicity, it is worthwhile exploring what computations a feedforward network can handle. In this section, we show that a feedforward network with one layer of weights cannot compute an extraordinarily simple function. Understanding the whys and wherefores of the limitations is instructive, and yields insights into the geometrical nature of feedforward networks. This is important, because it is the geometry of a network that determines what can be represented and how things can be represented; in appreciating that, we can see how to overcome these limitations:

### Exclusive “or”

The look-up table for a function called the exclusive “or” (XOR) was introduced earlier. The question now is whether this very function can be executed by a net; more specifically, the question concerns what sort of network architecture is necessary to execute this function. Finding a suitable architecture turns out to be instructive because of the failures and what they imply for a whole range of functions. To milk the lesson from the failures, we consider first the archetypal simple net. It consists of one output unit, taking value 0 or 1 (representing “false” and “true”), and two input units that carry the values of the component propositions.<sup>29</sup> This simple net has three free parameters: the two weights from the input units to the output units, and a single threshold or bias on the output unit. The architecture of this net determines the function for the output:



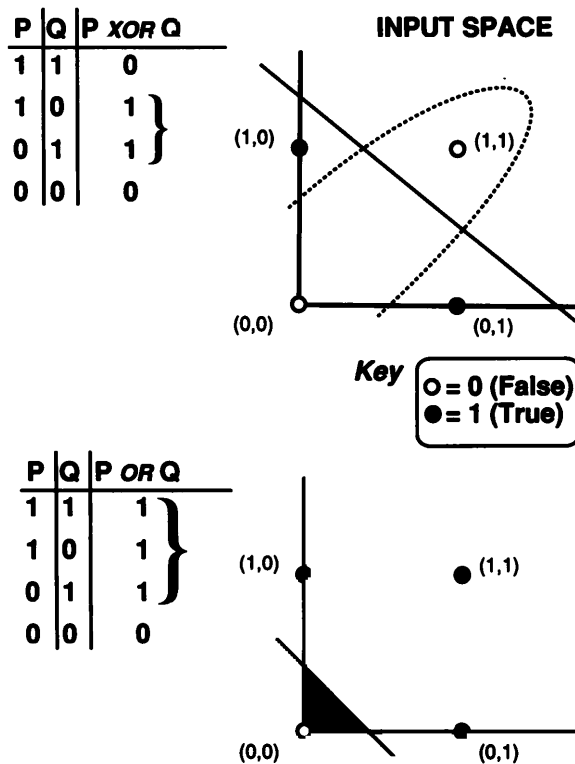


Figure 3.30 XOR is not a separable function. The truth table for XOR is shown on the upper left and is plotted on the upper right. No line in the plane can separate all of the closed dots (true, or 1) from all of the open dots (false, or 0). In contrast, the OR function, shown below, can be separated by the line shown in the bottom right. A network with one layer of weights can be found to represent a function if it is separable, but no such network can be found if the function is nonseparable, like XOR.

$$o = H(w_p P + w_Q Q + b) \tag{17}$$

where  $o$  is the output,  $H(\text{input})$  is a binary threshold function (figure 3.19),  $w_p$  and  $w_Q$  are the weights for the binary inputs  $P$  and  $Q$  respectively, and  $b$  is the bias.

Does there exist any configuration of weights and the bias such that the output unit correctly assigns values to the compound? For this simple net, the answer is “no,” and figure 3.30 (top) illustrates why. The input space has an axis for each of the two units, and points representing the four possible input vectors. If the output unit can solve the problem, it must be able to group together the inputs that give 1, and in another group, the inputs that give 0. Geometrically speaking, the function restricts the border between these two regions of the input space to a straight line. On one side of the decision border, all inputs drive the output over threshold, giving 1; on the other side, the inputs are below threshold, giving 0. No such straight line exists.

For contrast, the output unit of the simple net can execute the inclusive “or” (OR), and the input space for the same network architecture clearly does admit

of a straight line appropriately dividing the inputs (figure 3.30, bottom). Why does the decision border have to be straight? Because the architecture of the net is consistent only with a linear function, and hence limits how the inputs can be segregated for training to give the correct output. In other words, the exclusive “or” is not a *linearly separable function*, and hence no learning algorithm can find a solution to the weight configuration problem in the simple net because none exists. Intuitively, this can be seen by reflecting on the logic of the XOR. Analyzed in English, it comes out thus:  $(P \text{ XOR } Q)$  is true if and only if either  $P$  is true or  $Q$  is true, *but not both  $P$  and  $Q$  are true*. It is this extra twist on the back end of the basic OR function that needs to be accommodated. The point is that we need take the output of the more basic OR function, and operate on it again to get a higher-order property. Can the simple net be embellished to handle what is in effect a function on the output of a function? Yes, and the modification is both blindingly obvious in retrospect and was frustratingly opaque in prospect.

The crucial modification consists in adding an intervening unit—a hidden unit—that is interposed between the inputs and the outputs. This supplements the weights by three, and adds another bias unit. With a new total of seven parameters, the new question is this: are there weight-settings such that the net will solve the problem? This time the answer is “yes,” for the role of the hidden unit is to handle the second-order operation; that is, it gets its input from  $P$  and  $Q$ , and recognizes when not both  $P$  and  $Q$  are true. In fact, more than one weight configuration will suffice to do the job. The next question, of course, concerns automated training: is there a gradient-descent procedure for adjusting the weights? Insofar as the units are binary, gradient descent cannot be used to adjust the weights between the input units and the hidden unit. The trouble is that small changes to these weights will have no effect on the output, save in the case where it is close to the threshold of the hidden unit.

In the 1960s, model net research had developed to the point where the need for hidden units to handle nonlinearly separable functions was understood, but how to automate weight-setting, especially for the hidden units, was not (Rosenblatt 1961, Minsky and Papert 1969). As we saw earlier, automated adjustment of hidden unit weights was achieved in the Boltzmann machine in the early 1980s. How to do this for a feedforward network remained baffling. In 1986, Rumelhart, Hinton, and Williams, discovered<sup>30</sup> that the trick is to push the output of each hidden unit through a squashing function, that is, a smoothly varying function that maps the hidden units’ input onto output (figure 3.31). Hitherto, the output from the hidden units was a step function of the input. The smoothly varying function, however, means that small changes on the weights of the hidden unit’s inputs allow the hidden unit to abstract the higher-order property in small error-correcting steps, and hence to learn to recognize when both  $P$  and  $Q$  are 1. The net effect of adding hidden units and putting their output through a squashing function is that the input space can now be divided by a curvy decision border.

The backpropagation algorithm starts with small, randomly chosen weights and proceeds incrementally, just as in the earlier curve-fitting example. The

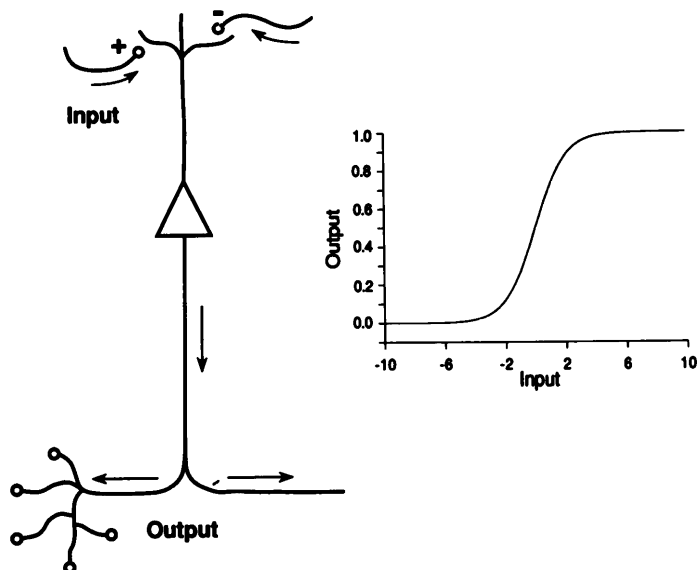


Figure 3.31 Nonlinear squashing function for a processing unit. The inputs are weighted and summed, and a bias is added (or threshold subtracted) before passing the total input through the sigmoid, shown on the right. The output of the unit is close to zero for large negative inputs, has a roughly linear region around zero input, and saturates for large positive inputs. This type of nonlinearity characterizes the firing rate of some neurons, such as motor neurons, as a function of the injected current from synaptic inputs on its dendrites, as shown on the left. Neurons also have complex temporal properties that are not captured by this static form of nonlinearity.

main difference is that the error surface for least-square curve fitting has a single minimum (figure 3.29), whereas the error surface for a network with hidden units may have many local minima. Consider a feedforward network such as the one in figure 3.32 with units having a nonlinear squashing function  $\sigma(x)$  as in figure 3.31:

$$\sigma(x) = \frac{1}{1 + e^{-x}} \quad (18)$$

For an input pattern that produces an output value  $o_i$ , the error is defined as

$$\delta_i(\text{output}) = (o_i^d - o_i) \sigma'_i(\text{output}) \quad (19)$$

where  $o_i^d$  is the desired value of the output unit provided by a “teacher,” and  $\sigma'(\text{output})$  is the derivative of the squashing function. This error can be used to modify the weights from the hidden layer to the output layer by applying the delta rule<sup>31</sup>:

$$\Delta w_{ij} = \epsilon \delta_i(\text{output}) h_j \quad (20)$$

where  $h_j$  is the output from the  $j$ th hidden unit. The next problem is to update the weights between the input units and the hidden units. The first step is to compute how much each hidden unit has contributed to the output error.<sup>32</sup> This can be done by using the chain rule. The result is:

$$\delta_j(\text{hidden}) = \sigma'_j(\text{hidden}) \sum_i w_{ij} \delta_i(\text{output}) \quad (21)$$

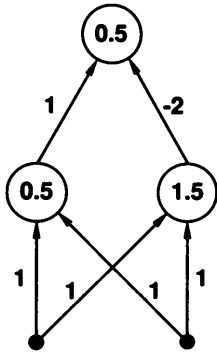


Figure 3.32 XOR network. The weights are shown on the connections (lines), and the thresholds are shown inside the units (circles). Thus, an input of  $\langle 0, 1 \rangle$  produces a pattern of  $\langle 1, 0 \rangle$  on the hidden units, which in turn activate the output unit. An input of  $\langle 1, 1 \rangle$  produces  $\langle 1, 1 \rangle$  on the hidden units, and the output unit will be turned off. In effect, the right hidden unit becomes a feature detector for the  $\langle 1, 1 \rangle$  pattern and overrides the influence of the left hidden unit. Other solutions are possible.

Once we know the error for each hidden unit, the same delta rule used for the output units (eq. 20) can be applied to the weights from the input layer to the hidden layer. This procedure (backpropagation of error and suitable weight modification) can be applied recursively through arbitrarily many layers of hidden units. As a practical point, the gradients for the weights can be accumulated for several patterns and the weights updated according to the average gradient.<sup>33</sup>

Let us now shift gears and think about this in terms of an error surface. Think of the error surface as a state space where the vertical axis represents percentage of error, and each of the remaining axes represents a weight in the system (figure 3.29). As the weights change, the position in error space will change. The error surface for fitting straight lines to data by minimizing the squared error is a concave basin with a single minimum. In contrast, the error surface of the XOR network with hidden units has a more complex error surface, one whose topography has ravines and assorted potholes known as local minima. If, however, the net starts out with small, randomly chosen values for the seven parameters, adjusting each weight to minimize the error over the set of four input–output conditions, then the system eventually ends up at a set of parameters that truly solves the problem (figure 3.32). In fact, there are many combinations of parameters that will do equally well, and depending on the random starting place, the system will find one or the other. If the initial weight-settings are too large, then the net may land in a local minimum that is not a solution to the problem, so the lore is to start the weights low. Although the backpropagation of error can be used to create networks that can solve the XOR problem, that problem is sufficiently simple that many other techniques can also be used to solve the problem.

Many problems resemble XOR in the respect that they are not linearly separable; indeed, one might say that most interesting computational problems

have that property. The discovery concerning the role of hidden units in extracting higher-order features and the versatility obtained by squashing functions on their outputs have therefore opened the door to network solutions to many complicated problems.<sup>34</sup> Even when a researcher does not have a clue what function maps input onto output, he may construct a network that does solve the input–output problem, whereupon he may then work backward to track down the function the network has learned to compute, though this may not always be a simple matter. In the next section, we illustrate an instance where a network was successfully trained even though the input–output function executed by the trained-up net was quite unknown to the modelers.

Finally, the *XOR* problem may seem pedagogically germane but biologically superfluous. Despite appearances, this turns out to be a hasty judgment, for *XOR* nets can be iterated into systems that have unexpectedly useful properties from a biological point of view. As we shall see in chapter 4, the basic *XOR* net is the electronic equivalent of a “gear” in the sense that it admits of many variations, and many *XOR* nets can be assembled into one large net that can solve very complex problems. Notice too that the negation of ( $P \text{ XOR } Q$ ) means the same as ( $P$  if and only if  $Q$ ), and thus training an interconnected array of negated *XOR* (*NXOR*) units is a way of finding necessary and sufficient conditions on certain higher-order representations.

Having shown that *XOR* can be represented and learned in a feedforward network, we now consider what other functions a feedforward net might compute. The surprising answer is that a feedforward net with a sufficiently large number of hidden units can be trained to approximate with an arbitrarily small error any mathematically well-behaved function (White 1989). To be sure, this is a reassuring theoretical result, but what does it really mean in practical terms? Networks with hundreds of hidden units and hundreds of thousands of weights have been trained successfully on a wide range of problems. In the next section, we present one example to illustrate the general approach. One important practical consideration, however, concerns how much computer time and how many examples a net needs to learn a function as the number of hidden units becomes very large. This is the *scaling* problem, and we shall return to this difficulty later in the chapter.

### **Discriminating Sonar Echoes**

Consider a feedforward net trained up by the backpropagation of error method to distinguish between sonar echoes of rocks and sonar echoes of mines (Gorman and Sejnowski 1988a, b) (figure 3.33). This is, in fact, a rather difficult problem because to the untrained ear, at least, no difference is discernible. The net has an input layer with 60 units, a hidden layer with 1–24 units, and two output units. To prepare the sonar echoes for input to the net, a given sonar echo is run through a frequency analyzer and is sampled for its relative energy level in 60 different frequency bands. These 60 values, normalized so that 1 is maximum, are then entered as activation levels in the respective input units

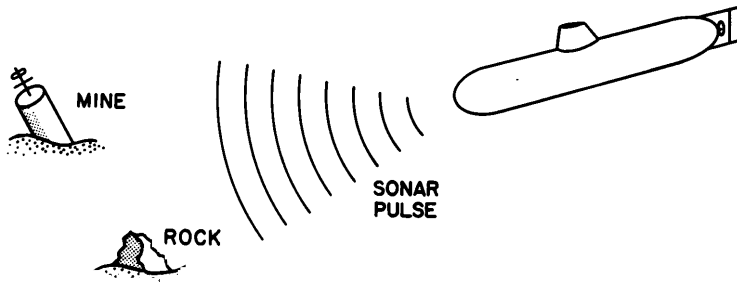
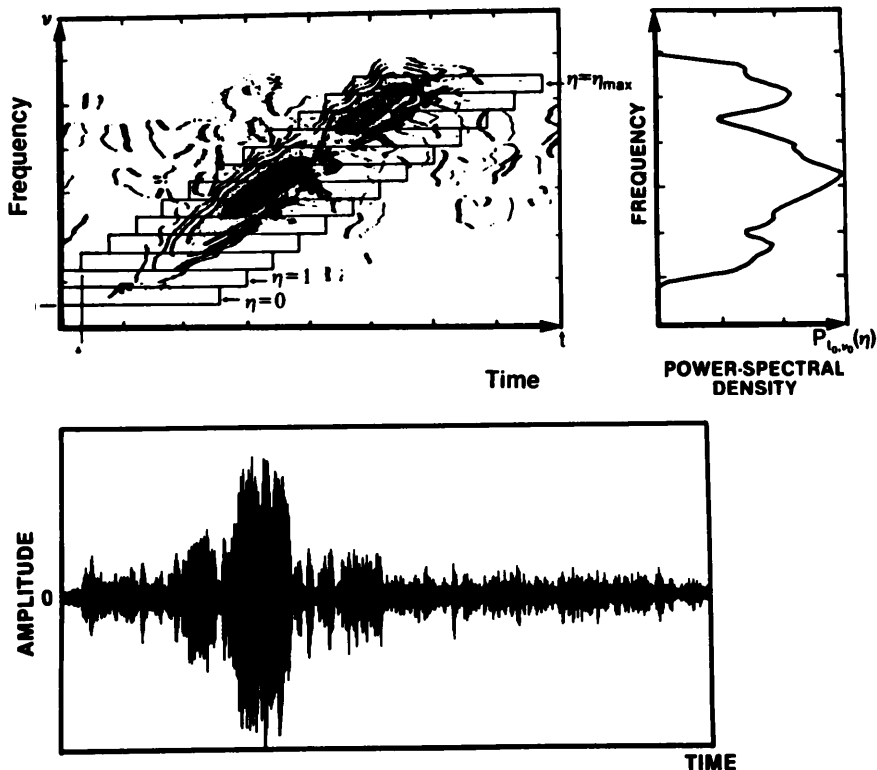


Figure 3.33 The mine–rock problem. Sonar echoes are returned from an object on the seabed. Is this a mine or a rock? There are subtle differences in the echoes that can be used to perform a pattern discrimination, but the differences between echoes from different sides of the same object are as great as the differences between echoes from different objects. Human sonar operators can be taught to make the discrimination after many training sessions. (From P. M. Churchland [1988] *Matter and Consciousness*, 2nd ed. Cambridge, MA: MIT Press.)

(figure 3.34). The activation is fed forward to the level of hidden units, there to be transformed as a function of the weights in the hidden units. The hidden units then pass activity to the two output units which may have any value between 0 and 1. Once the net is trained up, the output units signal  $\langle 1, 0 \rangle$  when a mine echo is entered as input, and  $\langle 0, 1 \rangle$  when a rock echo is entered as input. Initially, however, the weights are randomly set, and we cannot expect the net to give systematically correct outputs.

Training of the net correctly to categorize proceeds in the following way. We give the net examples of mine echoes and rock echoes, one by one. For each case, the actual values of the output units is measured against what the values ought to have been, given the input. This difference is a measure of error, which can then be used to compute small changes in the weights of the units in the system. This is a gradient-descent procedure, and slowly the weights of the network are adjusted so that when fed a mine echo, either a familiar old example or a brand new case, it gives a value of  $\langle 1, 0 \rangle$ , or close to that, and when fed a rock echo, it responds with something close to  $\langle 0, 1 \rangle$ . (For a more detailed but still basic account, see P. M. Churchland 1989.)

Following training, the accuracy of the classification of new echoes was very good—as good or better than trained humans and other classification methods. In a network with three hidden units, it was possible to analyze the features discovered by the training procedure (figure 3.35). The most important features of the input signals were the frequency bandwidth, the onset time, and the rate of decay of the signal. These general features, which could have been discovered by data analysis techniques, accounted for about 50% of the successfully classified echoes. The remainder of the echoes were more difficult to classify because they did not follow the general trend. To classify these exceptional cases, the hidden units developed weights that recognized clusters of echoes that shared the same spectral features. The more closely the input resembles the prototype, the more near will be the activation vector to the prototypical activation vector. The two-pronged strategy adopted by the hid-



#### NETWORK ARCHITECTURE

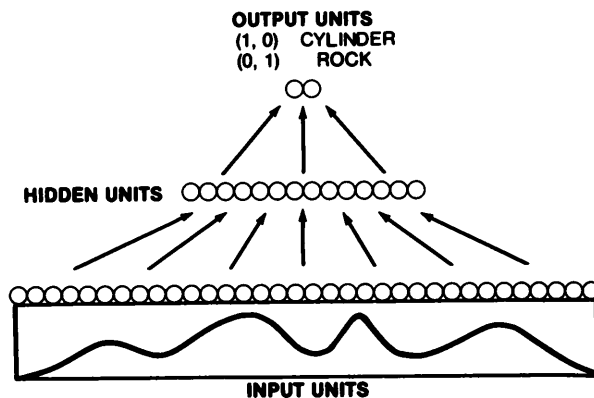


Figure 3.34 Preprocessing for sonar target recognition network. (Center) Time course of a typical sonar echo. (Top) Spectrogram of sonar echo power as a function of frequency and time showing that the frequency of the band containing the most power (black regions) increases with time. The integrated power as a function of frequency, graphed on the right, is used as the input to the network. (Bottom) Network architecture with 60 input units, 1–24 hidden units, and 2 output units. The output units are continuous-valued, and when the net is trained, the output for a metal object will be close to (1, 0) and for a rock, will be close to (0, 1). (From Gorman and Sejnowski, 1990.)

den units exploited large-scale regularities and finer scale distinctions in different ways.

## NETtalk

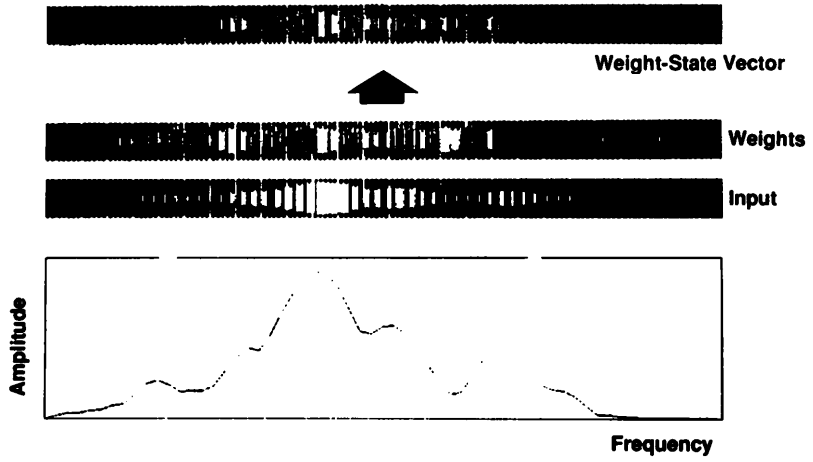
Another example where analysis of the hidden units revealed that different strategies were discovered for different types of inputs is NETtalk, a network that was trained to pronounce English words (Sejnowski and Rosenberg 1987). The input to NETtalk was letters of the English alphabet arranged in a window of seven letters. The output layer could represent 54 different phonemes, and each output is in effect the answer to the question of how to pronounce the central letter in the input window. The words marched through the window, one letter at a time, and the output of the network provided a string of phonemes that were played through a speech synthesizer (figure 3.36). The activity patterns on the hidden units were analyzed with a clustering technique to discover how the different letter-to-sound correspondences were coded. Interestingly, the vowels were segregated from the consonants and followed a different coding scheme. For vowels, the most important partitioning factor was the letter, but for consonants, the partitioning depended more on similarity in the sounds than on letters. What may account for this difference is that any given vowel letter may have a relatively large range of phonemic possibilities, but consonants are much more limited. Contrast, for example, the range of different sounds that may be associated with the letter "e" and those with the letter "f."

Essentially the same clustering emerged in all networks trained with the same words, even though they differed in the way that the hidden units shared the patterns. As in the mine-rock network, NETtalk found general patterns that would suffice for the preponderance of cases, dealing with the remaining exceptional cases by finding some way to cluster them, and coding that clustering into the weights. The way to view this two-step strategy is that the network finds a kind of default activation pattern for the standard cases, but when it detects a special feature indicative of an exceptional case, the default response is overridden. Only about 15% of the hidden units become significantly activated by a particular input, so the coding scheme was neither local nor completely distributed.

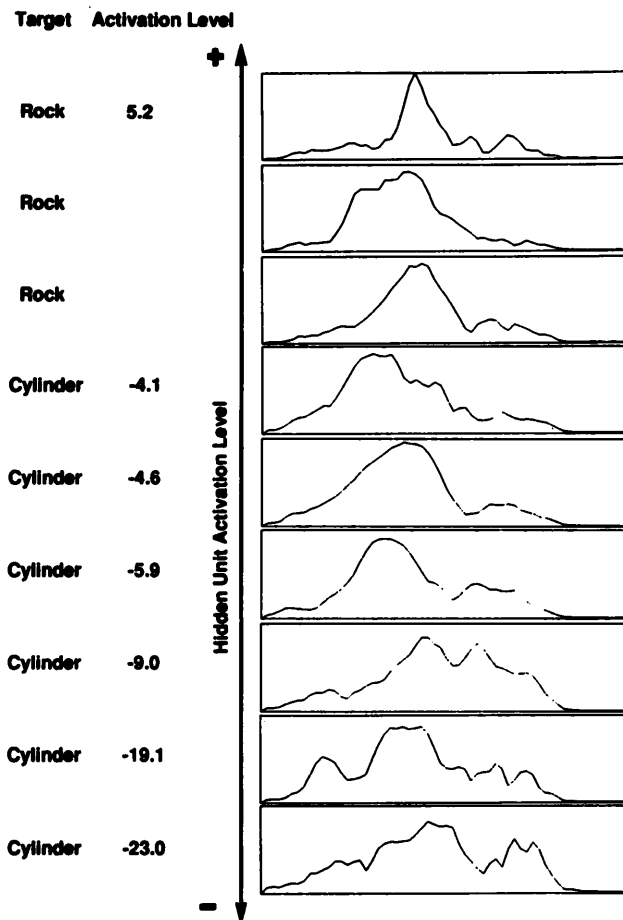
## 9 RECURRENT NETS

The mine-rock network, trained by a parameter-adjusting procedure, is feed-forward, in the sense that the direction of information flow is strictly from input to the first layer, passing forward through intervening layers, to the output layer. True, the error signal is passed backward to adjust the weights, but this is better thought of as external tinkering with the weights than as information downflow—as part of the *weight modification* rather than *unit activation*. More precisely, there was no flow of information *as input* from higher-level to lower-level units. Notice that a purely feedforward system is a purely





A



B

reactive system; that is, one which responds with an output only to the input, where its response is a function of the external input signals together with the existing configuration of weights. What does feedback, conceived as *internal* input, do for a network (figure 3.37)?

The general answer is that feedback endows a network with several important capacities: (a) to incorporate multiple time scales into the processing units, (b) to process temporally extended sequences of inputs, (c) to generate oscillations and modifiable rhythms of varying durations, and (d) to resolve ambiguities such as figure–ground ambiguities and segmentation ambiguities. Nets with feedback are also called *recurrent nets*.<sup>35</sup> In a recurrent net, the effect of an external input is not isolated from what went on in the net before, since internal inputs (feedback) also contribute to the activation of the hidden units. In recurrent nets the significance of external input varies across three general types of case: (1) the net may have output only when there is both external and internal input; (2) the net may have output even when there is no external input, but the continuous activity must be initially triggered by external input; or (3) internal input alone will suffice to activate an output, though the net's output can be modified by the addition of external input.

A theme that will be sounded and resounded throughout this book concerns time and the necessity for network models to reflect the fundamental and essential temporal nature of actual nervous systems. External processes and events are extended in time and for a nervous system successfully to recognize and respond may require temporally extended representation; movements required for behavior involve sets of bodily motions sequenced in time; short-term memory is a trick for allowing present access to the recent past, and longer-term memory to the more remote past; learning is adapting to the present on the evolutionary-tried assumption that the future resembles the past. Birds and humans recognize patterns of temporally extended song; recognizing that someone is waving or becoming angry is not recognizing merely a single input vector, it is recognizing an ordered *sequence* of vectors. We shall see in later chapters how network models of visual functions, behavior, and sensory–motor integration deal with the matter of temporal realism. The

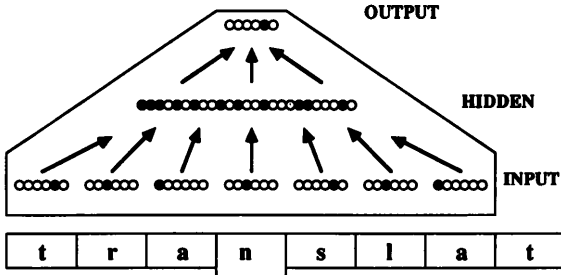
Figure 3.35 Typical spectral envelopes of sonar signals used as inputs to a network and their categorization by a trained network. (A) Input pattern is amplitude as a function of frequency (below), which corresponds to activity levels of input units (above). The area of each white rectangle is proportional to the amplitude of the signal in each frequency band. These input values are multiplied by the weights to a hidden unit to produce a weight-state vector (top). Inhibitory weights are shown as black rectangles. The input to a hidden unit is the sum of the components in the weight-state vector. (B) Prototypical input patterns ranked according to the activity level evoked in a single hidden unit. Each input pattern, shown on the right, is the average for a cluster of similar weight-state vectors. Each average pattern activated the hidden unit according to the level shown on the left. The features that characterized the rock for these prototypes were frequency bandwidth, onset time, and decay rate. Each of three hidden units in the network preferred a different onset time but had the same preference for bandwidth and decay rate. Exceptional input patterns did not fall into any of these clusters and were discriminated with a different type of coding. (From Gorman and Sejnowski, 1988a)

**TEACHER:**

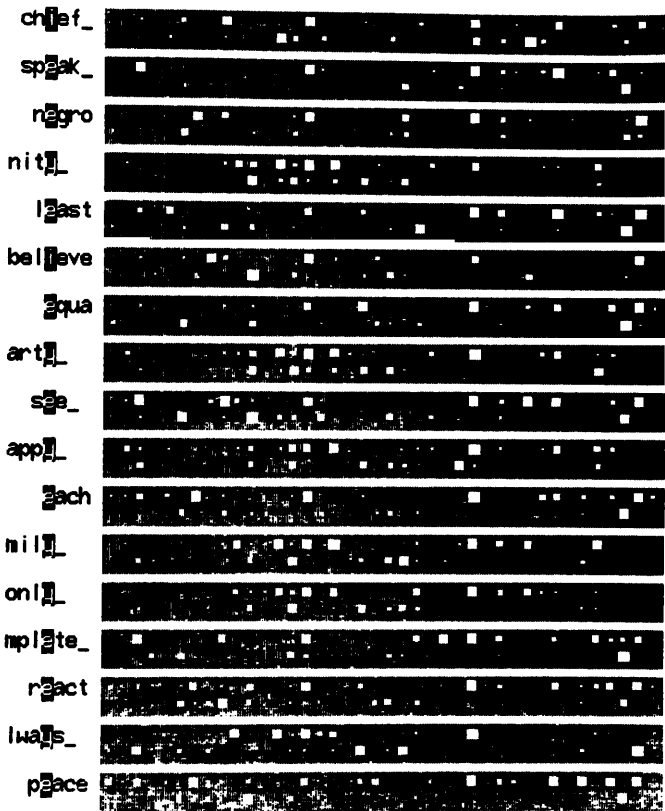
/t/	/r/	/æ/	/n/	/z/	/l/	/e/	/s/
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**GUESS:**

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**INPUT TEXT:**



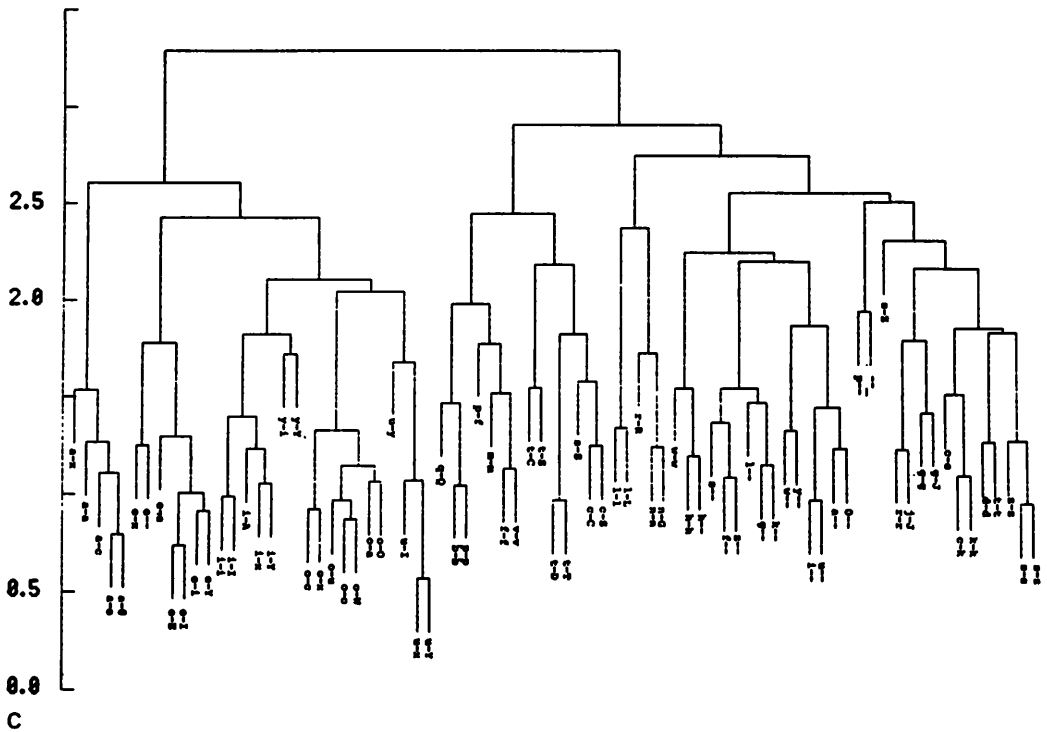


Figure 3.36 (A) Schematic of NETtalk architecture showing only some units and connectivity. Each group of 29 input units represents a letter. The 7 groups of input units were transformed by 80 hidden units. These hidden units then projected to 26 output units, which represented 54 phonemes. There were a total of 18,629 weights in the network. (B) Activity patterns on the 80 hidden units for the words shown on the left. The highlighted letters in the center of the window are all pronounced with the same sound. The area of each white square is proportional to the activity level of a single hidden unit. (C) Hierarchical cluster analysis of the average activity levels on the hidden units for each letter-to-sound correspondence (l-p for letter “l” and phoneme “p”). The closest branches correspond to the most nearly similar activation vectors of the hidden units. (From Sejnowski and Rosenberg 1987. Parallel networks that learn to pronounce English text. *Complex Systems* 1: 145–168.)

goal here will be only to understand the general features of recurrent nets that render them temporally responsive.

A crude but instructive first step in handling temporal structure with nets is to map a temporal sequence onto a spatial sequence, and then rely on the proven capacity of networks to do spatial recognition tasks. Vice versa, a spatially extended sequence such as the written word can be moved past a time “window.” (See, for example, Sejnowski and Rosenberg’s NETtalk, figure 3.36.) In this approach, a vanilla feedforward net will suffice, where temporal sequences with “before” and “after” relations are transformed into spatial sequences with “to the left of” and “to the right of” relations. In a speech recognition problem, for example, this is accomplished by pushing the train of input events through the input units from one side to the other. Each time-batch of sound hops from unit to unit until it has been through the entire set of

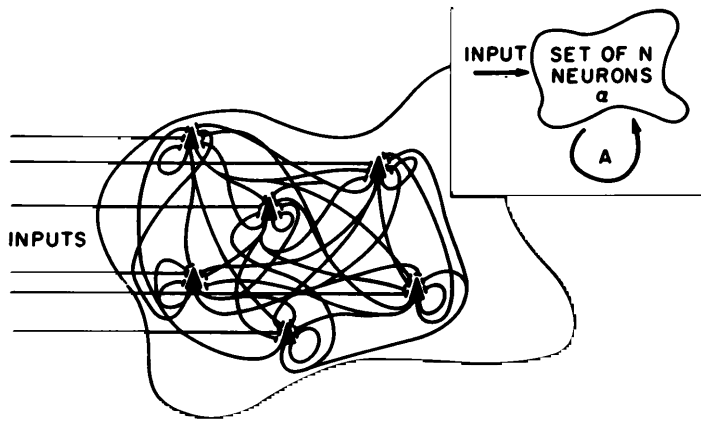


Figure 3.37 General recurrent network model. The units in the network form connections with each other, and their responses can outlast incoming inputs. (From Anderson et al. 1981.)

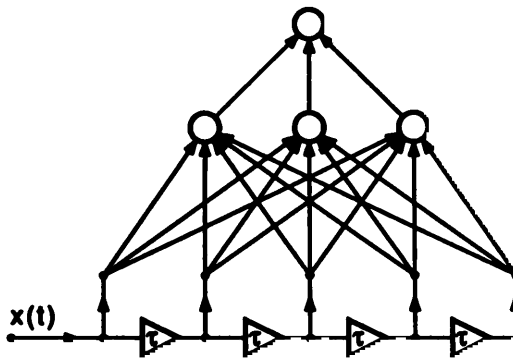


Figure 3.38 A time-delay neural network. The input  $x(t)$  enters the network on the left and each input is successively delayed by  $\tau$ . Thus, the input to the feedforward network at time  $t$  is  $x(t)$ ,  $x(t - \tau)$ ,  $x(t - 2\tau)$ , ...,  $x(t - 4\tau)$ . This type of architecture has been popular for speech recognition (Tank and Hopfield 1987, Elman and Zipser 1988, Waibel et al. 1989, Lippmann 1989). (From Hertz et al. 1991.)

inputs, the first one in being the first one out. Simplifying somewhat, a subset of hidden units thus see the phonemes in order, e.g., first “c,” then “a,” then “t,” and its flanking hidden units respond to the peripheral phonemes as context. In engineering this arrangement for pushing through the input is known as a tapped delay line (figure 3.38). Such a net can still be purely feedforward, but it is rather limited in the temporal complexity it can accommodate. Feedback loops turn out to be a remarkably fruitful architectural modification for transforming a sheerly static, reactive net into a temporally replete, internally generative system. How can feedback connections allow for this?

The fundamental point here is disarmingly simple: for short time scales, on the order of milliseconds, let the temporal properties of representation derive from the properties of the physical interactions in the network itself. As Carver Mead (1987) is fond of putting it, “Let time be its own representation.” The

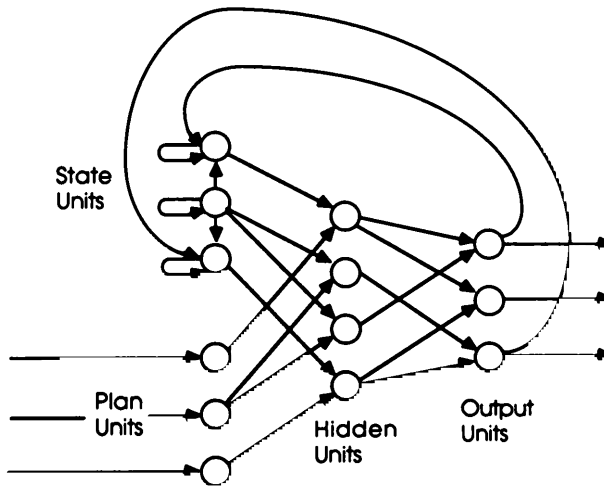


Figure 3.39 Recurrent Jordan network. In addition to the feedforward inputs, an additional set of inputs receives copies of the output units. These input units, through self connections, preserve a decaying copy of the last several outputs. Different sequences of outputs can be generated. (From Jordan 1989.)

point is, the network has intrinsic temporal structure: activation arrives at the hidden units before it arrives at the output units, signal summing and passing takes time, and so forth. Thus Mead's intent is that we exploit the existing temporal properties of activity in the network to do such things as represent temporal patterns of sensory stimuli. For a network to be sensitive to what happened in the immediate past, it must have a memory of what happened; this can be a spatial memory in which "to the left of" means "before," or it can be a dynamical memory in which, for example, recurrent loops keep a signal "alive" or transient changes in synapses keep the memory alive. Longer time intervals—for example, remembering that one learned to drive before Kennedy was assassinated—require a very different style of representation.

There are many ways of putting feedback into a network, including lateral interactions between units within a layer, feedback from a higher layer to lower layers, or, in the most general case, any unit may have reciprocal connections. In this event, any unit then can be an input unit, or an output unit, or both. To illustrate how feedback connections can greatly enhance the power of a feedforward net, we have chosen a recurrent net endowed with restricted feedback connections (Jordan 1989; figure 3.39). The goal of the network is to produce a sequence of actions  $a_1, a_2, a_3 \dots$  when given a single input, characterized as a command, such as "pick up an apple" or "say the word 'popsicle,'" or, for the Jordan net, "draw a rectangle." For nervous systems to execute commands such as these, a large number of muscles must each receive, over an extended time period, its appropriate sequence of activation. Additionally, since the various muscles must be coordinated for the right things to happen, the various sequences of activation must themselves be coordinated. The Jordan net tackles the basic issue of how a net might produce the appropri-

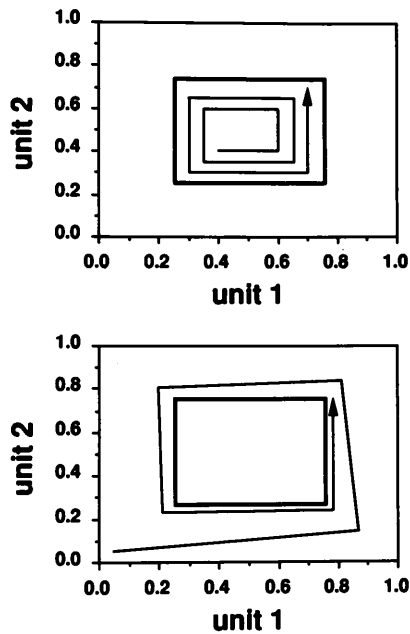


Figure 3.40 Output of a recurrent network trained to trace a rectangle. The values of two output units are plotted on the  $x$  and  $y$  axes, and successive points in time are joined by a straight line. (Top) Trajectory of a network that was started from a point inside the rectangle. (Bottom) Trajectory taken when the network was started outside the rectangle. The rectangle is called a stable limit cycle of the network because the closed repetitive trajectory can recover from small perturbations. (Based on Jordan 1989.)

ate temporally extended sequence of outputs given a command, and his architectural modification to the vanilla feedforward net consists of two types of feedback connections.

The task for the Jordan net is to draw a rectangle, as shown in figure 3.40. The Jordan net copies the values of the output units into the input layer; specifically, they are copied onto a selected set of units that serve to provide internal input. In the Jordan net, these special input units also have positive feedback connections onto themselves. The long recurrent connections provide the hidden units with information about the recent history of the output layer via the special input units. On a given pass, the hidden units will get both *brand-new* external information from the regular input units together with *recent history* information from the special input units. Notice also that the output of the network can continue to deliver and even to change its delivered messages despite freezing the external inputs. The reason is simply that the internal inputs continue to activate the hidden units, and indeed this is what endows the network with the capacity to generate temporal sequences.

What is achieved by the short recurrent connections—the self-exciting connections? Their effect is to create a short-term memory, inasmuch as a signal that produces a level of activity in the unit will decay slowly rather than cease abruptly, for the self-excitation maintains the activity. (This is equivalent

to making the unit a leaky capacitor, which is analogous to the membrane time constant of a neuron.) At a given moment, therefore, a special input unit represents a weighted average of previous values of the output. Thus not only does the network have available to it information about the current output, but it has a history, albeit a temporally decaying history, of previous outputs as well. Accordingly, contraction of muscle C can be influenced by what muscle B was doing 20 msec before, and by what muscle A was doing 20 msec before that. In this way, a smooth sequence of behavior can be orchestrated.

Note that unless the Jordan net is halted externally, its output is an infinite temporal sequence (see figure 3.40). That is because it will endlessly retrace its path once it finishes the last side of the rectangle and returns to the rectangle's first side. This is an achievement denied to Hopfield nets and Boltzmann machines despite their recurrent connections. These latter networks have only stable attractors (they converge to a point, not a trajectory), owing to the symmetry of the feedback connections. In such a network, information cannot circulate repetitively.

It should be emphasized that Jordan trained his recurrent network using the same backpropagation algorithm developed for plain feedforward networks. The weights of the *feedback* connections in this instance were fixed, though in a more general recurrent network, it may be necessary to train even these weights as well as the feedforward weights. Generalizations of the backpropagation technique have been developed for the wider range of cases, and examples will be given in chapters 4 and 5.

Not only did Jordan's network train up nicely to execute the desired trajectory, but so trained, it has a robust representation of its goal. That is, when the net starts out from some arbitrary initial state, or if it is perturbed off the trajectory, it will head to the correct output pattern. In the mathematical theory of dynamical systems, this behavior is called a *stable limit cycle*. The reason this is interesting is that the output pattern might well not have been stable, in which case any small deviation due to noise or an imperfection in the input would send the net careening off into useless behavior. This is important because for real neural nets, noise and imperfection are the order of the day. Imagine training networks, such as motor networks in the brain, to guide a hand to produce a complicated trajectory such as a signature. The signature will not be identical each time, owing to differences in the writing surface, the writing instrument, the musculature, the starting position, and so forth. A network that has the property of being stable when perturbed will compensate for those deviations, and nervous systems appear to be like that.

Although the Jordan net trains up well on the "draw-a-rectangle" task, more difficult problems demand not just a mapping of one input to an output sequence, but a variety of different inputs to their appropriate output sequences, and more difficult yet again, a range of *sequences of inputs* to suitable sequences of outputs. Here we bump up against the limitations of the Jordan net. It cannot be trained up on these more difficult tasks because the temporal memory provided by the recurrent connections decays in time. This constant decay rate means that an older input may not be able to exert a significant effect at a



more distant time, even though at that time it is the needed piece of information. Such problems occur routinely in language, both spoken and written, where there may be long-range interactions between words, as when a pronoun refers back to a proper name or a verb must agree with its earlier-mentioned subject. If the sentence is long, containing many embedded clauses, as much as a minute may pass before the verb or pronoun that must agree with the subject makes its appearance. Humans typically have little problem nonetheless, in either production or comprehension. Somewhere in the system, therefore, a representation of the word is on hold for a duration longer and with an impact greater than that allowed by the brief recirculating types of memory exhibited by the Jordan network. Yet the on-hold duration is also shorter than the weight modification corresponding to long-term memory.

What can be done to accommodate this time requirement? Basically, there are three general options: (1) change the network's time constants—for example, by increasing the temporal duration of an input's influence; (2) change the architecture—for example, by trying different configurations of feedback, of hidden layers, and so forth<sup>36</sup>; (3) change the activation function. For brevity, we consider only the third option, and that only succinctly. Recall that the original activation function described earlier specified the output of a unit as the weighted sum of the inputs, operated on by a squashing function to get nonlinearity. One modification defines the output as the weighted *product* of the inputs:

$$y_i = \sigma \left[ \sum_{jk} w_{ijk} x_j x_k \right] \quad (22)$$

where  $\sigma(x)$  is the squashing function shown in figure 3.31, and  $w_{ijk}$  is a weight that represents the influence of the  $j$ th and  $k$ th input units together on the  $i$ th output unit.

This results in what are called "higher-order nets," in contrast to the first-order nets that use the traditional activation function (Giles et al. 1990). It is possible with these second-order recurrent networks to model what are called "finite state automata." These are defined as devices that take sequences of input vectors and produce sequences of output vectors, and whose state transitions may depend on an internal but finite memory. Although networks of second-order units can model finite state automata, the drawback of continuing to higher and higher orders is that the number of weights in the network increases with the power of the order of the network. This quickly constitutes a practical obstacle.

Each of these revisions to the basic net has its strengths and its limitations. What works best will depend on the problem the net is asked to solve. The point of emphasis then is that there are oodles of ways to tailor a net, and the choices are governed by the fit between problem and solution. It may not be too rash to suggest that evolution tries various wrinkles in network design and seizes upon those that solve the problems. The nervous system may not, therefore, conform throughout to a single network blueprint, but may exhibit a variety of principles in a variety of places, depending on the task and how

things shook out in the evolutionary hurly-burly. The matter of problem-solution fit has become a fertile area for research by mathematicians who have been able to analyze the capacities of various network designs, and by engineers who have found networks to be an effective medium for matching problems and solutions.

## 10 FROM TOY WORLD TO REAL WORLD

The technical journals contain many examples of model nets that can solve dazzlingly difficult problems, but the cautious and sceptical will wonder whether the successes are marched into the limelight while the black sheep are herded backstage. In particular, it will be asked whether the model nets can solve only problems cleanly isolated from their messiness *au naturel*; whether they solve problems in the midst of their real-world welter and with their real-world complexity. Whether a solution adequate to a pasteurized fragment of a complex problem is also adequate to the problem entire and on the hoof is by no means obvious.

Real-worldliness has two principal aspects. (1) Real-world inputs generally have many more dimensions than toy-world inputs. The scaling problem concerns whether a net scaled-up to incorporate all the relevant dimensions can still perform the task in real time. If the scaling is exponential, then the net fails; if the scaling is polynomial, the net scores better but still poorly; if the scaling is linear, then the net may be acceptable. Best of all, it should have constant scaling. (2) Real-world inputs do not come to nervous systems informationally packaged into separate batches earmarked for separate problems. For example, visual information concerning motion, stereo, shape, etc. has to be separated by the nervous system, and objects do not arrive at the retina bagged and labeled. This is another instance of the segmentation problem (section 4). (See Abu-Mostafa 1989b.)

Assuming evolution availed itself of a “more is better” ploy in upgrading its neural nets, then perhaps we can follow that ploy and just make the standard design larger and larger. In fact, however, model nets of 1980s vintage do not scale very well, and the scaling gimmicks evolution lucked on to have not been fully figured out by neuromodelers. For example, a network that successfully recognizes phonemes presented in isolation typically flounders when it has to deal with phonemes ensconced in their natural habitat—continuous speech from a variety of speakers. A speech recognition system may succeed in identifying the vowels of one person’s voice, or single words in isolation, but fares poorly when confronted with the natural flow of speech from a commonplace range of voices—male, female, children, whispers, gruff, squeaky, bell-like, accented, etc. Why this happens can be seen quite clearly in figure 3.41, where the sound patterns from a female speaker saying soft “a” may overlap with those of a child saying soft “e.”

How might the standard model nets be modified to improve their scalability? In line with the “more is better” adage, the simplest approach is just to enlarge the network. The justification goes like this: if a net with ten input units

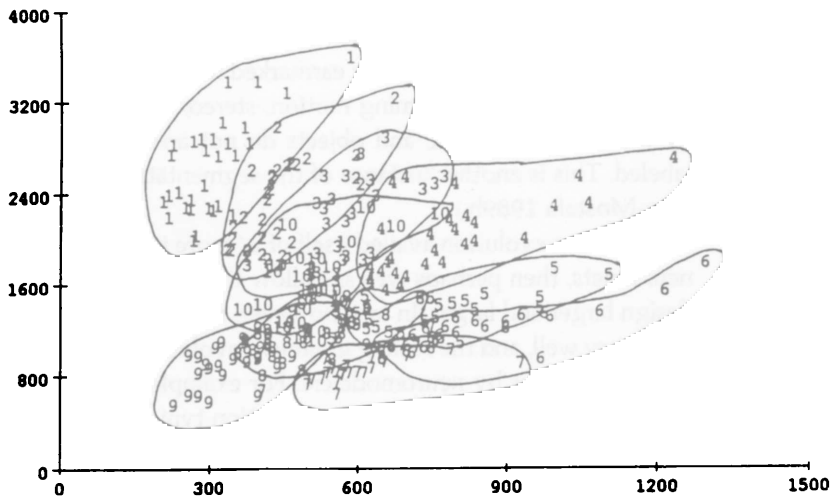
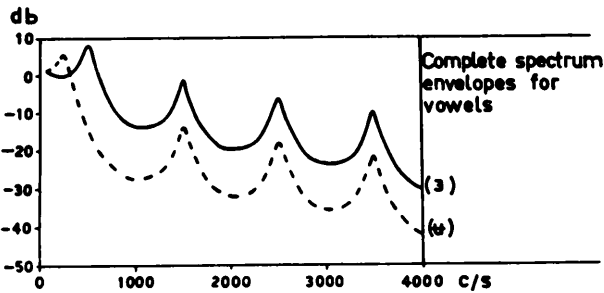
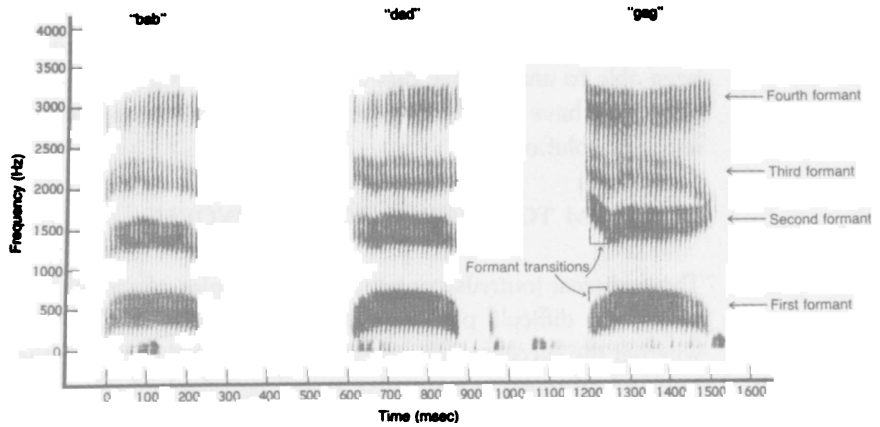


Figure 3.41 Vowel recognition. To see what is involved, the first step is to analyze the frequencies in utterances containing the vowel, for example, "bab," "dad," and "gag," as shown. The spectrogram for an utterance of each word is shown in the top panel. The areas with the highest power density are darkest, and the segment relevant to the vowel occurs about halfway through each spectrogram. The next step is to locate the formants. In the middle panel, power is plotted as a function of frequency for two vowels. The leftmost peak in a line corresponds to the bottommost dense area (around 500 Hz) of one spectrogram for the vowel segment (e.g., for "a" in "bab"), and is called the first formant; the next peak (second formant) corresponds to the second dense area (around 1500 Hz). Note the different location of the first formant for the two vowels. (From G. Fant 1973.) The third step is to assess similarity in how different speakers utter

can do speech recognition for one speaker, perhaps a network with 100 units can cope with any normal speaker. The “fatten-it-up” approach generally works up to a point, but invariably fattening-up brings its own serious difficulties. First, as the number of connections in the network increases, the amount of data required to train a network becomes very large and the amount of training time goes up enormously. The reason is that each weight in the network is a degree of freedom that needs to be constrained by data. Therefore, the more settable weights, the more data needed to constrain them, and hence the larger the training set required to do the job. A second and more serious problem concerns how information is distributed in the network.

Consider what happens when a new voice is tested on the speech recognition network. Either the network recognizes the voice’s patterns or it does not. If the network succeeds, then all is well. But if the network errs on the new voice, then this failure is remedied by training the network on that voice, with concomitant adjustments to the weights. The trouble is that though these weight modifications are needed to accommodate the new voice, they may well degrade the weight configurations for the old voices. To avoid losing the previous recognition capacities, therefore, the net must be trained anew on the entire old training set *plus* the new pattern. Obviously this procedure gets increasingly cumbersome proportionally to the size of the training set. One reason the standard net scales poorly is that changing one weight in the network repartitions the hidden unit activation space, and that means it changes the hidden unit activation vector for any input, old and familiar though it may be.

The aforementioned trouble reflects the fact that in a net there is an interaction between the data and the weights, in the sense that training on new data has an impact on all the weights, not just a preselected subset of the weights. A further and deeper trouble derives from the interaction between the weights. Error information is used to compute the gradients for the weights. Error, however, is a function of all the data *and* all the weights. When the net is trained up on a new example, there is not only an interaction between data and weights, but also an interaction between the weights. For if one weight changes in response to error, so do other weights. In other words, the gradients must be recalculated when a weight changes.

What can be done to avoid retraining holus-bolus and thus to avoid the time cost of scaling-up? One answer is to allow hidden units to be sensitive only to a limited range of input patterns.<sup>38</sup> This can be accomplished by using radial basis functions as the activation functions of the hidden units. Formally, what this means is that given an input vector  $x_i$ , then the output of a hidden unit that receives this input is given by:

the same vowel. The analysis proceeds by taking each speaker’s utterance of a particular vowel sound (coded by a number; 1 stands for  $\bar{e}$  as in “heed”) and plotting the first formant (horizontal) against the second formant (vertical). The analysis of ten vowel sounds uttered by 30 speakers shows that there is considerable overlap in the regions occupied by different vowel sounds depending on which speaker utters the sound. (From Nowlan 1990.)

$$F(\mathbf{x}) = e^{-\sum_i ((x_i - k_i)/\sigma)^2} \quad (23)$$

where  $k_i$  is at the center of the radial basis function, and  $\sigma$  is the width of the Gaussian distribution specified by the function. Informally, this means that there is an activation function according to which a hidden unit's largest response occurs when the input vector matches  $k_i$ , and the response falls off rapidly corresponding to the degree of mismatch. Considered three-dimensionally, the radial basis function carves out a sphere in the input space. Considered two-dimensionally, the radial basis function is rather like the tuning curve of a sensory cell, where the cell's best input is the one to which it maximally responds. Analogously, a hidden unit maximally responds when the input vector matches the center of its "tuning curve."

The main advantage of the radial basis function is that during the process of training, a given input affects only a few of the hidden units at a time, so part of the network can be modified without affecting how the rest of the network responds to other inputs. It will be evident, however, that in addition to weighting the radial basis functions for the various patterns the net is to recognize, one must also specify the centers  $k_i$  for the functions and their widths,  $\sigma$ . If the input space is low dimensional, one trick is uniformly to cover the space with spheres of a given size, in effect hand-wiring the tuning curves of the hidden units. In a high-dimensional space, however, the number of spheres required uniformly to cover the space may be very large, for the number of spheres goes up with the power of the dimension,  $n^N$ , where  $n$  is the number of spheres for covering each dimension, and  $N$  is the number of dimensions. Fewer spheres may be required if only some portions of the input space are of interest. So although one aspect—the interaction between weights—of the scaling problem is addressed by this strategy, other problems arise.

A related answer also pursues the decoupling strategy, but this time by decoupling the network so that subnets work on independent elements of the problem and training modifies only the relevant subnet. The answer implies that one can use a solution to the segmentation problem to help solve the scaling problem. Subdividing the network might be done by hand, in effect designing individual networks for individual elements of the problem. This is a rather ad hoc remedy. Worse, it presupposes that one already knows how to sort out the elemental problems and knows to which subnet information is relevant. We stand to be cruelly disappointed if we bank on this presupposition. Additionally, the holus-bolus problem may merely have been exchanged for the new and vexing problem of how to integrate these individual nets.

A more sophisticated proposal is that the network should *learn* how to cluster related information in subnetworks, each of which disposes of the information proper to it, but interacts minimally with other subnets. On this proposal, the network finds its own problem-elements and segregates the input accordingly. As we have seen, competitive, unsupervised learning algorithms have been designed to segregate input by staging a competition between units for input patterns. The way this works is that the unit most highly activated by a particular pattern wins, in the sense that it alone has its weight modified to

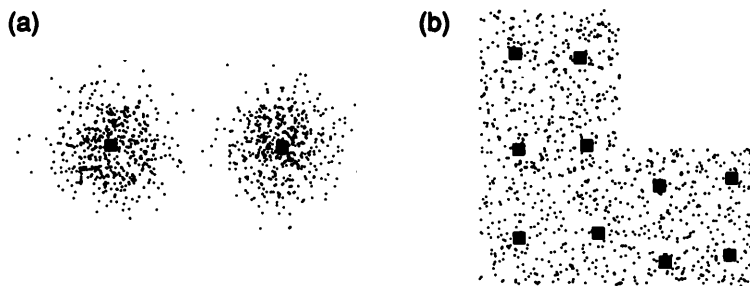


Figure 3.42 Vector quantization by competitive learning. Each input pattern is a point in the plane. Inputs that maximally stimulate an output unit are shown as black squares. During the competition for inputs, the output units station themselves strategically to cover the inputs. The output units are thus prototypes and each input is assigned to the nearest one. In (a) the inputs are from a pair of Gaussian probability distributions and in (b) the inputs are uniformly distributed over an L-shaped region. (From Hertz et al. 1991.)

become even more sensitive to that pattern, thus earning the right to represent that vector. *Ipsa facto*, it will be less sensitive to very different input patterns, allowing some other unit to muscle in and win the right to represent the different pattern. This is called “vector quantization,” reflecting the strategy of quantizing a group of related vectors into a single vector. By following this weight-modification principle, the net eventually fits itself out with units that are prototypes, inasmuch as each unit gathers to itself the range of input patterns that is more similar to its prototype vector than to the prototype vector of any other unit (figure 3.42). The network accordingly partitions the input space into groups of similar vectors, thus performing a preprocessing task.

Although unsupervised clustering successfully segregates the incoming information, it does not solve the problem of creating subnetworks. The idea of competition between the units can, however, be applied to whole networks with the result that independent subnets are created (Nowlan 1990, Jacobs et al. 1991). The strategy is this: appoint “mini-nets” instead of single units to compete for representation rights, where the mini-nets have their private array of hidden units, modifiable weights, and connections (figure 3.43). Mini-nets not only compete for the right to represent an input pattern, they are also trained by backpropagation of error to represent their patterns more and more correctly. Thus early in the training phase, mini-net *C* may give an output closer to the desired output than any of its competitors, *A* and *B*. The “teacher” then picks it out, and using the error measure, adjusts *C*’s weights in the correct direction using backpropagation of error. The other mini-nets are on recess for that input pattern. Each mini-net is activated by the input vector, but a winner-take-all strategy decides which mini-net is trained.

How is it decided which mini-net output is *the* answer to the input question? On the side, so to speak, there is another net that is trained up at the same time. This can be thought of as a “referee net,” trained to select winning mini-nets for any given input pattern. The referee net takes the same inputs as the other

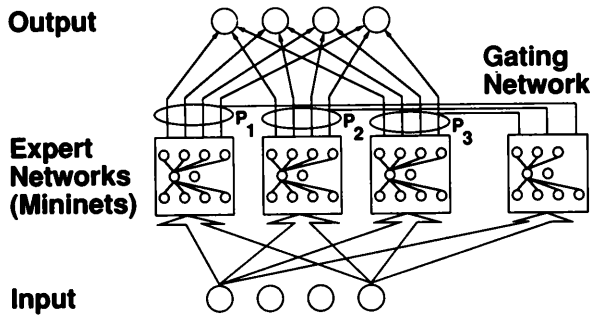


Figure 3.43 A system of mini-nets (experts) with a gating network (referee). Each expert is a feedforward network, and all experts receive the same input and have the same number of outputs. The gating network is also feedforward, with normalized outputs ( $P_j$ ), and an input which is the same as the input received by the expert networks. The referee acts like a multiple-input, single-output, stochastic switch. The probability that the switch will select the output from expert  $j$  is  $\text{Prob } P_j$ , which is the  $j$ th output of the gating network. The expected value of the output of the system is:  $\sum_j p_j o_j$ , where  $o_j$  is the output of the mininet  $j$ .

mini-nets, and its output is its probabilistic prediction of which mini-net has the right answer. The teacher computes the error measure here as well, and sends modification signals back to the referee net. The upshot is that once the whole slew is trained up, the teacher can retire, and the trained-up referee will correctly select which mini-net answer is the answer for any given pattern-recognition question. (This is highly simplified, but see Nowlan 1990 and Jacobs et al. 1991.) No referee was required in the simple clustering configuration because the winner is simply the most active unit. In the Jacobs et al. approach, the winner is determined by which mini-net is the expert for the particular input vector.

The Jacobs et al. configuration scores very well on the multiple-speaker vowel recognition problem, and it can efficiently process 74 different voices, correctly identifying vowels of these voices. This gets us a bit closer to real-world speech recognition. An analysis of the mini-nets reveals that they tend roughly to divide labor so that some end up an expert on children's voices, others on women's voices, and yet others on men's voices. The lesson of consequence, however, is that some measure of success in coping with the scaling problem can be achieved by configuring nets so that with experience they specialize. Specialization by substructures is a principle that fits well with neurobiology and with findings from human subjects. For example, in direct cortical stimulation of bilingual subjects, George Ojemann has observed interference with Greek only and not English, or English only and not Greek, where the intervening distance may be as small as 10 mm (Ojemann 1988, 1990).

## 11 WHAT GOOD ARE OPTIMIZATION PROCEDURES TO NEUROSCIENCE?

A common misconception is that an artificial net is a waste of time if the parameter-adjusting procedure component of the triple <architecture, dynam-

ics, procedure) is not maximally biological; that essentially nothing can be inferred about the actual net simulated by the model net; and that the expectation that it will be useful is just wishful thinking in the worst of the tradition of black-boxology. According to this view, until we know how nervous systems parameter-adjust—and there may be many procedures that govern parameter-adjusting in nervous systems—model nets are charming demonstrations that an input–output function can be executed, and that weight-adjusting will lead a net to the correct input–output function, but nothing can be revealed about how real neural nets execute that function unless the parameter-adjusting procedures are the same, or at least similar. Why is this a misconception?

The fast answer, to be duly expanded below, is this: assuming the architecture is relevantly similar to the anatomy, and assuming the dynamics are relevantly similar to the physiology, then so long as both the actual net and the model net use some parameter-adjusting procedure to minimize error, then they will each end up at locations on the error surface that are rather close. How close the final positions are depends on how similar the architecture and dynamics are, but the critical point is that *error minimization is an optimization procedure*, so it is reasonable to expect that however a given net finds its error minimum, it will be as close to the error minimum found by another net as long as the architecture and dynamics of the two nets are closely similar.

How a physical system comes to be configured such that it computes some function may be—indeed is virtually certain to be—different from how the theorist goes about finding out what function the system is computing. As we shall see anon, modelers sometimes use optimization procedures such as backprop as a way of shaping a network model into an input–output configuration that resembles the input–output configuration of an actual neural system. One aim may be to have an accessible “preparation” to analyze in order to find out what function the neural system is computing. Another aim, as even most sceptics emphasize, is to generate ideas from the organization and behavior of the net. Although backprop is enormously helpful in smithing up a model with capacities analogous to the actual neural network, it is *not* assumed that the neural system came to be organized as *it* is by backprop. Obviously, one might say. Nevertheless, this bears noting inasmuch as criticism of computational models is often directed toward optimization techniques for getting a model into suitable neural configuration, on grounds that the technique is not very biological. Whatever other criticisms might be apt, this one is surely misdirected. Think of backprop not as aiming to mimic neurogenesis or real synaptic modification, but rather as a tool to aid discovery of what function a grown-up network is in fact computing and how in fact it manages to compute that function. These discoveries are what enables us to use the net as a source of ideas.

As a means of clarifying the argument, let us work up to the test case by first considering several easier cases. Suppose two model nets are constructed, with identical architecture and identical dynamics, but rather different procedures for parameter adjusting to find the error minimum, and suppose, to make it



more relevant, that one was supervised and the other was monitored. They then learn, by the parameter-adjusting procedure, the same input–output function. What would you predict about the properties of the nets once each has found its error minimum? Well, you would expect that the free parameters at training end have the same values, or close to. One net may take a circuitous route down the error surface, the other may be more direct, but they are bound to end up in the same, or closely adjacent, places. In this game we assumed the identity of architecture and dynamics in order to make the point that each model could use a distinct route to wend down to its error minimum.

Imagine now a slightly different game where the identity of architecture is not given at the outset, but the net's function is given. Suppose that the Zygons deliver us an up-and-running model network with its input–output function pinned to its shirt, but whose architecture and dynamics we are to discover by experimental techniques that can give us mostly only local information. The game is to figure out how Zygon-net works. To this end, we construct a model net, call it Home-net, constraining its architecture and dynamics by using whatever local information we can get about Zygon-net. We then train Home-net to execute the same input–output function that we know Zygon-net executes, where Home-net uses an off-the-shelf parameter-adjusting procedure for minimizing error. The Zygons being good engineers, we reasonably expect they trained up their net using some parameter-adjusting procedure or other, though its specifics we are never told. The crucial question is this: can one infer anything about Zygon-net's global properties from the global properties of Home-net? Would it be useful to make predictions about undiscovered local properties of Zygon-net on the basis of what Home-net's properties imply about those local properties? The answers appear to be positive in both cases. To be sure, the inferences about Zygon-net's global properties—and hitherto unknown local properties—are only probabilistic. Consequently, the degree of probability the hypotheses enjoy will be a function of the similarity between the architecture and dynamics of Zygon-net and Home-net, notwithstanding whatever differences may exist in the parameter-adjusting procedures. The important point is that the learning procedures are error-minimizing procedures, so the Zygon-net and Home-net are similar in the respects that matter. This “just-so” story brings us one step closer to the neurobiological case.<sup>37</sup>

Now we cannot make this next step unless we have reason to think the brain is in the error-minimization business. Is it? Four basic considerations are relevant to answering this question: (1) In nervous systems generally, and most obviously in mammals, there are too many parameters (e.g.,  $10^{15}$  synapses in human brains) for them all to be set genetically, so at least some must be set by some other procedures. (2) During development there is massive synaptogenesis and also massive cell death, some of which appears to be governed by competitive principles (Rakic 1986, Constatine-Paton and Ferrari-Eastman 1987), that have the character of an optimizing process. Crudely speaking, the connections which are most robust and useful as the substrate for some func-

tions tend to survive. (3) In both the developing and the adult animal, some of these parameters are set as the nervous system uses feedback to adapt behavior to circumstances. There are many examples of homeostatic error-correcting mechanisms, such as changing the gain of the vestibulo-ocular reflex in response to magnifying goggles (see chapter 6), calibrating motor performance in learning how to play tennis, and fine-tuning the matching of images from the two eyes. (4) Natural selection culls nervous systems that are outperformed by those of predators, prey, or conspecifics in the reproduction game. To this extent, and relativized to in-place structures, the selection pressure on nervous structures can be characterized as error-minimizing. This is just to state the familiar thesis of natural selection in a neurobiological context: the modifications to nervous systems that are preserved are by and large those modifications that contribute to (at least do not undermine) the organism's survival in its niche.

A possible misunderstanding should be forestalled here. In describing the evolutionary modification of nervous structures as error minimization (and hence as optimization), we do not assume anything Panglossian about evolution. Consequently we are not letting ourselves in for a scolding from Gould and Lewontin<sup>39</sup> for the sin of supposing that if natural selection slides down an error gradient, characterized relative to available structure and environmental niche, the nervous system is therefore the best of all possible systems. First, the parameter-adjusting procedures at the evolutionary level may find only a local minimum, not necessarily the global minimum. In other words, evolution may find not the best *possible* solution, but only a satisfactory solution. "Satisficing" is good enough for survival and reproduction, and apart from natural selection there is really nothing to push evolution to do better, nor, of course, is there a particular path for it to follow.

Returning now to the relevance of model nets to real neural nets, imagine that Critter-net is an up-and-running neural circuit in some living nervous system. Suppose, for example, that it is the neural circuit for visual tracking of moving objects when the head is moving. By experimentation in anatomy, physiology, and pharmacology, the values of many of the parameters in the system are known. Thus we may know the number of cell types, we may have rough estimates of the numbers of each type, what cells project to where, the receptive field properties of cells, whether certain synapses are excitatory or inhibitory, and so on. The specific weights, however, are unknown. Suppose Computer-net is constructed by fixing the known parameters. Those parameters whose values are unknown, such as the weights, will be fixed as Computer-net is trained up on the input-output function using an error-minimization procedure for adjusting the parameters. Can we infer anything about Critter-net's global properties from the global properties of Computer-net? Would it be useful to make predictions about undiscovered local and global properties of Critter-net on the basis of the local and global properties of Computer-net? Given that nervous systems are probably computing error minimization, or at least cost functions of some kind, then the answers appear to be positive. As

before, however, *the probability of the inference depends on the degree of similarity between the architecture and dynamics of Critter-net and Computer-net.*

A different but related point concerns the significance of parameter asymmetries between nets with identical architecture and dynamics. Learning algorithms can be thought of as efficient devices for searching the parameter space for combinations of values that optimize some input–output function. When there are many thousands of parameters, the probability that the global minimum of the real neural net and that of the model net are precisely the same, weight for weight, is actually rather low. This may prompt the inference that the model net is next to useless in understanding the real neural net. In fact, the situation is nothing like so gloomy. To begin with, experience with parameter-adjusting procedures applied to many problems shows that networks can perform equivalently even though the specific values of the weights may be quite different.

In the simplest case, a net and its mirror image are equivalent. In a rather backhanded way, the fact that optimization procedures cannot be counted on to find the global minimum, but only local minima, helps upgrade the probability of a model net's being useful. Regardless of the starting point in parameter space, if the net keeps going downhill and improving its performance, it is likely to find a good solution at the bottom, though it may not be the very best. This means that a net trained up on many different occasions from randomly set starting weights carves out a region of parameter space of different but equivalent solutions—of different but equivalent weight-assignments. And the same is likely to be true of nervous systems. That is, *even homozygotic twins' brains may be very different in their weight-by-weight (parameter-by-parameter) configuration, even if their circuits and their capacities be functionally equivalent.* The idea is then that two *regions* of parameter space are, on sheerly mathematical grounds, more likely to overlap than two *points* in parameter space. So if an optimizing procedure circumscribes regions rather than localizing points, this is all to the good. Thus when a model net is highly constrained by neurobiological data, the probability is nontrivial that the region of parameter space defined by the model net and the real neural net will overlap. In either case, one can use additional neurobiological data to error-correct one's way closer to the parameter-space region of the real neural net. [For the statistical analysis of learning in artificial neural nets, see White (1989).]

The main point, therefore, is that model nets may be a valuable source of ideas relevant to real neural nets. By analyzing the features of the trained-up net, one can make predictions concerning the actual nervous system, which can then be tested neurobiologically. This is especially useful when the model's results illuminate global properties, for these are surpassingly difficult to find by neurobiological techniques but are easy to reveal in artificial nets. The useful results are by no means restricted to global properties, for model nets may also reveal important but unanticipated local properties. Consequently, surprising results can be gleaned from a model net that would not be discov-

ered by looking only at a real neural net. Newfound neurobiological parameters can then be ploughed back into the model as added constraints. The newly parametrized model will generate new hypotheses and predictions, and the co-evolutionary gambit can be repeated. Notice that co-evolution of model net and neural knowledge is really an error-correcting process, where the goal is minimizing error in the model net by comparison with the real neural net.

The basic argument regarding the value of model nets to neuroscience has a number of important pieces, and it can be summed up as follows: (1) It is reasonable to assume that the evolution of nervous systems can be described by a cost function; development and learning in nervous systems are probably also describable by a cost function. In other words, by dint of parameter-adjusting procedures, nervous systems, ontogenetically and phylogenetically, appear to be finding local minima in their error surfaces. (2) Model nets that are highly constrained by neurobiological data concerning architecture and dynamics of the neural circuit being simulated may use backprop as a search procedure to find local minima. (3) Identical nets using the same cost function and sliding into error minima will nonetheless vary considerably in the specific values assigned to their parameters. This is because the triple  $\langle$ architecture, dynamics, error-minimization procedure $\rangle$  carves out a *region* of weight space, and many different weight configurations can be found in that region. (4) There is no guarantee that the local minima found by the model net will overlap the local minima found by the real neural network, but it is reasonable to assume so given points (1) and (3). That is, it is not unlikely that the region of weight space carved out by the equivalent model nets and the neural nets will at least overlap. (5) That assumption can be tested against the nervous system itself, and additional constraints derived from neurobiological data can be added to the model net to move it closer to the real neural net's region of parameter space. This is itself an error-minimization procedure at the theory-generating level. (6) Thus the model nets can be viewed as hypothesis generators.<sup>40</sup>

Until rather recently, setting the parameters in neurobiological models was done largely by hand. (See, for example, Hodgkin and Huxley 1952, which is discussed further in chapter 6.) But in large nets with many parameters and nonlinear hidden units, hand-setting parameters is impractical to say the least. As we have argued, model nets, in the context of the error-correcting co-evolution with neurobiology, can lead to interesting results, and in general to better results than obtained via guess-and-by-golly or hunch-driven parameter setting. The point is important, but it should not be oversold. To repeat an earlier caution, computer models of nets are a tool—but only one tool among others; they are not a replacement for the basic neurobiological techniques that have sustained neuroscience so far. The proof of the proverbial pudding is of course in the eating, and thus it is by examples of useful models that the case for network modeling as a valuable tool is most convincingly made. The remaining chapters of the book are, therefore, largely devoted to presenting examples we have found useful or at least suggestive.

## 12 MODELS: REALISTIC AND ABSTRACT

In the previous section we leaned rather heavily on the desirability of constraining a model net with neurobiological data to increase the probability that the model can tell us something about the real neural net. There is an important dimension in which that must be qualified and explained. In neuroscience, as anywhere else in science, no model is 100% realistic. A good and useful model of the solar system, for example, will not necessarily have actual gas clouds drifting around Jupiter; a good and useful model of magnetism will not necessarily provide for the rusting of iron. The central point is this: what goes into the model depends on what one is trying to explain, and in the nervous system, that is intimately related to the level of organization one is targeting. (Recall levels of organization in chapter 2, and figure 2.1.) A little more exactly, if one is modeling a function or task of a given level of brain organization, the model should be sensitive to structural constraints from the level below and to input–output properties described for the level above.

Not uncommonly, a model will be criticized as unrealistic for failing to include very low-level properties. A model of a neural circuit such as the vestibulo-ocular reflex (VOR) (see chapter 6) may include only the pathways required by the model to perform equivalently to the real net, it may average over dendritic integration, and it may ignore altogether the details of membrane channel properties. Does this mean the model is too unrealistic to be useful? We shall show more directly and specifically in chapter 6 why the model can be useful nonetheless, but for the moment, suffice it to say that lower-level properties such as channel properties are not necessary to simulate a neuron's contribution to that aspect of the VOR up for explanation, namely image stabilization. The model certainly needs to incorporate constraints regarding latencies and feedback loops (level above) and constraints regarding the net effect at synapses and the firing rate of neurons in the circuits (level below), but it does not need to be sensitive to the precise mechanisms by which a neuronal membrane operates to yield these firing rates (*two* levels below). There may be other aspects of the VOR circuit where these properties will be required for the explanation sought—for example, exactly how synaptic plasticity is managed. When synaptic plasticity *is* what is being modeled, however, then these properties should be included. More generally, if one were modeling how a neuron integrates signals, then membrane properties are relevant and must be included. In that event, however, higher-level properties, such as receptive field and feedback connections (*two* levels up), are probably not relevant.

Some modeling discussions seem to presuppose a kind of “realism pecking order.” For example, it may be argued that until the whole neuron is thoroughly and completely modeled, modeling even a small circuit such as the VOR is premature. According to this argument, a circuit model will have to idealize the neuron, leaving out such details as the membrane channel types and their physiology. This, it will be complained, makes the model “unrealistic,” and hence dismissable. An even more pure realist can dismiss the whole

neuron-modeling project on grounds that there is no point in modeling the neuron until one has completely modeled the dynamics of transmitter release, including such constraints as numbers of vesicles that fuse, spatial layout of receptors, and production and packaging of neurotransmitters. Undoubtedly the biophysicist can top that; he wants first a model of protein folding. But this is surely silly. Do we really need a model of protein folding in order to get a grip on the essentials of how the VOR achieves stabilization of a visual image during head movement? Part of what perpetuates the realist pecking order is this: any given modeler tends to think his favored modeling level is *the* important level, that lower levels are properly ignorable, and modeling levels higher than his favored level is premature and unrewarding.

Realist one-upmanship needs to be put in perspective. First, models that are excessively rich may mask the very principles the models were built to reveal. In the most extreme case, if a model is exactly as realistic as the human brain, then the construction and the analysis may be expensive in computational and human time and hence impractical. As noted in chapter 1; modeling may be a stultifying undertaking if one slavishly adheres to the bald rule that the more constraints put in a model, the better it is. Every level needs models that are simplified with respect to levels below it, but modeling can proceed very well in parallel, at many levels of organization at the same time, where sensible and reasonable decisions are made about what detail to include and what to ignore. There is no decision procedure for deciding what to include, though extensive knowledge of the nervous system together with patience and imagination are advantageous. The best directive we could come up with is the woefully vague rule of thumb: make the model simple enough to reveal what is important, but rich enough to include whatever is relevant to the measurements needed.

### 13 CONCLUDING REMARKS

The look-up table was introduced as our first and simplest parade case of computation. Because look-up tables appeared to be rather limited in their capacity to solve difficult computational problems, other computational principles were sought. It is surprising then to realize that a trained-up network model can be understood as a kind of look-up table. Once the parameters are set, the network will give the output suitable to the input, and the answer to any given question is stored in the configuration of weights. Not, to be sure, the way answers are stored on a slide rule, but in the sense that an input vector pushed through the matrix of weights (and squashing function) is transformed so that the output vector represents the answer. Not, notice, by way of many intervening computational steps, but merely by vector-matrix transformation.

By analogy with the ⟨board position/next position⟩ pairs prestored in the Tinkertoy computer, the net's weight configuration, characterized as a matrix through which the input vector is pushed, can be thought of as "storing" prototypes as ⟨input vector/hidden unit activation⟩ pairs, "storing" being in scare quote to reflect the extension of its customary sense. As we saw above, when the net has learned to distinguish rock echoes from mine echoes so no

further weight-adjusting is required to deliver correct answers, the weights partition the activation space of the hidden units in such a way that activation values of the hidden units fall on one side or the other of the partition (see next chapter, figure 4.17). The key difference between the run-of-the-mill look-up table and the trained-up network is that the network can correctly classify novel signals and thus has the capacity to generalize from training cases to new cases. In this respect, trained-up networks have a flexibility denied to run-of-the-mill look-up tables. This flexibility of a net is not mysterious. It derives from the net's assorted design features; for example, the output values of its hidden units may be continuous, and working as groups the units can interpolate smoothly between samples.

These networks might be considered examples of "smart look-up tables." They operate in very high-dimensional spaces, since weight space will have as many dimensions as there are weights, and activation space for the hidden units will have as many dimensions as there are hidden units. The consequence of these design features is that though the training set is finite, the network will give good answers to inputs it has never seen before. The inputs will, however, have some resemblance to previously seen inputs, and that will be enough to ensure correct categorization. It must be emphasized that the learning process is not itself a look-up table operation—rather, parameter-adjusting is a relaxation process. Similarly, fitting the Tinkertoy pieces together is not itself a look-up table operation. In the network, it is only the *result* of parameter-adjusting procedures that produces something construable as having a look-up table configuration. Moreover, a single (smart) look-up table can be traded in for a hierarchy of (smart) mini-look-up tables, so that an approximate answer can be cranked out at one stage, then shunted to a further stage for finer tuning. In this event, speed is traded for spatial miniaturization. Some of the speed can, however, be bargained back by adopting parallel search.

The insight that trained-up nets are look-upish raises the question of whether this might be useful in understanding circuits in nervous systems. Is it possible that some parts of the brain are taking advantage of the look-up table principle in some highly evolved version of that genre? Time considerations suggest they might well be. The time delays for conduction of a signal down an axon and across a synaptic cleft, together with the time delays for signal integration in the dendrites and cell body, add up to about 5 or 10 msec per neuronal step. If a nervous system is to give a motor response to a sensory stimulus with a latency of a few hundred milliseconds or less, then for certain stages in processing, the neuronal anatomy is probably configured for look-up short-cuts. Visual pattern recognition, for example, can be done in about 200–300 msec, which means there is only time for about 20–30 neuronal steps from retinal stimulation to motor output (Thorpe and Imbert 1989, Thorpe 1990).

Evidently the response latency for many tasks, including visual recognition, shows that there is insufficient time for the brain to be engaged in following the massive set of 3000–50,000 steps (or more) found in conventional computer vision programs (Feldman and Ballard 1982). Figuring out the next move

in chess or figuring out how to make a bridge with popsicle sticks is, by contrast, relatively slow, and clearly involve many steps, but whether these are steps in a long sequence of look-ups representing possible <move-next move> pairs, or whether some rely on different principles altogether remains to be seen. Given their finite capacity, nervous systems cannot store answers for every possible contingency. To cope with novelty, nervous systems must cycle through multiple states to search for an adequate solution. With practice, however, the new problem–solution pairs can be compiled into a look-up table.<sup>41</sup>

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