The Three Languages of the Brain:
Quantum, Reorganizational, and Associative

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1 Introduction

Progress in science is reflected in a corresponding development of language. The vistas opened up by the microscope, the telescope, tomography and other sensing devices have resulted in the naming of new entities and processes. Quantum theory has led to the supersession of the classical atomic picture and one speaks in terms of tangled processes and non-binary logic. Quantum theory has also led to deep questions related to the definition of the observer and the observed. This has been one path to the examination of the mystery of mind. The other paths are rooted in ancient philosophical traditions and the psychological theories of the past century.

The language for the description of the mind in scientific discourse has not kept pace with the developments in the physical sciences. The mainstream discussion has moved from the earlier dualistic models of common belief to one based on the emergence of mind from the complexity of the parallel computer-like brain processes. The two old paradigms of determinism and autonomy, expressed sometimes in terms of separation and interconnectedness, show up in various guises. Which of the two of these is in favor depends on the field of research and the prevailing fashions. Although quantum theory has provided the foundation for physical sciences for seventy years, it is only recently that holistic, quantum-like operations in the brain have been considered. This fresh look has been prompted by the setbacks suffered by the various artificial intelligence (AI) projects and also by new analysis and experimental findings. It is being recognized that stimulus-response constructs such as "drive" are often inadequate in providing explanations; and one invokes the category "effort" to explain autonomous behavior. Karl Pribram's classic *Languages of the Brain* (1971) describes many paradoxes in the standard linguistic and logical categories used in describing brain behavior. Since that book was written many new approaches have been tried and found wanting in resolving these paradoxes.

The languages used to describe the workings of the brain have been modeled after the dominant scientific paradigm of the age. The rise of mechanistic science saw the conceptualization of the mind as a machine. In our present computer age, the brain is often viewed as a computing machine; Neural networks are the engines of this machine. The Appalachian Conferences on Behavioral Neurodynamics have been in the forefront in questioning long-standing assumptions at the basis of brain science. These meetings and several books (e.g. Pribram, 1991, 1993, 1994; Penrose, 1994; King and Pribram, 1995) have shown that the standard paradigm based on the computer-like signal processing model of the brain is flawed in many ways.

Although the neural network approach has had considerable success in modeling many counterintuitive illusions, there exists other processes in human and nonhuman cognition that appear to fall outside the scope of such models. Scholars have expressed the opinion that brain processing cannot be described by Turing machines. We do not wish to go into the details of these arguments; rather we will examine the question in the broadest terms.

Briefly, the classical neural network model does not provide a resolution to the question of binding of patterns: How do the neuron firings in the brain come to have specific meanings or lead to specific images? The proposal that 40-Hz waveforms are characteristic of consciousness and may somehow bind the activity in different parts of the brain is too vague to be taken seriously. Furthermore, machines have been unable to match many computing capabilities of nonhumans. Is that because computers lack the self-organizational feature of biological systems?

In unified theories of physics one speaks of a single force that, upon symmetry breaking, manifests itself into three or four distinct forces. Analogously, we argue that the quantum language of the brain manifests itself in terms of other languages. In this paper I consider the computational aspects of the problems of perception and adaptation in light of dual and associative processes. First, I summarize the limitations of computational models by considering questions raised by new researches in animal intelligence. The central insight obtained from the study of animal intelligence is that it is predicated on continual self-organization, as seen, for example, in superorganisms. That biological processing has a quantum basis has been argued by several authors. Quantum models provide a natural explanation for the unity of awareness in addition to explaining other puzzling features of brain behavior. In one class of such models, quantum behavior is postulated within neurons. But this does not resolve the question of the continuing self-organization of a biological system. My own proposal (Kak, 1992, 1995b) looks at organization and information as new quantum mechanical variables and I call this holistic view as quantum neural computing. This topic is reviewed and its implications are described.

For any quantum phenomenon there should be classical approximate representations. Since self-organization is the basic feature of biological processing, one needs to consider an explicit signaling scheme for this. This additional signal provides a dual to the usual neural transmissions in parallel with the many-component vectors of a quantum description. This bottom-up dual signaling regime for the brain may be taken to complement the top-down quantum view.

This paper also considers the *associative learning* problem, that deals with the most basic linguistic category of how associations are implemented. When a pattern is presented to a system for the first time, the synaptic weights that can resonate, or generate, this in the neural circuitry don't exist. So notions of supervised learning cannot be realistic biologically.

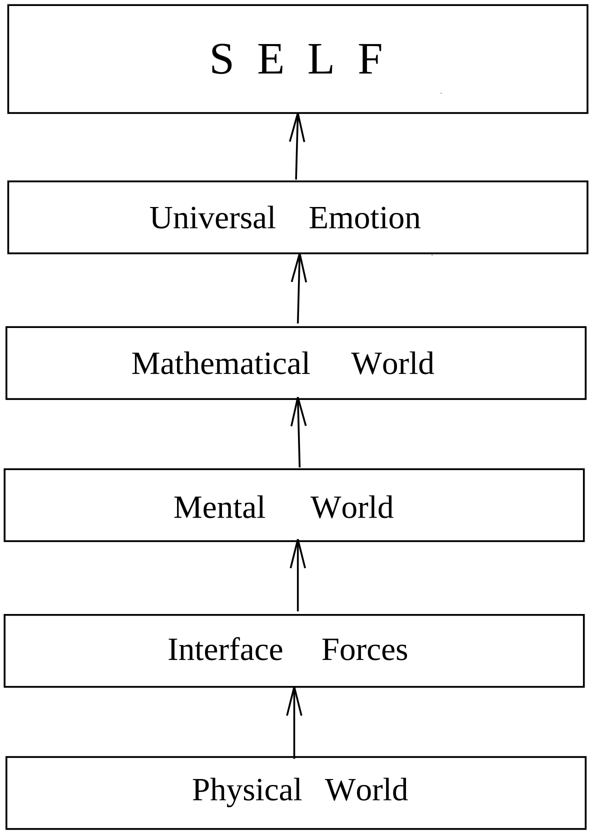

Figure 1: The Vedic model for the mind

A scheme is presented that can find synaptic weights instantaneously.

In summary, our paper speaks of the three languages of brain: quantum, reorganizational, and associative. Our learning scheme provides a basis for the interiorization of the last two languages. How these languages fit into the overarching quantum framework remains to be investigated.

2 Old and New Models of Mind

The puzzle of cognition was undoubtedly a part of the discourse of all ancient civilizations. Often the mystery was expressed by the notion of god or spirit: the gods were the cognitive centers of the mind. In at least one culture, namely the Vedic civilization of India, an astonishingly sophisticated cognitive theory emerged.

The Vedic model of mind, that goes back to at least 2000 B.C., provides a hierarchical structure with a twist that allows it to transcend the categories of separation and wholeness. Figure 1 presents this structure. Notice that the lowest level is the physical world or body, with higher levels of interface forces, the mind, scientific intuition, emotion, with the universal self sitting atop. The lower levels are machine-like whereas the self is the sole entity of consciousness. The individual's idea of consciousness arises out of associations with events, illuminated by the consciousness principle.

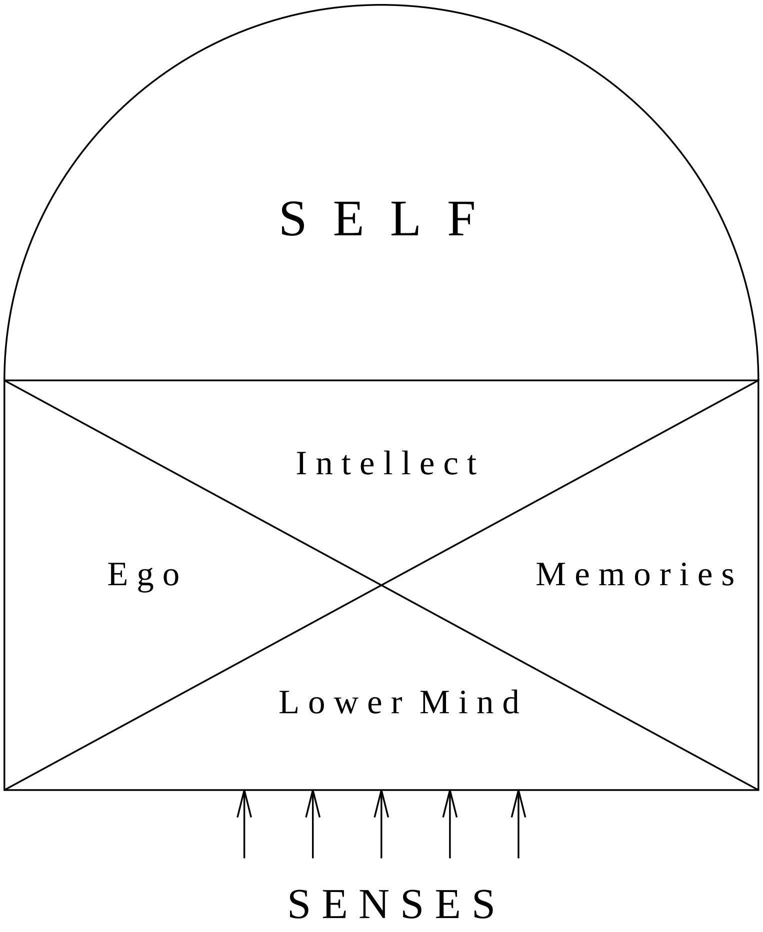

Figure 2: Mind's structure

Figure 2 provides greater details in terms of the relationship of memories, I-ness or ego that provides unity, intellect for judgment and the universal self. The I-ness is taken to arise from associations; and intellect represents decision making whose basis is also taken to be associative. In this view the lower mind is machine like, and it is the self that provides the binding to the associations of the lower mind.

The most striking part of this model is the nature of the universal self. Considered to transcend time, space and matter, the self engenders these categories on the physical world. For this reason the Vedic model is often taken to be an idealist model but that is not an entirely correct interpretation. According to the Vedic view any description of reality is inevitably paradox ridden. This is so since consciousness, through which we observe the universe, is also a part of it. The original sources speak of consciousness transcending categories of space, time and matter. There are two interpretative traditions that have a long history in India:

- A theory where consciousness is the ground-stuff from which time, space and matter emerge.
- A theory where consciousness is a field separate from time, space and matter. The

> duality in this conception is more apparent than real having taken form after the first separation of the two categories.

According to these traditions mind itself must be seen as a complex structure. Whereas mind is emergent and based on the capabilities of neural hardware, it cannot exist without the universal self. One implication of these ideas is that machines, which are based on classical logic, can never be conscious (Kak, 1993a).

It is not well known that this model had an important influence on the development of quantum mechanics. In 1925, before his creation of wave mechanics, Erwin Schrödinger wrote:

> This life of yours which you are living is not merely a piece of this entire existence, but in a certain sense the "whole"; only this whole is not so constituted that it can be surveyed in one single glance. This, as we know, is what the Brahmins express in that sacred, mystic formula which is yet really so simple and so clear: *tat tvam asi,* this is you. Or, again, in such words as "I am in the east and the west, I am above and below, *I am this entire world.*" (Schrödinger, 1961 (1925); Moore, 1989, page 170-3)

Schrödinger's influential *What is Life?* also used Vedic ideas. According to his biographer Walter Moore, there is a clear continuity between Schrödinger's understanding of Vedanta and his research:

> The unity and continuity of Vedanta are reflected in the unity and continuity of wave mechanics. In 1925, the world view of physics was a model of a great machine composed of separable interacting material particles. During the next few years, Schrödinger and Heisenberg and their followers created a universe based on superimposed inseparable waves of probability amplitudes. This new view would be entirely consistent with the Vedantic concept of All in One. (Moore, 1989, page 173)

For a summary of the Vedic theory of mind and its later developments see Kak (1993a); and for chronological issues see Kak (1994a), Klostermaier (1994), and Feuerstein et al (1995). During its evolution, a strand of the Vedic tradition took consciousness to be the sole reality. This anticipates several contemporary speculative ideas of physics.

The Vedic theory of mind is part of a recursive approach to knowledge (e.g. Kak, 1994a). The Vedas speak of three worlds, namely the physical, the mental, and that of knowledge. Consciousness if the fourth, transcending world. There is also reference to four kinds of language: gross sound, mental imagery, gestalts, and a fourth that transcends the first three and is associated with the self (Kak 1993a).

Plato's ideas are less comprehensive than the Vedic model, but they go beyond the common-sensical dichotomy of body and mind. He enlarged this dichotomy by speaking of a third world of ideas or forms. In his parable of the cave, Plato speaks of ideas that have independent existence of which our senses only see the traces or shadows on the wall. Plato's model represents the lower four levels of the Vedic model of Figure 1, with the second

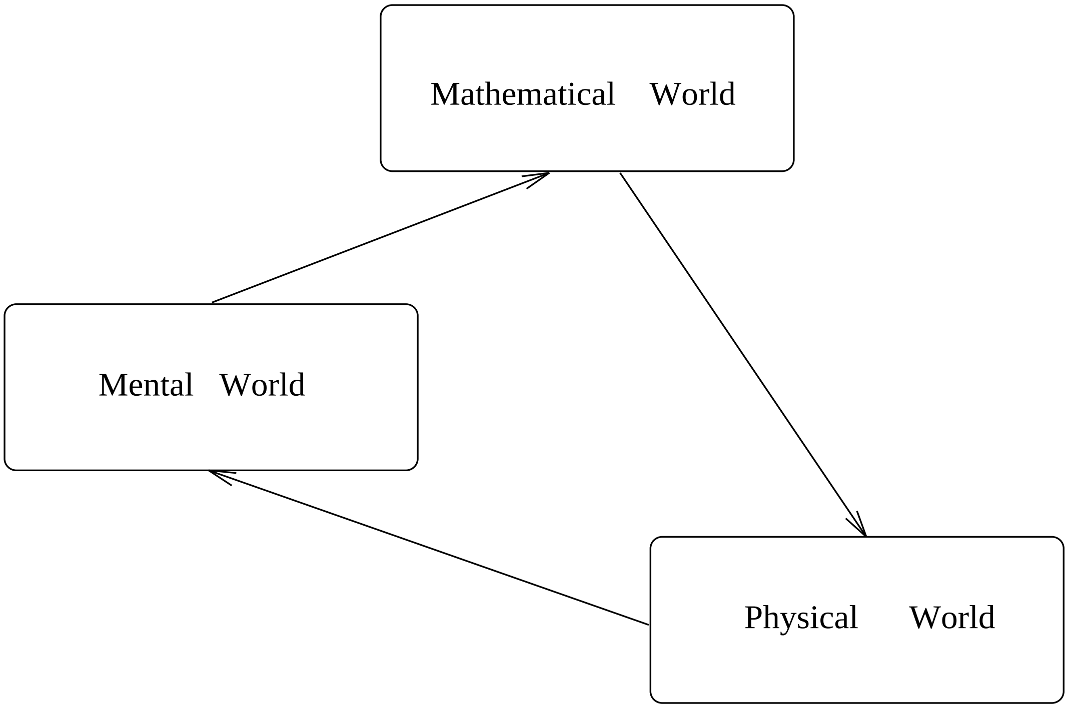

Figure 3: The three worlds: physical, mental, mathematical

level of interface forces subsumed into the mental world. It has exercised great influence on Western philosophy and its variants have been examined by many writers. In contemporary debate (Popper and Eccles, 1977; Goswami, 1993; Penrose, 1994) the world of ideas has been interpreted as objective knowledge. Consider Figure 3. This shows three worlds: the physical, the mental, and the world of mathematical or scientific ideas. The puzzle is: How is a part of the physical world which generates the mental picture which, in turn, creates the scientific theory is able to describe nature so well. This has been termed by one scientist as the unreasonable effectiveness of mathematics. In truth, objective knowledge consists of many paradoxes (Kak, 1986). Accumulation of knowledge often amounts to making ad hoc choices in the underlying formal framework to conform to experience. The most fundamental, and a very ancient, antinomy is that between determinism and free will. Formal knowledge can at best be compared to a patchwork.

2.1 New models

Considering that the physical world is described at its most basic level by quantum mechanics, how can classical computational basis underlie the description of the structure (mind) that in turn is able to comprehend the universe? How can machines, based on classical logic, mimic biological computing? One may argue that ultimately the foundations on which the circuitry of classical computers is based is at its deepest level described by quantum mechanics. Nevertheless, actual computations are governed by a binary logic which is very different from the tangled computations of quantum mechanics. And since the applicability of quantum mechanics is not constrained, in principle, by size or scale, so classical computers do appear to be limited.

Why cannot a classical computer reorganize itself in response to inputs? If it did, it will soon reach an organizational state associated with some energy minimum and will then stop responding to the environment. Once this state has been reached the computer will now merely transform data according to its program. In other words, a classical computer does not have the capability to be selective about its inputs. This is precisely what biological systems can do with ease.

Most proposals on considering brain function to have a quantum basis have done so by default. In short the argument is: There appears to be no resolution to the problem of the binding of patterns and there are non-local aspects to cognition; quantum behavior has non-local characteristics; so brain behavior might have a quantum basis. But these models do not explain the self-organizing part of brain structure. Other quantum models consider the organization of the brain itself to be a quantum variable.

Since a model of mind (i.e. Vedic) was influential in the early development of quantum theory, it is very fitting that quantum mechanical ideas should, in turn, shape the unfolding of new ideas in brain science.

How one might go about devising a system that is more capable than a classical system? If one takes the parallel with the early development of quantum mechanics, it is necessary to speak of vectors—rather than scalars— carrying information. This was recognized early by Karl Pribram who has long been a proponent for moving beyond the classical computer paradigm for the brain. In Pribram (1971) a dual signal model that stresses the significance of reorganization was proposed:

> The unit of analysis for brain function has classically been the neuron. The present proposal for a two-process mechanism recognizes an additional unit: the neuron junction, whose activity can become part of an organization (the slow potential microstructure) temporarily unrelated to the receptive field of any single neuron. Neural junctions are thus much more than just way stations in the transmission of nerve impulses; they compose, at any moment, a neural state that is operated upon by arriving nerve impulses. In turn, nerve impulses generated by neurons are influenced by this state. (page 25)

Newer analysis has led to the understanding that one needs to consider reorganization as a primary process in the brain— this allows the brain to define the context. Does a field govern the process of reorganization? The signal flows now represent the processing or recognition done within the reorganized hardware. Such a change in perspective can have significant implications. Dual signaling schemes eventually need an explanation in terms of a binding field; they do not solve the basic binding problem in themselves but they do make it easier to understand the process of adaptation.

3 Machine and Biological Intelligence

For all computational models, the question of the emergence of intelligence is a basic one. Solving a specified problem, that often requires searching or generalization, is taken to be a sign of AI, which is assumed to have an all or none quality.

From an evolutionary point of view it may be assumed that intelligence has gradation. If such gradation exists, does it manifest itself on top of a minimum that is common to life? If this minimum intelligence cannot be replicated by machines then it would follow that machine intelligence, based on classical logic, can never match biological intelligence.

In the biological realm, we find that all animals are not equally intelligent at all tasks; here intelligence refes to performance of various tasks, and this performance may depend crucially on the animal's normal behavior. It may be argued that all animals are *sufficiently* intelligent because they survive in their ecological environment. Nevertheless, even in cognitive tasks of the kind normally associated with human intelligence animals may perform adequately. Thus rats might find their way through a maze, or dolphins may be given logical problems to solve, or the problems might involve some kind of generalization (Griffin, 1992). These performances could, in principle, be used to define a gradation.

If we take the question of AI programs, it may be argued that the objectives of each define a specific problem solving ability, and in this sense AI programs constitute elements in a spectrum. But machine intelligence has not been predicated on some basic, benchmark tests.

3.1 Can machines think?

If we define thinking in terms of language or picture understanding then, by current evidence, machines cannot think. As we will see in the next subsection, machines cannot even perform abstract generalization of the kind that is natural for birds and other animals. But the proponents of strong-AI believe that, notwithstanding their current limitations, machines will eventually be able to simulate the mental behavior of humans. They suggest that the Turing (1950) test should suffice to establish machine intelligence.

We first show that Turing test is not suitable to determine progress in AI (Kak, 1995d). According to this test the following protocol is used to check if a computer can think: (1) The computer together with a human subject are to communicate, in an impersonal fashion, from a remote location with an interrogator; (2) The human subject answers truthfully while the computer is allowed to lie to try to convince the interrogator that it is the human subject. If in the course of a series of such tests the interrogator is unable to identify the real human subject in any consistent fashion then the computer is deemed to have passed the test of being able to think. It is assumed that the computer is so programmed that it is mimicking the abilities of humans. In other words, it is responding in a manner that does not give away the computer's superior performance at repetitive tasks and numerical calculations.

The asymmetry of the test, where the computer is programmed to lie whereas the human is expected to answer truthfully is a limitation of the test that has often been criticized. This limitation can be overcome easily if it is postulated that the human can take the assistance of a computer. In other words, one could speak of a contest between a computer and a human assisted by another computer. But this change does not mitigate the ambiguity regarding the kind of problems to be used in the test. The test is not objectively defined; the interrogator is a human.

It has generally been assumed that the tasks that set the human apart from the machine are those that relate to abstract conceptualization best represented by language understanding. The trouble with this popular interpretations of the Turing test, which was true to its intent as best as we can see, is that it focused attention exclusively on the cognitive abilities of humans. So researchers could always claim to be making progress with respect to the ultimate goal of the program, but there was no means to check if the research was on the right track. In other words, the absence of intermediate signposts made it impossible to determine whether the techniques and philosophy used would eventually allow the Turing test to be passed.

In 1950, when Turing's essay appeared in print, matching human reasoning could stand for the goal that machine intelligence should aspire to. The problem with such a goal was that it constituted the ultimate objective and Turing's test did not make an attempt to define gradations of intelligence. Had specific tasks, which would have constituted levels of intelligence or thinking below that of a human, been defined then one would have had a more realistic approach to assessing the progress of AI.

The prestige accorded to the Turing test may be ascribed to the dominant scientific paradigm in 1950 which, following old Cartesian ideas, took only humans to be capable of thought. That Cartesian ideas on thinking and intelligence were wrong has been amply established by the research on nonhuman intelligence of the past few decades (Griffin, 1992).

To appreciate the larger context of scientific discourse at that time, it may be noted that interpretations of quantum mechanics at this time also spoke in terms of observations alone; any talk of any underlying reality was considered outside the domain of science. So an examination of the nature of "thought", as mediating internal representations that lead to intelligent behavior, was not considered a suitable scientific subject. Difficulties with the reductionist agenda were not so clear, either in physical sciences or in the study of animal behaviour.

3.2 Animal intelligence

For considerable time it was believed that language was essential ground for thought; and this was taken as proof that only humans could think. But nobody will deny that deaf-mutes, who never learnt a language, do think. Language is best understood as a subset of a large repertoire of behavior. Research has now established that animals think and are capable of learning and problem solving.

Since nonhumans do not use abstract language, their thinking is based on discrimination at a variety of levels. If such conceptualization is seen as a result of evolution, it is not necessary that this would have developed in exactly the same manner for all species. Other animals learn concepts nonverbally, so it is hard for humans, as verbal animals, to determine their concepts. It is for this reason that the pigeon has become a favorite with intelligence tests; like humans, it has a highly developed visual system, and we are therefore likely to employ similar cognitive categories. It is to be noted that pigeons and other animals are made to respond in extremely unnatural conditions in Skinner boxes of various kinds. The abilities elicited in research must be taken to be merely suggestive of the intelligence of the animal, and not the limits of it.

In a classic experiment Herrnstein (1985) presented 80 photographic slides of natural scenes to pigeons who were accustomed to pecking at a switch for brief access to feed. The scenes were comparable but half contained trees and the rest did not. The tree photographs had full views of single and multiple trees as well as obscure and distant views of a variety of types. The slides were shown in no particular order and the pigeons were rewarded with food if they pecked at the switch in response to a tree slide; otherwise nothing was done. Even before all the slides had been shown the pigeons were able to discriminate between the tree and the non-tree slides. To confirm that this ability, impossible for any machine to match, was not somehow learnt through the long process of evolution and hardwired into the brain of the pigeons, another experiment was designed to check the discriminating ability of pigeons with respect to fish and non-fish scenes and once again the birds had no problem doing so. Over the years it has been shown that pigeons can also distinguish: (1) oak leaves from leaves of other trees, (ii) scenes with or without bodies of water, (iii) pictures showing a particular person from others with no people or different individuals.

Other examples of animal intelligence include mynah birds who can recognize trees or people in pictures, and signal their identification by vocal utterances—words—instead of pecking at buttons, and a parrot who can answer, vocally, questions about shapes and colors of objects, even those not seen before (for references see Griffin, 1992). The intelligence of higher animals, such as apes, elephants, and dolphins is even more remarkable.

Another recent summary of this research is that of Wasserman (1995):

> [Experiments] support the conclusion that conceptualization is not unique to human beings. Neither having a human brain nor being able to use language is therefore a precondition for cognition... Complete understanding of neural activity and function must encompass the marvelous abilities of brains other than our own. If it is the business of brains to think and to learn, it should be the business of behavioral neuroscience to provide a full account of that thinking and learning in all animals—human and nonhuman alike.

An extremely important insight from experiments of animal intelligence is that one can attempt to define different gradations of cognitive function. It is obvious that animals are not as intelligent as humans; likewise, certain animals appear to be more intelligent than others. For example, pigeons did poorly at picking a pattern against two other identical ones, as in picking an A against two B's. This is a very simple task for humans.

Wasserman (1993, 1995) devised an experiment to show that pigeons could be induced to amalgamate two basic categories into one broader category not defined by any obvious perceptual features. The birds were trained to sort slides into two arbitrary categories, such as category of cars and people and the category of chairs and flowers. In the second part of this experiment, the pigeons were trained to reassign one of the stimulus classes in each category to a new response key. Next, they were tested to see whether they would generalize the reassignment to the stimulus class withheld during reassignment training. It was found that the average score was 87 percent in the case of stimuli that had been reassigned and 72 percent in the case of stimuli that had not been reassigned. This performance, exceeding the level of chance, indicated that perceptually disparate stimuli had amalgamated into a new category. A similar experiment was performed on preschool children. The children's score was 99 percent for stimuli that had been reassigned and 80 percent for stimuli that had not been reassigned. In other words, the children's performance was roughly comparable to that of pigeons. Clearly, the performance of adult humans at this task will be superior to that of children or pigeons.

Another interesting experiment related to the abstract concept of sameness. Pigeons were trained to distinguish between arrays composed of a single, repeating icon and arrays composed of 16 different icons chosen out of a library of 32 icons (Wasserman, 1995; Wasserman et al, 1995). During training each bird encountered only 16 of the 32 icons; during testing it was presented with arrays made up of the remaining 16 icons. The average score for training stimuli was 83 percent and the average score for testing stimuli was 71 percent. These figures show that an abstract concept not related to the actual associations learnt during training had been internalized by the pigeon.

Animal intelligence experiments suggest that one can speak of different styles of solving AI problems. Are the cognitive capabilities of pigeons limited because their style has fundamental limitations? Can the relatively low scores on the sameness test for pigeons be explained on the basis of wide variability in performance for individual pigeons and the unnatural conditions in which the experiments are performed? Is the cognitive style of all animals similar and the differences in their cognitive capabilities arise from the differences in the sizes of their mental hardware? And since current machines do not, and cannot, use inner representations, is it right to conclude that their performance can never match that of animals? Most importantly, is the generalization achieved by pigeons and other nonhumans beyond the capability of machines?

Donald Griffin (1992) expresses the promise of animal intelligence research thus:

> Because mentality is one of the most important capabilities that distinguishes living animals from the rest of the known universe, seeking to understand animal minds is even more exciting and significant than elaborating our picture of inclusive fitness or discovering new molecular mechanisms. Cognitive ethology presents us with one of the supreme scientific challenges of our times, and it calls for our best efforts of critical and imaginative investigation. (Page 260)

3.3 Recursive characteristics

A useful perspective on animal behavior is its recursive nature, or part-whole hierarchy. Considering this from the bottom up, animal societies have been viewed as “superorganisms”. For example, the ants in an ant colony may be compared to cells, their castes to tissues and organs, the queen and her drones to the generative system, and the exchange of liquid food amongst the colony members to the circulation of blood and lymph. Furthermore, corresponding to morphogenesis in organisms the ant colony has sociogenesis, which consists of the processes by which the individuals undergo changes in caste and behavior. Such recursion has been viewed all the way up to the earth itself seen as a living entity. Parenthetically, it may be asked whether the earth itself, as a living but unconscious organism, may not be viewed like the unconscious brain. Paralleling this recursion is the individual who can be viewed as a collection of several “agents” where these agents have sub-agents which are the sensory mechanisms and so on. But these agents are bound together and this binding defines consciousness.

A distinction may be made between simple consciousness and self-consciousness. In the latter, the individual is aware of his awareness (Eccles, 1979, 1989). It has been suggested that while all animals may be taken to be conscious, only humans might be self-conscious. It is also supposed that language provides a tool to deal with abstract concepts that opens up the world of mathematical and abstract ideas only to humans.

Edelman (1992) suggests that selection mechanism might be at work that has endowed brains, in their evolutionary ladder, with increasing complexity. But this work does not address the question of holistic computations at all. From an evolutionary perspective if the fundamental nature of biological computing is different from that of classical computers then models like that of Edelman cannot provide the answers we seek. We cannot also accept the line of reasoning according to which complexity, once it crosses a certain threshold, leads to consciousness and, furthermore, beyond another threshold leads to self-consciousness.

4 Holistic Processing and Quantum Models

Neural activity in the brain is bound together to represent information; but the nature of this binding is not known. The brain constantly reorganizes itself based on the information task. Now quantum mechanics has provided a new understanding of the physical world although its philosophical implications are quite contentious and murky. Quantum mechanics is a theory of "wholes" and in light of the fact that the eye responds to single photons (Baylor et al, 1979)—a quantum mechanical response—and that the mind perceives itself to be a unity, one would expect that its ideas would be applied to examine the nature of mind and of intelligence. But for several decades the prestige of the reductionist program of neurophysiology made it unfashionable to follow this path.

Meanwhile, the question of the nature of information, and its observation, has become important in physics. The binding problem of psychology, and the need to postulate a mediating agent in the processing of information in the brain, has also brought the "self" back into the picture in biology. Oscillations and chaos have been proposed as the mechanisms to explain this binding. But we think that the strongest case can be made for a quantum mechanical substratum that provides unity to experience. Such quantum mechanical models of consciousness have attracted considerable attention; this work is reviewed in Kak (1995 a,b), Penrose (1994).

Quantum computing in the style of Feynman (1986) is considering the use of lattices or organo-metallic polymers as the apparatus; but the idea here is to perform computations in a tangled manner that can provide speedup over classical computers. This research does not consider the question of modeling of mind. It has been argued (Feynman, 1982; Kak, 1995c) that it is not possible to simulate quantum mechanics on a traditional computer. If it is accepted that intelligence has a quantum mechanical basis, then it follows that Turing-machine models of intelligence are inadequate. This, in turn, leads to several questions: What hardware basis is required before intelligence can emerge out of a quantum structure? Does intelligence require something more than a quantum basis, the presence of the notion of self?

Microtubules, the skeletal basis of cells that consist of protein polymers, have been proposed by Hameroff and others (Jibu et al, 1994; Penrose, 1994) as supporting quantum mechanical processes. It has been suggested by Fröhlich (1975) that Bose-Einstein condensation might be responsible for quantum coherence in biological structures. Fröhlich's model requires large energy of metabolic drive and extreme dielectric properties of the materials. The large scale quantum coherence is predicted to appear in the frequency range of 10^{11} to 10^{12} Hz and there is some evidence that such oscillations actually take place (Grundler and Keilmann, 1983). Hameroff and his associates (Jibu et al, 1994) have suggested that water in the microtubules provides this quantum coherence. But it is not shown how quantum coherence can leap across the synaptic barrier. This work also does not deal with the issue of what structures are needed before consciousness can arise. Most significantly, this does not address the issue of the self-organizing ability of biological systems.

My own work (Kak, 1976, 1984, 1995a,b) has examined the basic place of information in a quantum mechanical framework and its connections to structure. This work shows that although many processes that constitute the mind can be understood through the framework of neural networks, there are others that require a holistic basis. Furthermore, if each computation is seen as an operation by a reorganized brain on the signals at hand, this has a parallel with a quantum system where each measurement is represented by an operator. I also suggest that the macrostructure of the brain must be seen as a quantum system.

Study of animal intelligence provides us with new perspectives that are useful in representing the performance of machines. For example, the fact that pigeons learn the concept of sameness shows that this could not be a result of associative response to certain learnt patterns. If evolution has led to the development of specialized cognitive circuits in the brain to perform such processing, then one might wish to endow AI machines with similar circuits. Other questions arise: Is there a set of abstract processors that would explain animal performance? If such a set can be defined, is it unique, or do different animal species represent collections of different kinds of abstract processing that makes each animal come to achieve a unique set of conceptualizations?

One striking success of the quantum models is that they provide a resolution to the determinism- free will problem. According to quantum theory, a system evolves causally until it is observed. The act of observation causes a break in the causal chain. This leads to the notion of a participatory universe (Wheeler, 1979-1981). Consciousness provides a break in the strict regime of causality.

It would be reasonable to assume that this freedom is associated with all life. But its impact on the ongoing processes will depend on the entropy associated with the break in the causal chain.

4.1 A universal field

If one did not wish for a reductionist explanation as is inherent in the cytoskeletal model, one might postulate a different origin for the quantum field. Just as the unified theories explain the emergence of electromagnetic and weak forces from a mechanism of symmetry breaking, one might postulate a unified field of consciousness-unified_force-gravity from where the individual fields emerge.

Eugene Wigner (1961) spoke of one striking analogy between light and consciousness:

"Mechanical objects influence light—otherwise we could not see them—but experiments to demonstrate the effect of light on the motion of mechanical bodies are difficult. It is unlikely that the effect would have been detected had theoretical considerations not suggested its existence, and its manifestation in the phenomenon of light pressure." He also acknowledged one fundamental difference between light and consciousness. Light can interact directly with virtually all material objects whereas consciousness is grounded in a physico-chemical structure. But such a difference disappears if it is supposed that the physico-chemical structure is just the instrumentation that permit observations.

In other words, the notion of a universal field requires acknowledging the emergence of the individual's I-ness at specialized areas of the brain. This I-ness is intimately related to memories, both short-term and long-term. The recall of these memories may be seen to result from operations by neural networks. Lesions to different brain centers effect the ability to recall or store memories. For example, lesions to the area V1 of the primary visual cortex lead to blindsight. These people can "see" but they are unaware that they have seen. Although such visual information is processed, and it can be recalled through a guessing game protocol, it is not passed to the conscious self.

5 Quantum Neural Structures

5.1 The principles

We begin with a brief resume of quantum mechanics. Quantum mechanical objects are described by complex numbers known as amplitudes. The probability of a process is the square of the magnitude of the amplitude. The most fundamental principle in the theory is that of superposition: To compute the total amplitude for a process add the amplitudes of its component processes.

Quantum mechanics presents a view of reality which is a radical departure from the previous mechanistic viewpoint. Quantum mechanical objects do not have an objective existence before measurement.

In the path integral formulation of quantum mechanics, one needs to compute the sum of an infinite number of paths at each step. To summarize:

1. The probability $P(a, b)$ of a process moving from stage a to stage b is the square of the absolute value of a complex number, the transition function $K(a, b)$:

$$P(a,b) \; = \; |K(a,b)|^2.$$

2. The transition function is given by the sum of a certain phase factor, which is a function of the action S, taken over all possible paths from a to b:

$$K(a,b) \; = \; \sum_{paths} k e^{i2\pi S/h},$$

where the constant k can be fixed by

$$K(a,c) \; = \; \sum_{paths} K(a,b) K(b,c),$$

and the intermediate sum is taken over paths that go through all possible intermediate points b.

This second principle says that a particle "sniffs" out all possible paths from a to b, no matter how complicated these paths might be. In quantum theory a future state, within the bounds of time and space uncertainty, can also influence the present.

Information has a central role in quantum theory. Although Schrödinger's equation is linear, the reduction of the wave packet, upon observation, is a nonlinear phenomenon. Observation is thus tantamount to making a choice. From another perspective, there is an asymmetry in the preparation of a state in a quantum system and that of its measurement, because the measurement can only be done in terms of its observables. In a classical system also there is intervention at the beginning and the end of the physical process that defines the computation. Time-reversible equations of physics cannot, in themselves, explain communication of information. Creation of information requires reduction in entropy. Owing to the fact that these models must carry the input along, reversible models can become extremely slow, so as to become unable to solve the problem in any reasonable period of time.

Since measurement in a quantum system is a time-asymmetric process, one can speak of information transfer in a quantum observation. Let v, with eigenvalue equation

$$v|\psi_n\rangle \ = \ v_n|\psi_n\rangle,$$

be the dynamical variable of the system S being measured. Let the measurement apparatus A be characterized, correspondingly, by the eigenvalue equation:

$$M|A_n\rangle \ = \ M_n|A_n\rangle.$$

Let the system and the apparatus be in the states $\psi\rangle$ and $A_0\rangle$, respectively at the beginning of the measurement, where $\psi\rangle = \sum_m a_m|\psi_m\rangle$. The state of the system and the apparatus, $S+A$, will be $\psi\rangle A_0\rangle$. The Schrödinger equation $i\hbar\frac{d}{dt}|\psi\rangle = H|\psi\rangle$ will now define the evolution of this state.

If one uses the reduction postulate, the state $|\psi\rangle|A_0\rangle$ collapses to $|\psi_m\rangle|A_m\rangle$ with the probability $|a_m|^2$. But if one uses the Schrödinger equation then the initial state evolves into the unique state:

$$\sum_m a_m|\psi_m\rangle|A_M\rangle$$

If one were to postulate another apparatus measuring the system plus the original apparatus the reduction problem is not solved. In fact one can visualize such a process in the so-called von Neumann chain. According to Wigner (1961), the reduction should be ascribed to the observer's mind or consciousness.

According to the orthodox view, namely the Copenhagen interpretation, the workings of the measuring instruments must be accounted for in purely classical terms. This means that a quantum mechanical representation of the measuring apparatus in not correct. In other words, a measurement is contingent on localization.

In such a view the slogan that "computation is physics" loses its generality. It is not surprising that certain types of computations are taken to indicate the participation of conscious agents. Thus if we were to receive the digits of π in transmissions from outer space, we will take that as indication of life in some remote planet. The same will be true of other arithmetic computations.

In brief, signals or computations that simulate the world using models much less complex than the real world indicate intelligence.

Quantum mechanics may be viewed as a theory dealing with basic symmetries. The wavefunction can only be symmetric or antisymmetric, defining bosons and fermions, respectively. In a two-dimensionally constrained world there are other possibilities that have been named anyons (Wilczek 1990) but that need not concern us.

5.2 Quantum knowledge

Quantum theory defines knowledge in a relative sense. It is meaningless to talk of an abjective reality. When we talk, for example, that electric fields exist in a field, this implies that such measurements can be made. Knowledge is a collection of the observations on the reductions of the wavefunction ψ, brought about by measurements using different kinds of instrumentations.

The indeterminacy of quantum theory does not reside in the microworld alone. For example, Schrödinger's cat paradox shows how a microscopic uncertainty transforms into a microscopic uncertainty. Brain processes are not described completely by the neuron firings; one must, additionally, consider their higher order bindings, such as thoughts and abstract concepts, because they, in turn, have an influence on the neuron firings. A wavefunction describing the brain would then include variables for the higher order processes, such as abstract concepts as well. But such a definition will leave a certain indeterminacy in our description.

5.3 The fallacy of knowing the parts from the whole

If we knew the parts completely, one can construct a wavefunction for the whole. But as is well known (Schrödinger 1980; originally in 1935): "Maximal knowledge of a total system does not necessarily include total knowledge of all its parts, not even when these are fully separated from each other and at the moment are not influencing each other at all." In other words, a system may be in a definite state but its parts are not precisely defined.

To recapitulate, we claim that without going into the question of how the state function associated with the brain is to be written down there is a fundamental indeterminacy associated with the description of its component parts. This is over and above the reasons of complexity that one cannot discover the details of the workings of a brain. Now, in a suitable configuration space, where the state function is described in the maximal sense, quantum uncertainty will apply. Since the results of the interactions between the environment and the brain are in terms of the self-organization of the latter, clearly the structure, chosen out of the innumerably many possibilities, represents one of the quantum variables.

5.4 Structure

We must first distinguish between the structures of nonliving and living systems. By the structure of a nonliving system we mean a stable organization of the system. The notion of the stability may be understood from the perspective of energy of the system. Each stable state is an energy minimum.

But the structure in a living system is not so easily fixed. We may sketch the following sequence of events: As the environment (the internal and the external) changes, the living system reorganizes itself. This choice, by the nervous system, of one out of a very large number of possibilities, represents the behavioral or cognitive response.

We might view this neural hardware as the classical instrumentation that represents the cognitive act. This might also be viewed as a cognitive agent. Further processing might be carried out by this instrumentation. We may consider the cognitive categories to have a reality in a suitable space.

A living organism must have entropy in its structure equal to the entropy of its environment. If it did not, it will not be able to adapt (respond) to the changing environment.
Principle: The position of the organism in its ecological environment is determined by the entropy of its information processing system.

This defines a hierarchy. According to this view the universe for an organism shows a complexity and richness corresponding to the complexity of the nervous system. This idea should be contrasted from the anthropic principle where the nature of the universe is explained by the argument that if it was different there would not have been man to observe it. According to our view, the universe might come to reveal new patterns if we had the capacity to process such information. Computer assisted processing will then reveal new patterns.

It is characteristic of neurophysiology that activity in specific brain structures in given a primary explanatory role. But any determination of the brain structure is impossible. If the brain has 10^{11} neurons and 10^{14} synapses, then even ignoring the gradations in the synaptic behavior, the total number of structures that could, in principle, be chosen exceeds $2^{10^{14}}$, which is greater than current estimates of all elementary particles in the universe.

Assume a system that can exist in only two states. Such a system will find its place where the environment is characterized by just two states. So we can speak of an information theoretic approach to the universe.

Any structure may be represented by a graph as in Figure 4, which may, in turn, be represented by a number, or a binary sequence. Thus in a one dimension, the sequences

$$00111001, 10001101010, 11000001111$$

represent three binary-coded structures.

Assume that a neural structure has been represented by a sequence. Since this representation can be done in a variety of ways, the question of a unique representation becomes relevant.

Definition 1 *Let the shortest binary program that generates the sequence representing the structure be called* p.

Figure 4: Structures represented as graphs

The idea of the shortest program gives us a measure for the structure that is independent of the coding scheme used for the representation. The length of this program may be taken to be a measure of the information to be associated with the organization of the system. This length will depend on the class of sequences that are being generated by the program. Or in other words, this reflects the properties of the class of structures being considered. Evidence from biology requires that the brain be viewed as an active system which reorganizes itself in response to external stimuli. This means that the structure p is a variable with respect to time.

Assuming, by generalized complementarity, that the structure itself is not defined prior to measurement, then for each state of an energy value E, we may, in analogy with the Heisenberg's uncertainty principle, say that

$$\delta E \delta t \geq k_1 \tag{1}$$

where k_1 is a constant based on the nature of the organizational principle of the neural system.

The external environment changes when the neural system is observed, due to the interference of the observer. This means that as the measurement is made, the structure of the system changes.

This also means that at such a fundamental level, a system cannot be associated with a single structure, but rather with a superposition of several structures. Might this be a reason behind pleomorphism, the multiplicity of forms of microbes?

The representation described above may also be employed for the external environment.

Definition 2 *Let the shortest binary program that generates the external environment be called x.*

If the external environment is a eigenstate of the system, then the system organization will not change; otherwise, it will.

We may now propose an uncertainty principle for neural system structure:

$$\delta x \delta p \geq k_2 \tag{2}$$

This relation says that the environment and the structure cannot be simultaneously fixed. If one of the variables is precisely defined the other becomes uncontrollably large. Either of these two conditions implies the death of the system. In other words, such a system will operate only within a narrow range of values of the environment and structure.

We conjecture that $k_1 = k_2 = k$.

One may pose the following questions:

- Are all living systems characterized by the same value of k?
- Can one devise stable self-organizing systems that are characterized by a different value of k? Would artificial life have a value of k different from that of natural life?
- What is the minimum energy required to change the value of p by one unit?
- Does a Schrödinger type equation define the evolution of structure? It appears that in the original configuration space this indeed is true. But how might such an evolution be represented in terms of structure alone?

It is also clear that before a measurement is made, one cannot speak of a definite state of the machine, nor of a definite state of the environment.

Clearly, we can only talk in terms of generalities at this stage. In order to make further advance in our understanding it is essential to consider the notion of structure as a classical variable first. This we do by speaking of signals that might be exclusively dedicated to altering the organization of the system. These signals may be taken to be the dual to the neuron firings that constitute the better studied response of brains.

6 Reorganizing Signals

Pribram (1971) suggests a state composed of the "local junctional and dendritic (pre- and postsynaptic) potentials." Pribram also considered holographic models of memory which also require dual signaling of a certain kind. But the motivation here was more from the point of view of capacity to store information rather than self-organization.

A specific type of 40 Hz oscillation as a dual signal has been proposed (e.g. Niebur et al, 1993) to explain binding. But this model is too vague at this point to provide a satisfactory resolution to the problem of self-organization.

Living systems are characterized by continual adaptive organization at various levels. The reorganization is a response to the complex of signal flows within the larger system. For example, the societies of ants or bees may be viewed as single superorganisms. Hormones and other chemical exchanges among the members of the colony determine the ontogenies of the individuals within the colony. But more pronounced than this global exchange is the activity amongst the individuals in cliques or groups (Moritz and Southwick, 1992).

Paralleling trophallaxis is the exchange of neurotransmitters or electrical impulses within a neural network at one level, and the integration of sensory data, language, and ideas at other levels. An illustration of this is the adaptation of somatosensory cortex to differential inputs. The cortex enlarges its representation of particular fingers when they are stimulated, and it reduces its representation when the inputs are diminished, such as by limb deafferentation.

Adaptive organization may be a general feature of neural networks and of the neocortex in particular. Biological memory and learning within the cortex may be organized adaptively. While there are many ways of achieving this, we posit that nesting among neural networks within the cortex is a key principle in self-organization and adaptation. Nested distributed networks provide a means of orchestrating bottom-up and top-down regulation of complex neural processes operating within and between many levels of structure.

There may be at least two modes of signaling that are important within a nested arrangement of distributed networks. A fast system manifests itself as spatiotemporal patterns of activation among modules of neurons. These patterns flicker and encode correlations that are the signals of the networks within the cortex. They are analogous to the hormones and chemical exchanges of the ant or bee colonies in the example mentioned above. In the brain, the slow mode is mediated by such processes as protein phosphorylation and synaptic plasticity. They are the counterparts of individual ontogenies in the ant or bee colonies. The slow mode is intimately linked to learning and development (i.e., ontogeny), and experience with and adaptation to the environment affect both learning and memory.

By considering the question of adaptive organization in the cortex, our approach is in accordance with the ideas of Gibson (1976, 1979) who has long argued that biological processing must be seen as an active process. We make the case that nesting among cortical structures provides a framework in which active reorganization can be efficiently and easily carried out. The processes are manifest by at least two different kinds of signaling, with the consequence that the cortex is viewed as a dynamic system at many levels, including the level of brain regions. Consequently, functional anatomy, including the realization of the homunculus in the motor and sensory regions, is also dynamic. The homunculus is an evolving, and not a static representation, in this view.

From a mathematical perspective, nesting topologies contain broken symmetry. A monolithic network represents a symmetric structure, whereas a modular network has preferential structures. The development of new clusters or modules also represents an evolutionary response, and a dual mode signaling may provide a means to define context. It may also lead to unusual resiliences and vulnerabilities in the face of perturbations. We propose that these properties may have relevance to how nested networks are affected by the physiological process of aging and the pathological events characterizing some neurobiological disorders.

Reorganization explains the immeasurable variety of the response of brains. This reorganization may be seen as a characteristic which persists at all levels in a biological system.

Such reorganization appears to be the basis of biological intelligence. It was a mistaken emphasis on the characterization of life in terms of reproducibility by John von Neumann that led the AI community astray for decades.

6.1 Adaptive organization

Active perception can be viewed as adapting to the environment. In the words of Bajcsy (1988) : "It should be axiomatic that perception is not passive, but active. Perceptual activity is exploratory, probing, searching; percepts do not simply fall onto sensors as rain falls onto ground. We do not just see, we look."

It is not known how appropriate associative modules come into play in response to a stimulus. This is an important open question in neural computing. The paradigm of "active" processing in the context of memory is usually treated in one of two ways. First, the processing may be pre-set. This is generally termed "supervised learning", and it is a powerful but limited form of active processing. A second type of processing does not involve an explicit teacher, and this mechanism is termed "unsupervised learning". It is sensitive to a number of constraints, including the structure and modulation of the network under consideration.

We posit that active memories are inherently connected to the structure of the network. In particular, we propose that active memories can be defined in terms of a selection of a substructure of the nested organization. We see that this is complementary to associations in the manner of Hebb, where a memory is seen as an attractor in the states of the neurons. The Hebbian view considers the stable arrangements of firing neurons as memories. In a nested structure, the firing neurons contribute to multi-level memories. Individual neurons obey local rules, but because there are anatomical and functional boundaries between clusters, higher level memories may emerge from the combinations of lower level memories. Higher memories are actively formed by correlations among lower level memories and clusters. From this perspective, selecting a structure through adaptation to the stimulus is not really a departure from Hebb's perspective.

7 Nested Networks

There are different ways that biological memory may be self-organizing, and in this section, we suggest that the nesting of distributed neural networks within the neocortex is a natural candidate for encoding and transducing memory. Nesting has interesting combinatorial and computational features (Sutton et al, 1988, 1990; Sutton, 1995), and its properties have not been fully examined. The seemingly simplistic organization of nested neural networks may have profound computational properties, in much the same way as recent deoxyribonucleic computers have been put to the task of solving some interesting fundamental problems. However, we do not claim that nesting is the only important feature for adaptive organization in neural systems.

A natural consideration is to examine the structural properties of the forebrain, including the hippocampus and neocortex, which are two key structures in the formation and storage of memory. The hippocampus is phylogenetically an ancient structure, which among other functions, stores explicit memory information. To first approximation, this information is then transferred to the neocortex for long term storage. Implicit memory cues can access neocortical information directly.

The neocortex is a great expanse of neural tissue that makes up the bulk of the human brain. As in all other species, the human neocortex is made up of neural building blocks. At a rudimentary level, these blocks consist of columns oriented perpendicular to the surface of the cortex. These columns may be seen as organized in the most basic form as minicolumns of about 30 μm in diameter. The minicolumns are, in turn, organized into larger columns of approximately 500 - 1000 μm in diameter. Mountcastle estimates that the human neocortex contains about 600 million minicolumns and about 600,000 larger columns. Columns are defined by ontogenetic and functional criteria, and there is evidence that columns in different brain regions coalesce into functional modules (Mountcastle, 1978). Different regions of the brain have different architectonic properties, and subtle differences in anatomy are associated with differences in function.

The large entities of the brain are "composed of replicated *local neural circuits*, modules which vary in cell number, intrinsic connections, and processing mode from one large entity to another but are basically similar within any given entity." In other words, the neocortex can be seen as several layers of nested networks (Mountcastle, 1978, Sutton and Trainor, 1990). Beginning with cortical minicolumns, progressive levels of cortical structure consist of columns, modules, regions and systems. It is assumed that these structures evolve and adapt through the lifespan. It is also assumed that the boundaries between the clusters are plastic: they change slowly due to synaptic modifications or, more rapidly, due to synchronous activity among adjacent clusters.

Results from the study of neural circuits controlling rhythmic behavior, such as feeding, locomotion, and respiration, show that the same network, through a process of "rewiring" can express different functional capabilities (Simmers et al, 1995).

In a study of the pattern generator of the pyloric rhythm in lobster, it has been found that the behavior is controlled by fourteen neurons in the stomatogastric ganglion. The predominant means of communication between the neurons is through inhibitory synapses. The reshaping of the output of the network arises from neuromodulation. More than fifteen different modulatory neurotransmitters have been identified. These allow the rewiring of the network. Turning on the pyloric suppressors restructures the otherwise three independent networks in the stomatogastric nervous system into a single network, converting the function from regional food processing to coordinated swallowing.

> Rather than seeing a system as a confederation of neatly packaged neural circuits, each devoted to a specific and separate task, we must now view a system in a much more distributed and fluid context, as an organ that can employ modulatory instructions to assemble subsets of neurons that generate particular behaviors. In other words, single neurons can be called on to satisfy a variety of different functions, which adds an unexpected dimension of flexibility and economy to the design of a central nervous system (Simmers et al 1995, page 268).

Figure 5: Neocortex as a hierarchical system (2a,b) with clusters (2c) and nesting (2d). From Sutton and Trainor (1990).

7.1 Adaptive organization and modularity

We consider the issue of the reorganization of the structure or activity, in response to a stimulus, in more detail. We will motivate the reader in terms of visual inputs but the discussion is valid for other types of inputs as well. We sketch the following process:

1. The overall architecture of the nested system is determined by the external or internal stimulus, this represents the determination of the connections at the highest hierarchical levels and progresses down in a recursive manner. The learning of the connections in each layer is according to a correlative procedure. The sensory organs adjust to the stable state reached in the nearest level.

2. The deeper layers find the equilibrium state corresponding to the input in terms of attractors. Owing to the ongoing reorganization working in both directions, up to the higher levels as well as toward the lower levels, the attractors may best be labeled as being dynamic.

Superorganisms also have nested structures in terms of individuals who interact more with certain members than others. In the case of ants, the castes provide further "modular" structure (Sudd and Franks, 1987). For the case of honeybees:

> [It is important to recognize] subsystems of communication, or cliques, in which the elements interact more frequently with each other than with other members of the communication system. In context, the dozen or so honeybee workers comprising the queen retinue certainly communicate more within their group (including the queen) than they do with the one or two hundred house bees receiving nectar loads from foragers returning from the field. The queen retinue forms one communication clique while the forager-receiver bees form another clique. (Moritz and Southwick, 1992, page 145)

The parallel for two distinct pathways of communication is to be seen in superorganisms as well:

> [The] superorganism is a self-organizing system incorporating two very distinct pathways of communication. One mode is via localized individual worker interactions with low connectedness, and the other one via volatile or semiochemical pheromones with high connectedness. If we examine the communication modes at the functional level, we see that the pheromones reach the entire superorganism, more or less: a global message with a global reaction (for example, the queen pheromones simultaneously and continuously signal to every worker in the colony that it is queenright). (Moritz and Southwick, 1992, page 151)

An index of average system connectedness (ASC) has been defined as

$$ASC\ index\ =\ Actual\ dyads/Possible\ dyads. \tag{3}$$

For a fully connected network the index is 1. According to one study the linkages in the communication network of honeybees accepting water or dilute nectar from returning foragers under heat stress conditions was 0.031. An example is shown in Figure 6.

Figure 6: Histogram of communication linkages for honeybees. From Moritz and Southwick (1992).

Another fundamental communication within the superorganism is the one that defines its constitution. This is a much slower process which can be seen, for example, when a queen ant founds her colony. The queen governs the process of caste morphogenesis (Brian, 1983; Hölldobler and Wilson, 1994). Within the new colony, the queen, having just mated with her suitors and received more than 200 million sperm, shakes off her wings and digs a little nest in the ground, where she now is in a race with time to produce her worker offspring. She raises her first brood of workers by converting her body fat and muscles into energy. She must create a perfectly balanced work force that is the smallest possible in size, yet capable of successful foraging, so that the workers can bring food to her before she starves to death.

The queen produces the workers of the correct size for her initial survival and later, after the colony has started going, she produces a complement of workers of different sizes as well as soldier ants in order to have the right organization for the survival of the colony. When researchers have removed members of a specific caste from an ongoing colony, the queen compensates for this deficit by producing more members of that caste. The communication process behind this remarkable control is not known.

The communication mechanisms of the ant or the honeybee superorganisms may be supposed to have analogs in the brain.

8 Self-Organization by Association

Now we consider the question of the learning by association by the neural hardware. We assume here that such structures are realized as feedforward networks. Self-organization by association may also be viewed as learning.

As shown in Figure 7, the eyes wander in the process of perception; they jump, then come to rest momentarily which produces a dot on the record. This process skips areas with little details. These eye movements suggest that there in no fixing of any particular pattern in perception. It appears then that schemes such as backpropagation, where the synaptic weights are adjusted upon considerable training, are not realistic. We would expect that, to be biologically plausible, learning by association should be instantaneous.

A new approach to training such neural networks for binary data was proposed by me three years ago (Kak, 1993b, 1994b). Such a method might be relevant in the learning of organization. This is based on a new architecture that depends on the nature of the data. It was shown that this approach is much faster than backpropagation and provides good generalization. This approach, which is an example of prescriptive learning, trains the network by isolating the corner in the n-dimensional cube of the inputs represented by the input vector being learnt. Several algorithms to train the new feedforward network were presented. These algorithms were of three kinds. In the first of these (CC1) the weights were obtained upon the use of the perceptron algorithm. In the second (CC2), the weights were obtained by inspection from the data, but this did not provide generalization. In the third (CC3), the weights obtained by the second method were modified in a variety of ways that amounted to randomization and which now provided generalization. During such randomization some of the learnt patterns could be misclassified; further checking and adjustment of the weights was, therefore, necessitated. Various comparisons were reported in (Raina, 1994; Madineni, 1994). The comparisons showed that the new technique could

Figure 7: The shifting focus of the eye. In the girl's picture the record is for one minute, whereas in the pine forest scene the two records are for 2 and 30 minutes. From Yarbus (1967)

be 200 times faster than the fastest version of the backpropagation algorithm with excellent generalization performance.

Here we show how generalization can be obtained for such binary networks just by inspection. We present a modification to the second method so that it does provide generalization. This technique's generalization might not be as good as when further adjustments are made, but the loss in performance could, in certain situations, be more than compensated by the advantage accruing from the instantaneous training which makes it possible to have as large a network as one pleases. In other words, we present a plausible method of associative learning in the brain.

We assume that the reader is familiar with the background papers (Kak, 1993b, 1994b); for more details see Kak (1995e). We consider the mapping $Y = f(X)$, where X and Y are $n-$ and $m-$dimensional binary vectors. But for convenience of presentation, it will be assumed that the output is a scalar, or $m = 1$. Once we know how a certain ouput bit is obtained, other such bits can be obtained similarly. We consider binary neurons that ouput 1 if and only if the sum of the inputs exceeds zero. To provide for effective non-zero thresholds to the neurons of the hidden layer an extra input $x_{n+1} = 1$ is assumed. The weights in the output layer all equal 1.

A hidden neuron is required for an input vector in the training set if the output is 1. We might say that the hidden neuron "recognizes' the training vector. Consider such a vector for which the number of 1's is s; in other words, $\sum_{i=1}^{n} x_i = s$. The weights leading from the input neurons to the hidden neurons are:

$$w_j = \begin{cases} h & if \;\; x_j = 0, \;\; for \;\; j = 1, ..., n, \\ +1 & if \;\; x_j = 1, \;\; for \;\; j = 1, ..., n, \\ r - s + 1 & for \;\; j = n + 1. \end{cases} \tag{4}$$

The values of h and r are chosen in various ways. This is a generalization of the expression in (Kak, 1993b, 1994b) where w_j for $j = n + 1$ is taken to be $(r - s + 1)$ rather than $(1 - s)$, and where $h = -1$.

This change allows the learning of the given training vector as well as others that are at a distance of r units from it (for $h = -1$); in other words, r is the *radius of the generalized region.* This may be seen by considering the all zero input vector. For this $w_{n+1} = r$. Since, all the other weights are -1 each, one can at most have $(r - 1)$ different $+1$s in the input vector for it to be recognized by this hidden neuron.

The choice of r will depend upon the nature of generalization sought. If no generalization is needed then $r = 0$. For exemplar patterns, the choice of r defines the degree of error correction.

If the neural network is being used for function mapping, where the input vectors are equally distributed into the 0 and the 1 classes, then $r = \lfloor \frac{n}{2} \rfloor$. This represents the upper bound on r for a symmetric problem. But the choice will also depend on the number of training samples.

The choice of h also influences the nature of generalization. Increasing h from the value of -1 correlates patterns within a certain radius of the learnt sequence. This may be seen most clearly by considering a 2$-$dimensional problem. The function of the hidden node can be expressed by the separating line:

$$w_1x_1 + w_2x_2 + (r - s + 1) = 0. \tag{5}$$

This means that

$$x_2 = \frac{-w_1}{w_2}x_1 + \frac{-(r - s + 1)}{w_2}. \tag{6}$$

Assume that the input pattern being classified is (0 1), then $x_2 = 1$. Also, $w_1 = h$, $w_2 = 1$, and $s = 1$. The equation of the dividing line represented by the hidden node now becomes:

$$x_2 = -hx_1 - r. \tag{7}$$

When $h = -1$ and $r = 0$, the slope of the line is positive and only the point $(0, 1)$ is separated. To include more points in the learning, $h < 0$, because the slope of the line becomes negative.

Consider the all zero sequence (0 0 ... 0). After the appending of the 1 threshold input, we have the corresponding weights $(h\ h\ ...\ h\ r + 1)$. Sequences at the radius of p from it will yield the strength of $ph + r + 1$ at the input of the corresponding hidden neuron. For such signals to pass through

$$ph + r + 1 > 0. \tag{8}$$

In other words, generalization by a Hamming distance of p units is achieved if

$$h < \frac{-(r + 1)}{p}. \tag{9}$$

When $h = -1$; $p = r$. When $h = \textit{positive}$, all the input patterns where the $0s$ have been changed into $1s$ will also be passed through and put in the same class as the training sample.

The generalized prescriptive rule presented in this article makes it possible to train a neural network instantaneously. There is no need for any computations in determining the weights. This allows the building up of neural networks of unlimited size. The instantaneous method of neural network training described here could be the method at work in biological systems. Such a training scheme will bring about associative reorganization of the network.

9 Conclusions

We have reviewed different kinds of evidence in favor of an underlying quantum basis to brain behavior: response to single photons by the vision system, the unity of the awareness process, and the fact that the process of self-organization is best seen as triggering a reduction of the wavefunction corresponding to the thought process. The self-organizational signals are a response to a combination of the inner and the external sensory signals. If biological processing is distinct from classical computing then it is easy to see why machines are unable to do certain kind of holistic processing that is easily done by animals. We suggest that biological organization may be supposed to be a quantum macrostructure that is constantly interacting with the environment and reorganizing. This reorganization may parallel perception representing a reduction into an eigenstructure.

In several writings, Neils Bohr stressed how the principle of complementarity must include life. Although complementarity as a philosophy is not much in vogue these days due to the ascendancy of the computer metaphor, it is the only consistent interpretive approach to quantum mechanics. Schrödinger's cat paradox shows how indeterminacy is associated with macroscopic systems if they are interacting with quantum systems. Life cannot exist without light; from this perspective alone we are compelled to consider quantum models.

An implication of this reasoning is the rejection of the materialist position that considers the identity of the neural and thought processes. A complete description of the individual must be in an suitable dimensional space which includes thoughts and concepts.

The structure of system may be described in terms of a binary sequence. One can then speak of complementary variables relating the structure and the environment. Such a reformulation of quantum mechanics may allow it to include living organisms.

Brain processes may also be seen in terms of two kinds of communications: one faster and the other slower. This is illustrated by the example of superorganisms where we have localized individual worker interaction with low connectedness and a faster communication using semiochemical pheromones. A specific signaling that regulates organization could provide important clues to the development of the quantum mechanics of living systems.

A quantum theoretical basis to life provides resolution to several thorny questions although it raises other fresh problems. The most pleasing feature is that it acknowledges the reality of "effort," and "intention," "free will," which have no place in materialist or causal schemes. Neither can we consider consciousness as an epiphenomenon. If consciousness has independent existence then it is a universal function and a brain is to be considered as simply the hardware that reduces this function.

We have considered the most basic behavior in our description of the three languages of the brain. At higher levels of description we must speak of other languages.

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