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Human Cortical Information Processing

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Robert Hecht-Nielsen, PhD
University of California, San Diego, CA, USA
HNC Software Inc, San Diego, CA, USA

Thomas McKenna, PhD
Office of Naval Research, Arlington, VA, USA

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Preface

Formal study of neuroscience (broadly defined) has been underway for millennia. For example, writing 2,350 years ago, Aristotle[1] asserted that association – of which he defined three specific varieties – lies at the center of human cognition. Over the past two centuries, the simultaneous rapid advancements of technology and (consequently) per capita economic output have fueled an exponentially increasing effort in neuroscience research.

Today, thanks to the accumulated efforts of hundreds of thousands of scientists, we possess an enormous body of knowledge about the mind and brain. Unfortunately, much of this knowledge is in the form of isolated factoids. In terms of "big picture" understanding, surprisingly little progress has been made since Aristotle. In some arenas we have probably suffered negative progress because certain neuroscience and neurophilosophy precepts have clouded our self-knowledge; causing us to become largely oblivious to some of the most profound and fundamental aspects of our nature (such as the highly distinctive propensity of all higher mammals to automatically segment all aspects of the world into distinct holistic objects and the massive reorganization of large portions of our brains that ensues when we encounter completely new environments and life situations).

At this epoch, neuroscience is like a huge collection of small, jagged, jigsaw puzzle pieces piled in a mound in a large warehouse (with neuroscientists going in and tossing more pieces onto the mound every month). Few attempts to find pieces in the mound that fit together have succeeded. Based upon this record of failure, few such attempts are now launched. Neuroscience research today is largely centered on the activity of uncovering new factoids in a careful, systematic fashion and then tossing them on the mound.

1 Aristotle (350 BC, 1995) Collected Works, Sixth Printing with Corrections, Princeton NJ: Princeton University Press.

Among neuroscientists there is a general anticipation that someday (not soon) somebody will fit enough pieces of the puzzle together to discern a key concept that will trigger rapid and sustained progress in assembling the rest of the existing pieces and in discovering the still missing pieces. The purpose of this book is to try to hurry up this timetable by describing several different conceptual frameworks that indicate how some of the pieces of the neuroscience puzzle may fit together. Perhaps the *trigger concept* that will lead to the rapid assembly of the neuroscience jigsaw puzzle is in this book. Or, if not, perhaps this book will inspire creation of the trigger concept.

Chapter 1 of this book, by Larry Cauller (the chapters are organized alphabetically by author name), presents a dynamics approach to understanding cortical function. As with many of the models and constructs presented here, Cauller's theory has been computer implemented and has been shown to have interesting and relevant properties. In particular, he concludes that it is the dynamical attractors of neuronal networks which are the fundamental, repeatable, basic elements of information storage and processing. Ideas such as neurons functioning as simple "feature detectors" are rejected. The net result is an iconoclast and fresh viewpoint about the workings of cerebral cortex.

Chapter 2, by Oleg Favorov and colleagues, takes a radically different viewpoint in comparison with Chapter 1; namely, that Frank Rosenblatt had it right all along. In this view, the brain is composed of perceptron-like multilayer neuron networks trained by backpropagation.[2] Favorov's theory is well argued. The main point is that this concept jibes with many known properties of cerebral information processing and behavior. The fact that "connectionist" cognitive science has been astoundingly successful in building phenomenological models of many cortical information processing operations is another strong argument for this theory.

Chapter 3, by Walter Freeman, is philosophically in tune with Chapter 1, but takes the main point even further, invoking chaos as a key ingredient in brain dynamics. In Freeman's conception, each neuron participates in multiple, interlinked, dynamical interactions with other neurons. Going farther than Cauller, Freeman's theory views trajectories transitioning from one attractor to another as the representations of information. The learning and behaving processes hinge on the occurrences of these transitions, not on the sustained attainment of stable attractor limit cycles. Appropriate (goal-satisfying) transitions are reinforced and enhanced, neutral or goal-denying transitions are suppressed. Freeman's viewpoint has heft because its main tenets are behaviors that real neurons can probably achieve and because it helps explain why conventional concepts have had such little success in explaining brain information processing.

Chapter 4, by Robert Hecht-Nielsen, presents an almost entirely new, detailed and complete, high-level theory of thalamocortical information processing. It postulates that all thalamocortical information processing can be accounted for by two particular types of associative memory neural networks, each employed in abundance. The

[2] Frank Rosenblatt invented the multilayer perceptron over forty years ago (Rosenblatt, F. (1962) Principles of Neurodynamics, New York: Spartan). However, he never found a way to adaptively train the hidden layer neurons. Backpropagation training of hidden layer weights was popularized by Rumelhart and his colleagues (Rumelhart, D.E., Hinton, G.E., and Williams, R.J. (1986) Learning representations by back-propagating errors, Nature 323: 533–536).

first of these networks is a fast-acting two-step attractor system (implemented by reciprocal connections between cortex and thalamus) which casts all information into one of a few thousand fixed-for-life sparse neuronal codes (*representational tokens*). The cerebral cortex is presumed to be tiled with tens of thousands of these (only weakly interacting) networks. The second network learns to connect certain pairs of these tokens on different regions. The strength of connection is a novel "fuzzy" information theoretic quantity called *antecedent support*; which Hecht-Nielsen claims is the only information learned, stored, and used in the thalamocortex. The notion that the cortex is fundamentally symbolic may appeal to old-school AI researchers. "Computational Intelligence" fans may like the theory because the learned relationships between pairs of hard symbols are soft and yet information-theoretic in character. Neuroscientists may like it because the whole thing seems to exactly match the known anatomy and physiology of the thalamocortex and its related structures.

Chapter 5, by Henry Markram, is a tour de force of advanced insight into those most critical brain elements: synapses. Markram's synthesis of the huge and confusing literature on this subject is guided by his own world-leading experimental findings. In particular, in strong resonance with several other chapters of the book, he emphasizes the central importance of dynamics in synaptic transmission: the postsynaptic effect of an arriving action potential depends critically on the recent history of arrivals of other action potentials. Going far beyond a mere recitation of the facts, Markram presents a compelling synthesis that identifies and characterizes principal categories of synaptic dynamical behavior. This chapter provides abundant knowledge of great value to all interested in cortical theory.

Chapter 6, by Thomas McKenna, provides sage commentary on a variety of cortical theories and their relationships. In particular, McKenna emphasizes and explores the gaps that clearly exist between cortical theories and biology. These gaps are then used as pointers towards potentially profitable new directions of theory construction. A valuable feature of McKenna's chapter is his characterizations and comparisons of theories that operate at different levels of abstraction. Going far beyond the simple "top down" and "bottom up" taxonomy, theories are discussed in terms of their ability to succeed at their individual level of abstraction. Two hundred years from now any high school student will probably be able to give a simple explanation for how the brain represents objects, learns and stores facts about those objects and then uses those facts to carry out information processing. A key point is that a correct theory can function without gaps at any level of detail. Another issue addressed in this chapter is the applicability of cortical theories. For theories to be judged correct and complete they must support practical implementations which can solve high-value human problems.

Chapter 7, by Jeffrey Sutton and Gary Strangman, proposes that the cerebral cortex can be viewed as being composed of hierarchical groups of neural networks; or, as they term it, a Network of Networks (NoN). The main point of this theory is that only modeling individual associative memory networks will never, by itself, explain the function of the cerebral cortex. A key missing ingredient is that groups of such networks are used, controlled, and trained as an ensemble – not individually. The chapter then goes on to explain how this might be accomplished and why this view is so important in understanding the obvious hierarchicality of processing we are so intimately familiar with (our cortex can deal with "throw the ball" as a conceptual unit just as easily as "slightly increase bicep tension").

Chapter 8, by John Taylor, presents a theory of cerebral information processing that concentrates on how consciousness may emerge from the combined activity of ensembles of stimulus-driven cortical-subcortical control structures set up to tend to a variety of behavioral goals and needs. Taylor's analysis frees itself from the details by fixating on firmly established high-level brain information properties that any successful theory must explain. Mixing together insights from a variety of theoretical perspectives, Taylor integrates these into a whole that emerges as a vision of how collections of relatively straightforward "thermostat" brain functions can, because of the strong causal linkages between their activating stimuli, end up supporting a higher-level process that becomes self-aware. Unlike past toy-system-level studies of "emergent" properties, Taylor's theory gets to the heart of why and how conscious awareness phylogenetically emerged. This chapter illustrates the value, and provides a masterful example, of theory building at a high conceptual level.

Chapter 9, by Neill Taylor and John Taylor, addresses another key cortex theory issue: language. In particular, they provide a foundational study of how a neuronal architecture can be developed to implement Noam Chomsky's hypothetical "Language Acquisition Device." Central to their theory are structures for chunking and unchunking of word strings (i.e., hierarchical networks). Using these, they develop a set of neuronally plausible language processing components and procedures that exhibit many of the key properties that a "LAD" must have. The resulting theory is not intended as a final theory of language acquisition and understanding. However, it provides a nice jumping-off point for further research.

Chapter 10, by Richard Zemel, is a theory of the population codes that many researchers believe lie at the heart of cortical information processing. In the past, almost all studies of population codes have assumed that the collection of neurons making up such a code are "ON" (and that other nearby neurons are "OFF"). Even with this binary assumption, many interesting properties of such codes have been established. In the theory presented in this chapter, Zemel goes way beyond this assumption: he allows population codes to also have variable non-negative activity levels assigned to them. He then shows that these activity levels can be interpreted in terms of a related probability distribution. Zemel then argues that the process of activating a population code is itself a probability calculation. Furthermore, he shows that collections of linked population codes can interact to form a type of belief network; a belief network that seems highly compatible with cortical neuronal anatomy, physiology, and function. The net result is a foundation for a new and promising direction of research.

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Robert Hecht-Nielsen
Thomas McKenna

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Contributors

Chapter 1

Lawrence J. Cauller, PhD
Neuroscience Department
University of Texas, Dallas
Richardson, Texas USA

Chapter 2

Oleg Favorov, PhD
School of Electrical Engineering and Computer Science
University of Central Florida
Orlando, Florida USA

Dan Ryder
Department of Philosophy
University of North Carolina, Chapel Hill
Chapel Hill, North Carolina USA

Joseph T. Hester
Biomedical Engineering
University of North Carolina, Chapel Hill
Chapel Hill, North Carolina USA

Douglas G. Kelly
Department of Statistics
University of North Carolina, Chapel Hill
Chapel Hill, North Carolina USA

Mark Tommerdahl
Biomedical Engineering
University of North Carolina, Chapel Hill
Chapel Hill, North Carolina USA

Chapter 3

Walter J. Freeman
Department of Molecular and Cell Biology
University of California, Berkeley
Berkeley, California USA

Chapter 4

Robert Hecht-Nielsen
Department of Electrical and Computer Engineering
and Institute for Neural Computation
and Program in Computational Neurobiology
University of California, San Diego
La Jolla, California USA

Chapter 5

Henry Markram
Department of Neurobiology
Weizmann Institute for Science
Rehovot, ISRAEL

Chapter 6

Thomas McKenna
Office of Naval Research
Arlington, Virginia USA

Chapter 7

Jeffrey P. Sutton, MD, PhD
National Space Biomedical Research Institute and Neural Systems Group

Massachusetts General Hospital
Harvard-MIT Division of Health Sciences and Technology
Charlestown, Massachusetts USA

Gary Strangman, PhD
Massachusetts General Hospital Neural Systems Group
Harvard-MIT Division of Health Sciences and Technology
Charlestown, Massachusetts USA

Chapter 8

John G. Taylor
Department of Mathematics
Kings College
Strand, London UK

Chapter 9

Neill R. Taylor
Department of Mathematics
Kings College
Strand, London UK

John G. Taylor
Department of Mathematics
Kings College
Strand, London UK

Chapter 10

Richard Zemel
Department of Computer Science
University of Toronto
Toronto, Ontario CANADA