

Connectionist AI, Symbolic AI, and the Brain

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Abstract Connectionist AI systems are large networks of extremely simple numerical processors, massively interconnected and running in parallel. There has been great progress in the connectionist approach, and while it is still unclear whether the approach will succeed, it is also unclear exactly what the implications for cognitive science would be if it did succeed. In this paper I present a view of the connectionist approach that implies that the level of analysis at which uniform formal principles of cognition can be found is the *subsymbolic level*, intermediate between the neural and symbolic levels. Notions such as logical inference, sequential firing of production rules, spreading activation between conceptual units, mental categories, and frames or schemata turn out to provide approximate descriptions of the coarse-grained behaviour of connectionist systems. The implication is that symbol-level structures provide only approximate accounts of cognition, useful for description but not necessarily for constructing detailed formal models.

In the past few years a new approach to artificial intelligence (AI), called *connectionist modelling*, has been gaining increasing attention in research and development laboratories. Connectionist systems are large networks of extremely simple processors, massively interconnected and running in parallel. Each processor has a numerical *activation value* which it communicates to other processors along connections of varying strengths. The activation value for each processor constantly changes in response to the activity of the processors to which it is connected. The values of some of the processors form the input to the system, and the values of other processors form the output. The connections between the processors determine how input is transformed to output. In connectionist systems, knowledge is encoded not in symbolic structures but rather in the pattern of numerical strengths of the connections between processors.

The goal of connectionist research is to model both lower-level perceptual processes and such higher-level processes as object recognition, problem solving, planning and language understanding. There exist connectionist models of the following cognitive phenomena:

Speech perception,
Visual recognition of figures in the "Origami world",
Development of specialized feature detectors,
Amnesia,
Language parsing and generation,
Aphasia,
Discovering binary encodings,
Dynamic programming of massively parallel networks,
Acquisition of English past tense morphophonology from examples,
Tic-tac-toe play,
Inference about rooms,
Qualitative problem solving in simple electric circuits.

One crucial question is whether the computational power of connectionist systems is sufficient for the construction of truly intelligent systems. Explorations addressing this question form the bulk of the contributions to the connectionist literature: many can be found in the proceedings of the International Joint Conference on AI and the annual meetings of the American Association for AI and the Cognitive Science Society over the past several years. The connectionist systems referred to in the previous paragraph can be found in the collections in Hinton and Anderson (1981); *Cognitive Science* (1985); Rumelhart, McClelland and the PDP Research Group (1986); McClelland, Rumelhart and the PDP Research Group (1986); and the bibliography by Feldman *et al.* (1985). In the present paper I will not address the issue of computational power, except to point out that connectionist research has been strongly encouraged by successful formal models of the details of human cognitive performance, and strongly motivated by the conviction that the pursuit of the principles of neural computation will eventually lead to architectures of great computational power.

In addition to the question of whether the connectionist approach to AI can work, there is the question: What exactly would it mean if the approach *did* work? There are fundamental questions about the connectionist approach that are not yet clearly understood despite their importance. What is the relation between connectionist systems and the brain? How does the connectionist approach to modelling higher-level cognitive processes relate to the symbolic approach that has traditionally defined AI and cognitive science? Can connectionist models contribute to our understanding of the nature of the symbol processing that characterizes the mind, and its relation to the neural processing that characterizes the brain? These are the questions I address in this paper. In the process of addressing these questions it will become clear that the answers are important not only in their own right, but also as contributions to the determination of whether the connectionist approach has sufficient power.

Levels of analysis: neural and mental structures

It is best to begin with the question, how do accounts of intelligence relate to neural and mental structures? What are the roles of the neural and the symbolic levels of analysis? We first consider the answers from the traditional symbolic approach to AI, and then from a connectionist alternative.

The symbolic paradigm

We start with the mental structures of ‘folk psychology’: goals, beliefs, concepts, and so forth (see Fig. 1). In the symbolic approach, these mentalist concepts are formalized in terms of a ‘language of thought,’ as Fodor (1975) says; this language is supposed to provide a literal formalization of folk psychology. The rules for operating on this language are essentially Boole’s (1854/1961) ‘laws of thought.’ These symbolic structures are supported by a *physical symbol system* — a physical computing device for manipulating symbols — which in turn is supported by lower implementation levels in a computing device. The idea is that eventually, if we were to get low enough down in the human physical symbol system, we would see

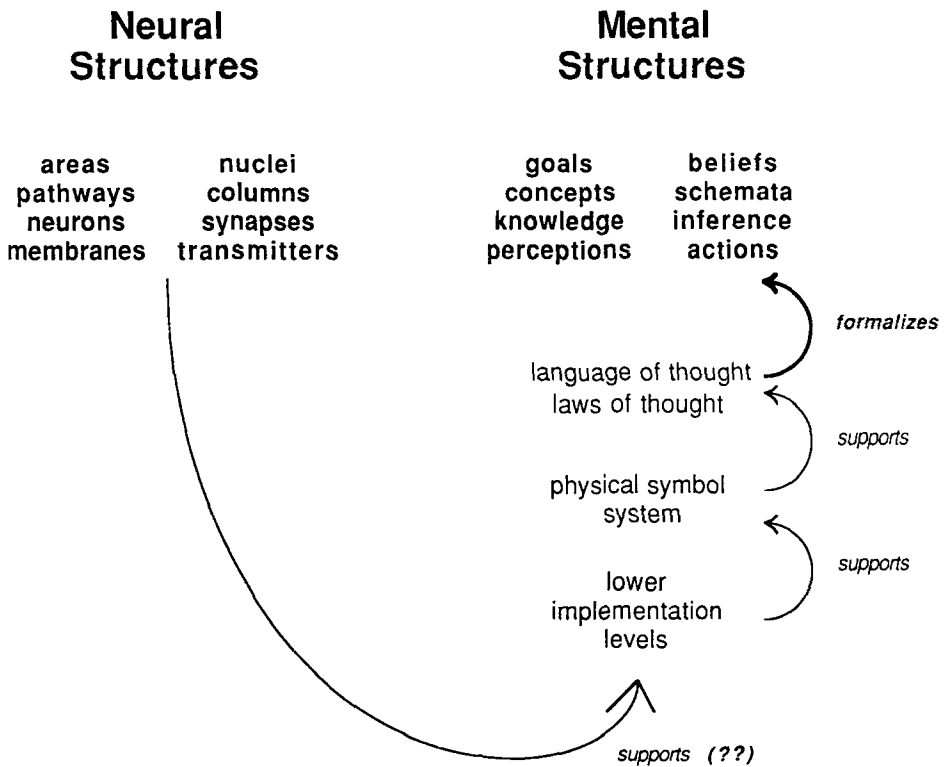


Fig. 1. Neural and mental structures in the symbolic paradigm.

something similar to neurons. In other words, from this account we have to figure out how to relate neural structures to the low implementation levels of a physical symbol system, and then we should understand the relation between neural structures and mental structures. If it were the case that increasingly lower levels of computers looked more and more like neural systems, this would be a promising approach; unfortunately, insights into the design and implementation of physical symbol systems have so far shed virtually no light on how the brain works.

To understand more clearly the connectionist alternative, it is helpful to articulate a number of the properties of the symbolic approach. Allen Newell (1980) formulated this paradigm best in his physical symbol system hypothesis: "The necessary and sufficient condition for a physical system to exhibit general intelligent action is that it be a physical symbol system" (p. 170). "General intelligent action" means rational behaviour (p. 171); "rationality" means that when an agent has a certain goal and the knowledge that a certain action will lead to that goal then the agent selects that action (Newell, 1982). (And physical symbol systems are physically realized universal computers.)

What all this means in the practice of symbolic AI is that goals, beliefs, knowledge, and so on are all formalized as symbolic structures, for example, Lisp lists, which are built of symbols, Lisp atoms, which are each capable of being semantically interpreted in terms of the ordinary concepts we use to conceptualize the domain. Thus, in a medical expert system, we expect to find structures like (IF FEVER THEN (HYPOTHEZIZE INFECTION)). These symbolic structures are operated on by symbol manipulation procedures composed of primitive operations like concatenating lists, and extracting elements from lists. According to the symbolic paradigm, it is in terms of such operations that we are to understand cognitive processes.

It is important to note that in the symbolic paradigm, levels of cognition are made analogous to levels of computer systems. The symbolic level that implements knowledge structures is alleged to be exact and complete. That means that lower levels are unnecessary for accurately describing cognition in terms of the semantically interpretable elements. This relegates the neural question to simply: how does the nervous system happen to implement physically a physical symbol system? The answer to this question does not matter as far as symbol-level AI systems are concerned.

There are a number of inadequacies of this paradigm, which Hofstadter (1985) has called "the Boolean dream". These inadequacies can be perceived from a number of perspectives, which can only be caricatured here:

From the perspective of neuroscience, the problem with the symbolic paradigm is quite simply that it has provided precious little insight into the computational organization of the brain.

From the perspective of modelling human performance, symbolic models, like Newell and Simon's General Problem Solver (1972), are successful on a coarse level, but the fine structure of cognition seems to be more naturally described by non-symbolic models. In word recognition, for example, it is natural to think about activation levels of perceptual units.

In AI, the trouble with the “Boolean dream” is that symbolic rules and the logic used to manipulate them tend to produce rigid and brittle systems.

The subsymbolic paradigm

An alternative to the symbolic paradigm is what I call the *subsymbolic paradigm* (see Fig. 2). In this paradigm, there is an intermediate level of structure between the neural and symbolic levels. This new *subsymbolic level* is supposed to be closer to each of the neural and symbolic levels than they are to each other. *When cognition is described at the subsymbolic level, the description is that of a connectionist system.*

The subsymbolic level is an attempt to formalize, at some level of abstraction, the kind of processing which occurs in the nervous system. Many of the details of neural structure and function are absent from the subsymbolic level, and the level of description is higher than the neural level. The precise relationship between the neural and subsymbolic levels is still an open research question; but it seems clear that connectionist systems are much closer to neural systems than are symbolic systems.

The relation between the subsymbolic and symbolic descriptions of cognition is illustrated in Fig. 2. If we adopt a higher level of description of what is happening in these subsymbolic systems (and that involves, to a significant degree, approximation) then we obtain descriptions that are approximately like symbolic accounts,

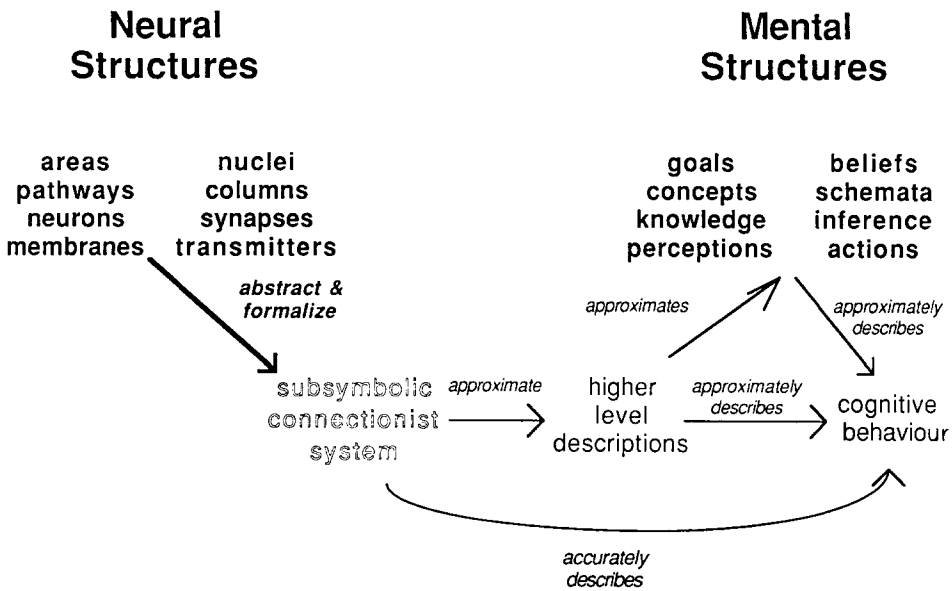


Fig. 2. Neural and mental structures in the subsymbolic paradigm.

like traditional AI constructs. While the subsymbolic paradigm is content to give approximate accounts of goals and beliefs, it is not prepared to compromise on actual performance. Behind the accounts of folk psychology and symbolic AI there are real data on human intelligent performance, and the claim is that subsymbolic systems can provide accurate accounts of this data.

Note that the subsymbolic paradigm gives an essentially different role to the neural part of the story: neural structures provide the basis (in some suitably abstract sense) of the formalism that gives the precise description of intelligence, while mental structures enter only into approximate descriptions.

The remainder of the paper elaborates on the nature of the subsymbolic level, and on the higher level descriptions of subsymbolic systems that approximate symbolic accounts. I want to indicate how formalizing cognition by abstracting from neural structures — rather than with symbolic formalizations of mental structures — provides new and exciting views of knowledge, memory, concepts, and learning.

Figure 2 illustrates an important part of the subsymbolic paradigm: that levels of cognition should *not* be thought of by analogy to levels of computer systems, all stacked underneath the 'mental' part of the diagram. Just as Newtonian concepts provide approximately valid descriptions of physical phenomena that are more accurately described by quantum concepts, so the symbolic concepts of folk psychology provide approximately valid descriptions of cognitive phenomena that are more accurately described by subsymbolic concepts. Mental structures are like higher-level descriptions of a *physical* system, rather than higher-level descriptions of a *computer* system.

Semantic interpretation

Perhaps the most fundamental contrast between the paradigms pertains to semantic interpretation of the formal models. In the symbolic approach, symbols (atoms) are used to denote the semantically interpretable entities (concepts). These same symbols are the objects governed by symbol manipulations in the rules that define the system. The entities which are capable of being semantically interpreted are *also* the entities governed by the formal laws that define the system. In the subsymbolic paradigm, this is no longer true. The semantically interpreted entities are *patterns of activation* over a large number of units in the system, whereas the entities manipulated by formal rules are the individual activations of cells in the network. The rules take the form of activation passing rules, of essentially different character from symbol manipulation rules.

This describes the particular kind of connectionist system where patterns of activity represent concepts, instead of the activation of individual elements in the network. (In the latter case, we would have a collapsing here of just the same kind that we have the symbolic paradigm.) Therefore, the subsymbolic paradigm involves connectionist systems using so-called *distributed representations*, as opposed to local representations. (The books by Rumelhart, McClelland and the PDP Research Group consider distributed connectionist systems; local connectionist systems are considered in Feldman & Ballard, 1982, and Feldman *et al.*, 1985.)

Thus in the subsymbolic paradigm, the formal system description is at a lower level than the level of semantic interpretation: the level of denotation is higher than the level of manipulation. There is a fundamental two-layer structure to the subsymbolic paradigm, unlike the symbolic approach. The higher semantic level is not necessarily capable of being formalized precisely, and the lower level is not 'merely implementation' of a complete higher level formalism. Both levels are essential: the lower level is essential for defining what the system is (in terms of activation passing) and the higher level is essential for understanding what the system means (in terms of the problem domain).

The subsymbolic level

I shall now characterize the subsymbolic level in more detail. Cognition looks quite different at this level than from the symbolic level. In the last part of the paper, we consider higher level descriptions of connectionist systems, where we can see some of the characteristics of the symbolic level emerging.

The subsymbolic formalism

At the fundamental level in subsymbolic systems we have a collection of dynamic variables. There are two kinds of variables: an activation level for each of the units and a connection strength for each of the links. Typically both kinds of variables are continuous. The rules that define these systems are activation passing rules and connection strength modification rules. These are differential equations (although they are simulated with finite difference equations). Typically the differential equations are not stochastic, but stochastic versions will enter briefly later.

The computational role of these two kinds of equations is this. The activation passing rules are in fact inference rules: not logical inference rules, but statistical inference rules. The connection strength modification rules are memory storage and learning procedures. These points will be expanded shortly.

Because the fundamental system is a dynamic system with continuously evolving variables, the subsymbolic paradigm constitutes a radical departure from the symbolic paradigm. The claim, in effect, is that *cognition should be thought of as taking place in dynamical systems and not in digital computers*. This is a natural outcome of the neurally-inspired rather than mentally-inspired formalism.

The relation between the subsymbolic formalism and psychological processing is, in part, determined by the time constants that enter into the differential equations governing activation and connection strength modification. The time required for significant change in activation levels is in the order of 100 ms; the time it takes for a connection strength to change appreciably is much longer, say, in the order of 1 min. Thus, for times less than about 100 ms, we have a single equilibration or 'settling' of the network; all the knowledge embedded in the connections is used in parallel. On this time scale, we have parallel computation. When we go beyond this, to cognitive processes that go on for several seconds, such as problem solving and extended reasoning, then we are concerned with multiple

settlings of the network, and serial computation. This is the part of cognition for which serial symbolic descriptions, e.g. Newell and Simon's General Problem Solver, provide a fairly good description of the coarse structure. The claim of the subsymbolic paradigm is that the symbolic description of such processing is an approximate description of the global behaviour of much parallel computation. Finally, if we consider still longer time scales, in the order of 1 min, then we have adaptation of the network to the situation in which it finds itself.

To summarize the contrasts between the symbolic and subsymbolic approaches, viewed at the fundamental level. In the subsymbolic paradigm we have fundamental laws that are differential equations, not symbol manipulation procedures. The systems described are dynamical systems, not von Neumann machines. The mathematical category in which these formalisms live is the continuous category, not the discrete category, so a different kind of mathematics comes into play. The differences are dramatically illustrated in the way memory is modelled in the two formalisms. In the von Neumann machine, memory storage is a primitive operation (you give location and contents, and storage just happens); memory retrieval is also a primitive operation. In subsymbolic systems these processes are quite involved: they are not primitive operations at all. When a memory is retrieved, it is a content-addressed memory: part of a previously instantiated activation pattern is put into one part of the network by another part of the network, and the connections fill out the rest of that previously present pattern. This is a much more involved process than a simple 'memory fetch.' Memories are stored in subsymbolic systems by adjusting connection strengths so that the retrieval process will actually work: this is no simple matter.

Subsymbolic inference and the statistical connection

At the fundamental level of subsymbolic formalism, we have moved from thinking about cognition in terms of discrete processes to thinking in terms of continuous processes. This means that different mathematical concepts apply. One manifestation of this, in computational terms, is the claim that inference should not be construed in the logical sense but rather in the statistical sense — at least at the fundamental level of the system. (Later we will see that at higher levels, certain subsymbolic systems do perform logical inference.)

I have encapsulated this idea in what can be called the Statistical Connection: the strength of the connection between two units is a measure of the statistical relation between their activity.

The origins of this principle can be easily seen. The relationship between statistics and connections was represented in neuroscience by Hebb's (1949) principle: a synapse between two neurons is strengthened when both are active simultaneously. In psychology, this relation appeared in the notion of 'strength of association' between concepts, an important precursor to connectionist ideas (although since this involved statistical associations between concepts, it was not, itself, a subsymbolic notion). From the point of view of physics, the Statistical

Connection is basically a tautology, since if two units are strongly connected, then when one is active the other is likely to be too.

From a computational point of view, the Statistical Connection has rather profound implications *vis-à-vis* AI and symbolic computation. Activation passing is now to be thought of as statistical inference. Each connection represents a *soft constraint*; the knowledge contained in the system is the set of all such constraints. If two units have an inhibitory connection, then the network has the knowledge that when one is active the other ought not be; but that is a soft constraint that can easily be overridden by countermanding excitatory connections to that same unit (if those excitatory connections come from units that are sufficiently active). The important point is that soft constraints, any one of which can be overridden by the others, *have no implications singly*; they only have implications collectively. That is why the natural process for using this kind of knowledge is *relaxation*, in which the network uses all the connections at once, and tries to settle into a state that balances all the constraints against each other. This is to be contrasted with *hard constraints*, like rules of the form 'if A, then B', which can be used individually, one at a time, to serially make inferences. The claim is that using soft constraints avoids the brittleness that hard constraints tend to produce in AI. (It is interesting to note that advocates of logic in AI have for some time now been trying to evade the brittleness of hard constraints by developing logics, such as non-monotonic logics, where all of the rules are essentially used *together* to make differences, and not separately; see for example, *Artificial Intelligence*, 1980.)

To summarize: in the symbolic paradigm, constraints are typically hard, inference is logical, and processing can therefore be serial. (One can try to perform logical inference in parallel, but the most natural approach is serial inference.) In the subsymbolic paradigm, constraints are soft, inference is statistical, and therefore it is most natural to use parallel implementations of inference.

Higher level descriptions

Having characterized the subsymbolic paradigm at the fundamental, subsymbolic level, I should now like to turn to higher level descriptions of these connectionist systems. As was stated earlier, in the subsymbolic paradigm, serial, symbolic descriptions of cognitive processing are approximate descriptions of the higher level properties of connectionist computation. I will only sketch this part of the story briefly, pointing to published work for further details. The main point is that interesting relations *do* exist between the higher-level properties of connectionist systems and mental structures, as they have been formalized symbolically. The view of mental structures that emerges is strikingly different from that of the symbolic paradigm.

The Best Fit Principle

That crucial principle of the subsymbolic level, the Statistical Connection, can be reformulated at a higher level, in what I call the Best Fit Principle: given an input, a

connectionist system outputs a set of inferences that, as a whole, give a best fit to the input, in a statistical sense defined by the statistical knowledge stored in the system's connections.

In this vague form, this principle is generally true for connectionist systems. But it is exactly true in a precise sense, at least in an idealized limit, for a certain class of systems in what can be called *harmony theory* (Smolensky, 1983, 1984a and b, 1986a, b and c; Riley & Smolensky, 1984).

To render the Best Fit Principle precise, it is necessary to provide precise definitions of 'inferences', 'best fit' and 'statistical knowledge stored in the system's connections.' This is done in harmony theory, where the central object is the 'harmony function' H which measures, for any possible set of inferences, the degree of fit to the input with respect to the soft constraints stored in the connection strengths. The set of inferences with the largest value of H , i.e. highest harmony, is the best set of inferences, with respect to a well-defined statistical problem.

Harmony theory basically offers three things: it gives a mathematically precise characterization of a very general statistical inference problem that covers a great number of connectionist computations. It informs us how that problem can be solved using a connectionist network with a certain set of connections. And it gives a procedure by which the network can learn the correct connections with experience.

The units in harmony networks are stochastic units, that is, the differential equations defining the system are stochastic. There is a system parameter called the *computational temperature* that governs the degree of randomness in the units' behaviour: it falls to zero as the computation proceeds. (The process is *simulated annealing*, as in the Boltzmann machine: Hinton & Sejnowski, 1983. See Rumelhart, McClelland & the PDP Research Group, 1986, p. 148, and Smolensky, 1986a, for the relations between harmony theory and the Boltzmann machine.)

Productions, sequential processing, and logical inference

A simple harmony model of expert intuition in qualitative physics was described in Riley and Smolensky (1984) and Smolensky (1986a and c). The model answers questions such as "what happens to the voltages in this circuit if I increase this resistor?" Higher level descriptions of this subsymbolic problem-solving system illustrate several interesting points.

It is possible to identify *macro-decisions* during the system's solution of a problem; each of these is the result of many individual *micro-decisions* by the units of the system, and each amounts to a large-scale commitment to a portion of the solution. These macro-decisions are approximately like the firing of production rules. In fact, these 'productions' 'fire' at different times, in essentially the same order as in a symbolic forward-chaining inference system. One can measure the total amount of order in the system, and see that there is a qualitative change in the system when the first micro-decisions are made: the system changes from a disordered phase to an ordered one.

It is a corollary of the way this network embodies the problem domain constraints, and the general theorems of harmony theory, that the system, when given a

well-posed problem, and infinite relaxation time, will always give the correct answer. So under this idealization, the competence of the system is described by *hard* constraints: Ohm's Law and Kirchoff's Law. It is as though it had those laws written down inside it. However, as in all subsymbolic systems, the performance of the system is achieved by satisfying a large set of *soft* constraints. What this means is that if we go outside the ideal conditions under which hard constraints seem to be obeyed, the illusion that the system has hard constraints inside is quickly dispelled. The system can violate Ohm's Law if it must, but if it doesn't have to violate the law, it won't. Thus, *outside the idealized domain of well-posed problems and infinite processing time, the system gives sensible performance*. It is not brittle in the way that symbolic inference systems are. If the system is given an ill-posed problem, it satisfies as many constraints as possible. If it is given inconsistent information, it does not fall flat, and deduce anything. If it is given insufficient information, it does not remain inactive and deduce nothing. Given finite processing time, the performance degrades gracefully as well, so that the competence/performance distinction can be made in a sensible way.

Returning to the theme of physics analogies rather than computer analogies, this 'quantum' system appears to be 'Newtonian' under the proper conditions. A system that has, at the micro-level, soft constraints, satisfied in parallel, appears at the macro-level, under the right circumstances, to have hard constraints, satisfied serially. But this is not actually true, and if one goes outside the 'Newtonian' domain, one sees that it has actually been a 'quantum' system all along.

The dynamics of activation patterns

In the subsymbolic paradigm, semantic interpretation occurs at the higher level of patterns of activity, not at the lower level of individual nodes. Thus an important question about the higher level runs: how do the semantically interpretable entities *combine*?

In the symbolic paradigm, the semantically interpretable entities are symbols, which combine by some form of *concatenation*. In the subsymbolic paradigm, the semantically interpretable entities are activation patterns, and these combine by *superposition*: activation patterns superimpose upon each other, in the same way that wave-like structures always do in physical systems. This difference is another manifestation of moving the formalization from the discrete to the continuous (indeed the linear) category.

Using the mathematics of the superposition operation, it is possible to describe connectionist systems at the higher, semantic level. If the connectionist system is purely linear (so that the activity of each unit is precisely a weighted sum of the activities of the units giving it input), it can easily be proved that the higher level description obeys formal laws of just the same sort as the lower level: the subsymbolic and symbolic levels are *isomorphic*. Linear connectionist systems are, however, of limited computational power, and most interesting connectionist systems are nonlinear. However, nearly all are *quasi-linear*, that is, each unit combines its inputs linearly even though the effects of this combination on the

unit's activity are nonlinear. Further, the problem-specific knowledge in such systems is in the combination weights, i.e. the linear part of the dynamical equations, and in learning systems it is generally only these linear weights that adapt. For these reasons, even though the higher level is not isomorphic to the lower level in nonlinear systems, there are senses in which the higher level approximately obeys formal laws similar to the lower level. (For details, see Smolensky, 1986b.)

The conclusion here is rather different from the preceding section, where we saw how there are senses in which higher level characterizations of certain subsymbolic systems approximate productions, serial processing, and logical inference. What we see now is that there are also senses in which the laws approximately describing cognition at the semantic level are *activation-passing laws* like those at the subsymbolic level, but operating between 'units' with individual semantics. These semantic level descriptions of mental processing (which include *local connectionist* models) have been of considerable value in cognitive psychology (McClelland & Rumelhart, 1981; Rumelhart & McClelland, 1982; Dell, 1985). We can see now how these 'spreading activation' accounts of mental processing relate to subsymbolic accounts.

Schemata

One of the most important symbolic concepts is that of the *schema* (Rumelhart, 1980). This concept goes back at least to Kant (1787/1963) as a description of mental concepts and mental categories. Schemata appear in many AI systems in the forms of frames, scripts, or similar structures: they are prepackaged bundles of information that support inference in stereotyped situations.

I will very briefly summarize the work on schemata in connectionist systems reported in Rumelhart, Smolensky, McClelland and Hinton (1986) (see also Feldman, 1981, Smolensky, 1986a and c). This work dealt with schemata for rooms. Subjects were asked to describe some imagined rooms using a set of 40 features, such as has-ceiling, has-window, contains-toilet, and so on. Statistics were computed from this data and these were used to construct a network containing one node for each feature, and containing connections computed from the statistical data by using a particular form of the Statistical Connection.

This resulting network can carry out inference of the kind that can be performed by symbolic systems with schemata for various types of rooms. The network is told that some room contains a ceiling and an oven; the question is, what else is likely to be in the room? The system settles down into a final state, and the inferences contained in that final state are that the room contains a coffee cup but no fireplace, a coffee pot but no computer.

The inference process in this system is simply one of greedily maximizing harmony. To describe the inference of this system on a higher level, we can examine the global states of the system in terms of their harmony values. How internally consistent are the various states in the space? It is a 40-dimensional state

space, but various two-dimensional subspaces can be selected and the harmony values can be graphically displayed. The harmony landscape has various peaks. By looking at the features of the state corresponding to one of the peaks, we find that it corresponds to a prototypical bathroom; others correspond to a prototypical office, and so on for all the kinds of rooms subjects were asked to describe. There are no units in this system for bathrooms or offices; there are just lower-level descriptors. The prototypical bathroom is a pattern of activation, and the system's recognition of its prototypicality is reflected in the harmony peak for that pattern. It is a consistent, 'harmonious' combination of features: better than neighbouring points, such as for example one representing a bathroom without a bathtub, which has distinctly lower harmony.

During inference, this system climbs directly uphill on the harmony landscape. When the system state is in the vicinity of the harmony peak representing the prototypical bathroom, the inferences it makes are governed by the shape of the harmony landscape. This shape is like a 'schema' that governs inferences about bathrooms. (In fact, harmony theory was created to give a connectionist formalization of the notion of schema; see Smolensky, 1986a and c.) By looking closely at the harmony landscape we can see that the terrain around the 'bathroom' peak has many of the properties of a bathroom schema: variables and constants, default values, schemata embedded inside schemata, and even cross-variable dependencies. The system behaves as though it had schemata for bathrooms, offices, etc., even though they are not 'really there' at the fundamental level: these schemata are strictly properties of a higher-level description. They are informal, approximate descriptions — one might even say they are merely metaphorical descriptions — of an inference process too subtle to admit such high-level descriptions with great precision. Even though these schemata may not be the sort of object on which to base a formal model, nonetheless they are useful descriptions — which may in the end be all that can really be said about schemata anyway.

Conclusion

The view of symbolic structures that emerges from seeing them as entities of high-level descriptions of dynamical systems is quite different from the view which emerges from the symbolic paradigm. 'Rules' are not symbolic formulae, but the cooperative result of many smaller soft constraints. Macro-inference is not a process of firing a symbolic production but rather of a qualitative state change in a dynamical system, such as a phase transition. Schemata are not large symbolic data structures but rather the potentially quite intricate shapes of harmony maxima. Similarly, categories turn out to be attractors in dynamical systems: states that 'suck in' to a common place many nearby states, like peaks of harmony functions. Categorization is not the execution of a symbolic algorithm but the continuous evolution of the dynamical system, the evolution that drives states into the attractors, to maximal harmony. Learning is not the construction and editing of formulae, but the gradual adjustment of connection strengths with experience, with

the effect of slowly shifting harmony landscapes, adapting old and creating new concepts, categories, schemata.

The heterogenous assortment of high-level mental structures that have been embraced in this paper suggests that the symbolic level lacks formal unity. This is just what one expects of approximate higher-level descriptions, which, capturing different aspects of global properties, can have quite different characters. The unity which underlies cognition is to be found not at the symbolic level, but rather at the subsymbolic level, where a few principles in a single formal framework lead to a rich variety of global behaviours.

If connectionist models are interpreted within what I have defined as the subsymbolic paradigm, we can begin to see how mental structures can emerge from neural structures. By seeing mental entities as higher level structures implemented in connectionist systems, we obtain a new, more complex and subtle view of what these mental structures really are. Perhaps subsymbolic systems can achieve a truly rich mental life.

References

- Artificial Intelligence*. (1980) Special issue on non-monotonic logic. **13**, Numbers 1–2.
- Boole, G. (1854/1961) *An Investigation of The Laws of Thought*. Dover, New York.
- Cognitive Science*. (1985) Special issue on connectionist models and their applications. **9**, Number 1.
- Dell, G. S. (1985) Positive feedback in hierarchical connectionist models: applications to language production. *Cognitive Science*, **9**, 3–23.
- Feldman, J. A. (1981) A connectionist model of visual memory. In: *Parallel Models of Associative Memory* (eds G. E. Hinton & J. A. Anderson) Erlbaum, Hillsdale, NJ, USA.
- Feldman, J. A. & Ballard, D. H. (1982) Connectionist models and their properties. *Cognitive Science*, **6**, 205–254.
- Feldman, J. A., Ballard, D. H., Brown, C. M. & Dell, G. S. (1985) Rochester connectionist papers: 1979–1985. *Technical Report TR 172*, Department of Computer Science, University of Rochester.
- Fodor, J. A. (1975) *The Language of Thought*. Crowell, New York.
- Hebb, D. O. (1949) *The Organization of Behavior*. Wiley, New York.
- Hinton, G. E. & Anderson, J. A. (Eds) (1981) *Parallel Models of Associative Memory*. Erlbaum, Hillsdale, NJ, USA.
- Hinton, G. E. & Sejnowski, T. J. (1983) Analyzing cooperative computation. *Proceedings of the Fifth Annual Conference of the Cognitive Science Society*. Rochester, NY, USA.
- Hofstadter, D. R. (1985) Waking up from the Boolean dream, or, subcognition as computation. In: *Metamagical Themas*, 631–665. Basic Books, New York.
- Kant, E. (1787/1963) *Critique of Pure Reason*. N. Kemp Smith, translator; 2nd edn, McMillan, London.
- McClelland, J. L. & Rumelhart, D. E. (1981) An interactive activation model of context effects in letter perception: part 1. An account of the basic findings. *Psychological Review*, **88**, 375–407.
- McClelland, J. L., Rumelhart, D. E. & the PDP Research Group. (1986). *Parallel Distributed Processing: Explorations in the Microstructure of Cognition. Volume 2: Psychological and Biological Models*. MIT Press/Bradford Books, Cambridge, MA, USA.
- Newell, A. (1980) Physical symbol systems. *Cognitive Science*, **4**, 135–183.
- Newell, A. (1982). The Knowledge level. *Artificial Intelligence*, **18**, 87–127.
- Newell, A. & Simon, H. A. (1972) *Human Problem Solving*. Prentice-Hall, Englewood Cliffs, NJ, USA.

- Riley, M. S. & Smolensky, P. (1984) A parallel model of (sequential) problem solving, *Proceedings of the Sixth Annual Conference of the Cognitive Science Society*. Boulder, CO, USA.
- Rumelhart, D. E. (1980) Schemata: the building blocks of cognition. In: *Theoretical Issues in Reading Comprehension* (eds R. Spiro, B. Bruce & W. Brewer) Erlbaum, Hillsdale, NJ, USA.
- Rumelhart, D. E. & McClelland, J. L. (1982) An interactive activation model of context effects in letter perception: part 2. The contextual enhancement effect and some tests and extensions of the model. *Psychological Review*, **89**, 60–94.
- Rumelhart, D. E., McClelland, J. L. & the PDP Research Group. (1986) *Parallel Distributed Processing: Explorations in the Microstructure of Cognition. Volume 1: Foundations*. MIT Press/Bradford Books, Cambridge, MA, USA.
- Rumelhart, D. E., Smolensky, P., McClelland, J. L. & Hinton, G. E. (1986) Schemata and sequential thought processes in parallel distributed processing models. In: *Parallel Distributed Processing: Explorations in the Microstructure of Cognition. Volume 2: Psychological and Biological Models* (eds J. L. McClelland, D. E. Rumelhart & the PDP Research Group) MIT Press/Bradford Books, Cambridge, MA, USA.
- Smolensky, P. (1983) Schema selection and stochastic inference in modular environments. *Proceedings of the National Conference on Artificial Intelligence*. Washington, DC, USA.
- Smolensky, P. (1984a) Harmony theory: thermal parallel models in a computational context. In: *Harmony theory: Problem Solving, Parallel Cognitive Models, and Thermal Physics*. Technical Report 8404 (eds P. Smolensky & M. S. Riley) Institute for Cognitive Science, University of California at San Diego, USA.
- Smolensky, P. (1984b) The mathematical role of self-consistency in parallel computation. *Proceedings of the Sixth Annual Conference of the Cognitive Science Society*. Boulder, CO, USA.
- Smolensky, P. (1986a) Information processing in dynamical systems: foundations of harmony theory. In: *Parallel Distributed Processing: Explorations in the Microstructure of Cognition. Volume 1: Foundations* (eds D. E. Rumelhart, J. L. McClelland & the PDP Research Group) MIT Press/Bradford Books, Cambridge, MA, USA.
- Smolensky, P. (1986b) Neural and conceptual interpretations of parallel distributed processing models. In: *Parallel Distributed Processing: Explorations in The Microstructure of Cognition. Volume 2: Psychological and Biological Models* (eds J. L. McClelland, D. E. Rumelhart & the PDP Research Group) MIT Press/Bradford Books, Cambridge, MA, USA.
- Smolensky, P. (1986c) Formal modeling of subsymbolic processes: an introduction to harmony theory. In: *Directions in the Science of Cognition* (ed N. E. Sharkey) Ellis Horwood, UK.