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Neuronal Post-Structuralism: A Humanist's Perspective on the Mathematics of the Construction of Memory

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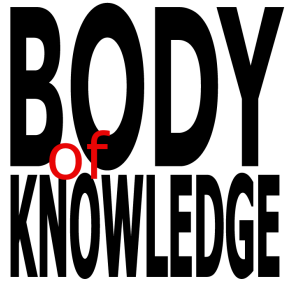
Author

Fuller, Michael A

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**Neuronal Post-Structuralism: A Humanist's Perspective on the Mathematics
of the Construction of Memory**

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Michael A. Fuller

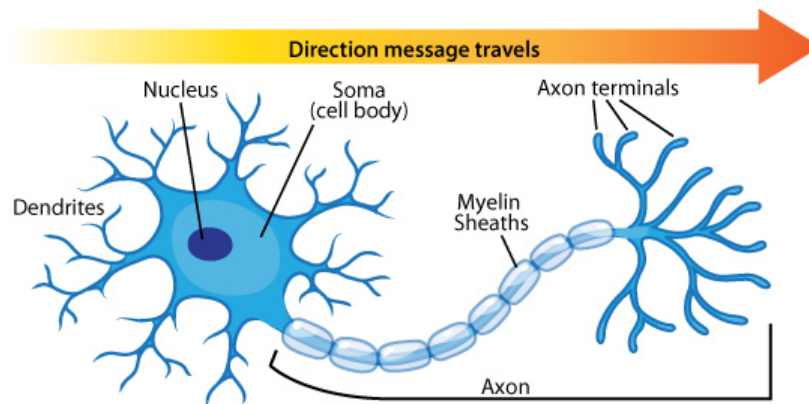
What is a neural network? Many of us start with a vague image of a mesh of cells in the brain somehow doing something that is analogous to the World Wide Web of which our various digital devices are a part and that a neural network, thus, operates essentially like a linked collection of microprocessors. I want to examine, however, how this image of a network of connected neurons in our head is at best a starting point and how understanding the actual dynamics of neural networks leads us far away from the computer model and into processes for the construction of embodied meaning that humanists will recognize as the poststructuralist world of our varied disciplines.

Biological neural networks work by rules different from those of serial computers (i.e. computers that function by following programs written as a sequence of rules for calculations and the logical branching conditions based on the results of those calculations). The complexities of human experience that arise within the neural networks of the brain work not through the decision logic of computers but according to massively parallel, widely distributed probabilistic procedures for pattern recognition that are expressible in the language of matrix mathematics. I seek here to illustrate the process by which, beginning in infancy, we develop deep structures of memory in the brain that are shaped by emotional systems that represent to the brain the needs and desires of the body. The mathematics of neural networks requires that these affectively shaped memory structures at the heart of our adult understanding of the nature of the self and the world are self-organized maps, and the “objects” of our experience arise as mutually differentiated regions within those maps rather than as discrete entities. This poststructuralist world of constructed maps within us is shaped by the developmental logic and basic mathematics of the brain. There is much here to which we, as humanists, can contribute—and much that we can learn—through joining the conversation about this embodied organization of meaning. But

to join this conversation we must learn something of the shared language of mathematics and neurobiology at the heart of the neural network model.

I. Modeling Neurons and Neural Networks

Let us begin at the most basic level of neuronal functioning: the working of synapses. Synapses are chemically mediated connections between an axon (output) terminal of one neuron and an (input) dendrite of another. When a neuron “spikes,” it sends a wave of electrical depolarization down its axon, and chemicals are released at its terminals. The dendrite of the receiving neuron has receptors that bind to the neurotransmitter released by the axon terminal at the synaptic junction. If enough dendrites for a neuron simultaneously bind in-coming neurotransmitters, this action produces a new spike of depolarization that the neuron sends down its axon.¹



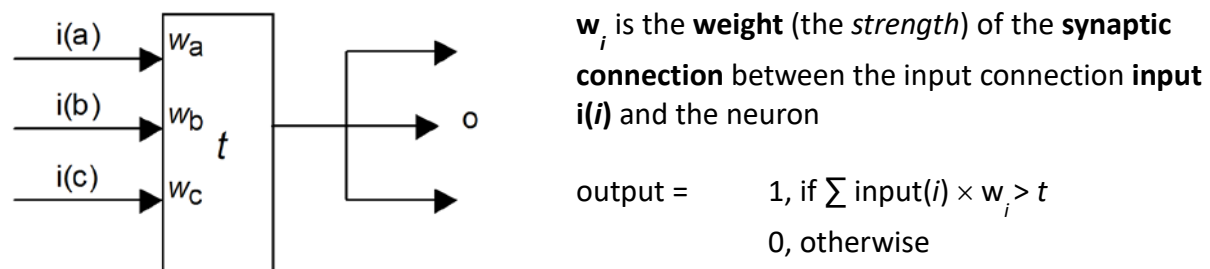
In the adult cortex there are 12-20 billion neurons. For each neuron there are about 7,000 synaptic junctions.² The average response time (between receiving the activation input at the dendrites and transmitting a pattern of activation to the axonal terminals) is about 5 milliseconds,

¹ While this description introduces the basic features of synapses, the reality is far more complicated. For example, there is a host of neurotransmitters—some excitatory, some inhibitory—and there are different types of receptors with different properties. There are many sources from which to learn more, including the contemporary standby, Wikipedia (<https://en.wikipedia.org/wiki/Synapse>)

² B. Pakkenberg et al., “Aging and the Human Neocortex,” *Experimental Gerontology* 38 (2003) 95–99.

while the average observable conscious response to a stimulus takes about 500 milliseconds.³ Thus the brain typically produces a response via about 100 steps of neuronal activation. This “one hundred step” process shows the inadequacy of the conventional computer analogy. While one can say that “computation” is occurring, it is at a vastly more complex level. Researchers have long understood that since one hundred instructions in assembly language—the base level of computation in a serial computer—does not get one very far, whatever the brain is doing to integrate external and internal conditions in its responses must be using approaches to computation made possible by the almost inconceivably massive parallelism of its neuronal networks, and that the brain’s mode of computation profoundly differs from the step-by-step logic of a serial computer program.

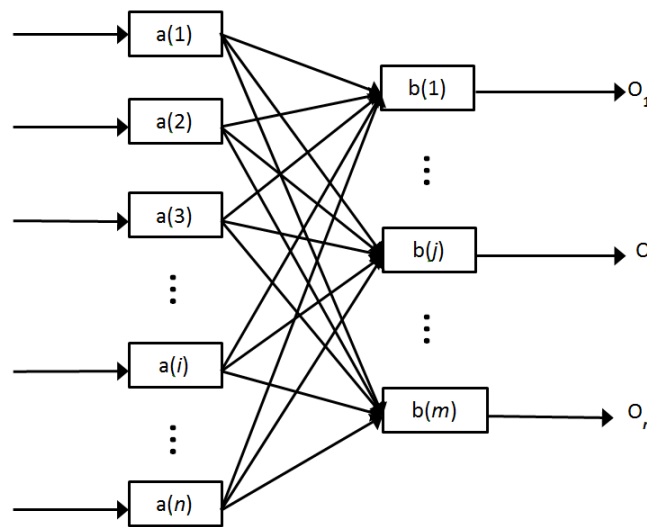
To explore how neuronal computation works, researchers began by building a simple model of a neuron:



That is, each neuron has a set of input synaptic connections, and each connection has a specific weight—a measure of the strength of the connection to the neurons to which it is attached. The fundamental calculation a neuron makes is whether to fire, to produce an activation to pass along to the next set of neurons in the network. To make this calculation, the neuron simply sums the activation state of the input neuron (either 0 or 1 in the simplest model) times the weight of the

³ Drawing of Neuron courtesy of Brett Szymik. “A Nervous Journey.” <http://askabiologist.asu.edu/neuron-anatomy>. © Arizona Board of Regents / ASU Ask A Biologist. Published under Creative Commons BY-SA 3.0

connection to the input neuron. If this weighted sum is higher than some threshold value t , the neuron fires.⁴ The individual neurons are part of layers of neurons. As illustrated in the following figure, in this model the behavior of any neuron in Layer B depends not on any single neuron in Layer A but on contributions from some or all the neurons in Layer A.⁵ Each connection between the neurons in the first layer and the neurons in the next layer has a connection weight $w_{i,j}$.



The set of these weights defines a **weighting matrix** of dimension (m,n) (columns for Layer A, rows for Layer B)

$$\mathbf{W}_{n,m} = \begin{bmatrix} W_{1,1} & W_{2,1} & \cdots & W_{n,1} \\ W_{1,2} & W_{2,2} & \cdots & W_{n,2} \\ \vdots & \vdots & \ddots & \vdots \\ W_{1,m} & W_{2,m} & \cdots & W_{n,m} \end{bmatrix}$$

⁴ More recently, more biologically informed models have used a so-called “leaky integrate and fire” design, in which cells leak (lose activation strength) and rely not on a simple, static activation value but on changes in the spiking rate of the input neurons (the rate at which the neurons send spikes of depolarization down the axon to the axonal terminals and release waves of neuronal transmitters across the synaptic junction). The neurons sum the change in spiking rate times the weight of the connection and, if the value is high enough, in turn increase their own rate of spiking transmitted to their axonal terminals. I have found Thomas P. Trappenberg, *Fundamentals of Computational Neuroscience* Second Edition (Oxford: Oxford University Press, 2010) to be an excellent account of the more contemporary mathematical models for neural network computation.

⁵ I have drawn a layer of fully connected neurons, but in most cases, neurons are **sparsely** connected, with not all the neurons in Layer A connected to all the neurons in Layer B

This weighting matrix is where the action is: **changing the weights is where learning happens.**

In 1949 Donald Hebb proposed a simple learning rule for training neural networks to develop stable responses to sets of patterns.⁶ The idea was that if the activation of a synaptic connection from a neuron in the layer below contributes to a neuron's firing, then one increases the strength of that connection. In mathematical terms:

$$\Delta w_{ij} = \eta a_i b_j$$

where

a_i and b_j = the output values for the i^{th} unit in Layer A

and the j^{th} unit in Layer B

Δw_{ij} = the change in the connection weight between the units

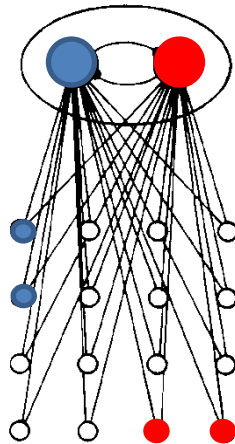
η = a learning parameter

Note that if either a_i or b_j is 0 (i.e., the neuron did not fire), then the connection weight does not change. The popular shorthand explanation of Hebb's rule has thus become "Neurons that fire together wire together."

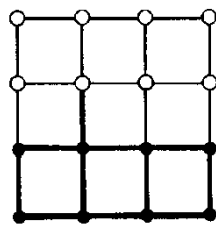
II. Neuronal Structuralism

What can such neural networks do? We begin with a simple pattern detection system that easily extends to help us think about how the visual system—which is the neural system that has been the best studied and has provided an important model for thinking about neural networks in general—works. Consider a pair of layers of neurons:

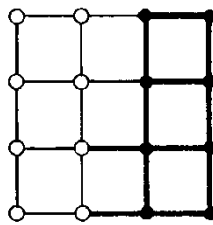
⁶ Donald O. Hebb, *The Organization of Behavior*. (New York: Wiley & Sons, 1949).



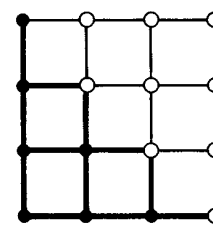
In this system, only two neurons in the first layer fire at a time, and they must be next to each other either horizontally or vertically. In the second layer, only one of the two neurons can fire at a time (they inhibit each other: the one that fires keeps the other from firing).⁷ The system begins with the weights of the connections between the neurons in the first layer and those in the second given random values and then is trained through many rounds of activation of pairs of neurons in the first layer. In different trials, the results were:



Trial 1



Trial 2



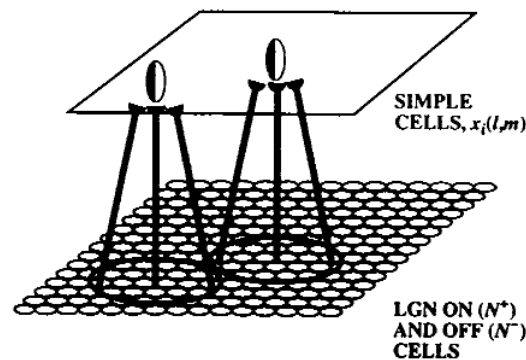
Trial 3

- Filled circle: Output Neuron 1 gave the input from that unit a higher weight,
 Empty circle: Output Neuron 2 gave the input from that unit a higher weight.
 Heavy line: When the two input units were active, Output Neuron 1 won
 Thin line: Output Neuron 2 won the competition.

At the end of each trial, when the system of weights and the pattern of activation have become

⁷ This example comes from D. E. Rumelhart and D. Zipser, "Feature Discovery by Competitive Learning," in David E. Rumelhart and James L. McClelland, and PDP Research Group, *Parallel Distributed Processing: Explorations in the Microstructure of Cognition, Volume 1: Foundations* (Cambridge, MA: MIT Press, 1986), pp. 170-177. Reprinted courtesy of The MIT Press.

relatively stable, the neural network has discovered a way to divide the input layer into two halves (i.e., it has discovered a topographic map), but in different trials, the system finds different solutions based on the initial weights. This is a very simple example, but it resembles the way in which the “simple cells” of the primary visual cortex (V1) learn to respond to the input from the “On” and “Off” neurons of the lateral geniculate nucleus (LGN) of the thalamus:⁸

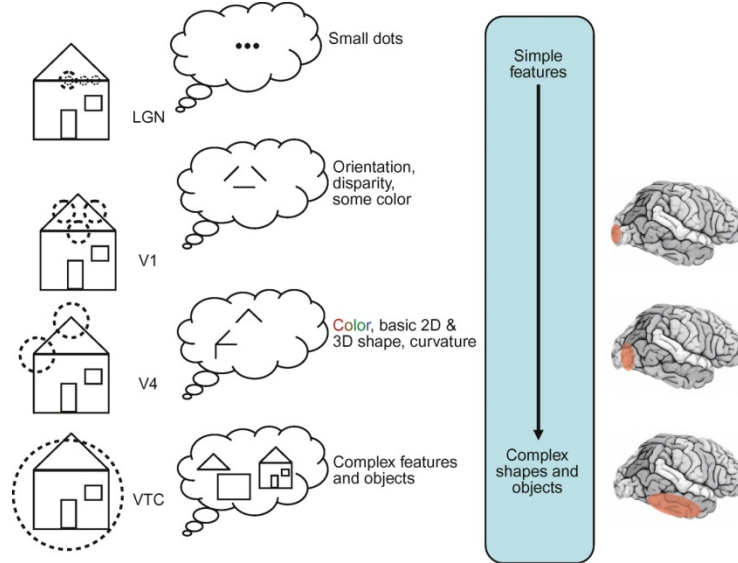


The cells in the LGN respond to whether, in a cluster of neurons in the retina, the central neuron is firing while those surrounding it are off (“On” cell) or if the central neuron is off and the surrounding are firing (“Off” cell). The “simple cells” in V1 in turn aggregate the input from LGN neurons and, through Hebbian learning, learn to respond to short line segments at different angles.⁹ The higher-order network aggregates the data from groups of neurons in the lower-level network. The neurons in the higher-order network collectively develop weighting values that produce patterns of activation to mutually differentiate features (like angles) in the lower level data. This construction of mutually differentiated feature detectors continues all the way up the visual cortex. The LGN starts with “on” and “off” cells; V1 detects angled line segments; V2

⁸ This model comes from Steven J. Olson and Stephen Grossberg, “A neural network model for the development of simple and complex receptive fields within cortical maps of orientation and ocular dominance,” *Neural Networks* 11 (1998):189-208.

⁹ The “complex” cells in V1 learn to detect additional features like movement.

detects clusters of segments that form mutually differentiated shapes, and on and on:¹⁰



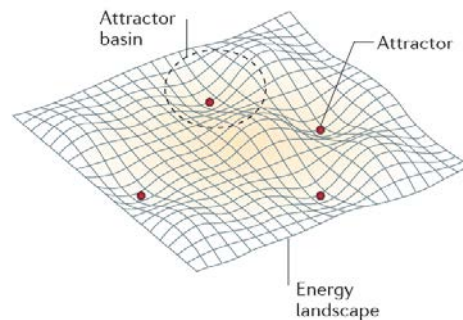
However, while the initial training of the visual system in early infancy follows simple Hebbian rules, the story is actually more complex because the patterns of activation in processing the data from the retinas not only flow upward (retina → LGN → V1 → V2 ...) but also downward in ways that create more complex training rules as increasingly higher level cortical regions mature. Even before activations from higher cortical regions begin to inform the structuring of the visual neural networks, the top-down activation serves a very important function in the visual cortex's role in identifying the "objects" differentiated in V5: when the patterns transmitted from the retinas are incomplete (because of lighting conditions or because the "objects" are blocked) the top-down activations from layer to layer all the way back to the LGN represent the best guess of what the received pattern is and can greatly speed up the ability of the visual system as a whole in settling on a pattern it identifies.¹¹

Within this system of recurrent connections, researchers call the sets of mutually

¹⁰ See Bernard J. Baars and Nicole M. Gage, *Cognition, Brain, and Consciousness: Introduction to Cognitive Neuroscience*, Second edition (Academic Press, 2010), p. 166.

¹¹ See, for example, the discussion of recurrent connectivity in Randall C. O'Reilly, et al., "Recurrent processing during object recognition," *Frontiers in Psychology* 4 (April 2013), pp. 1-14.

differentiated patterns stored in the weighting matrices “attractor basins.” That is, if an input activation is similar to one of the learned patterns, the network will return that learned pattern to the layer below it, which then will adjust its firing to look yet more like the expected pattern, and, in a few cycles, the input pattern will come to match the expected one. Thus the learned pattern “attracts” input activations initially close to it to settle into its “basin.”¹²



Recent work on neural networks has developed the sophisticated learning algorithms of “deep belief networks” that are distant cousins of the simple Hebbian routines. These are “belief” networks because each layer of the network models the structure of the input “world” of the layer below it. The mathematics of these systems here becomes more complex and draws on the well-developed field of physics called statistical mechanics. Based on this analogy with physics, researchers think in terms of the “energy” of the neural network system—as in the drawing above—and have found the idea of attractor “basins” as low-energy states to be a very powerful way of thinking through network dynamics.

¹² See the discussion in Rafael Yuste, “From the neuron doctrine to neural networks,” *Nature Reviews: Neuroscience* 16 (August 2015), p. 492. Yuste adapted the figure from Chris Eliasmith, “Attractor Networks” in *Scholarpedia* 2(10):1380. (http://www.scholarpedia.org/article/Attractor_network copyright [Creative Commons Attribution-NonCommercial-ShareAlike 3.0 Unported License](https://creativecommons.org/licenses/by-nc-sa/3.0/)) Yuste provides an excellent overview of the relation of computational modeling and neuroscientific research. Also see Patricia S. Churchland and Terrence J. Sejnowski, “Blending computational and experimental neuroscience,” *Nature Reviews: Neuroscience* 17 (November 2016), pp. 667-68.

However, whether the learning follows Hebb's rule or draws on Deep Learning algorithms, the basic logic of the neural networks that emerge is the same: what the training defines is a set of mutually differentiated regions in a high-dimensionality space. Moreover, memory accrues at every synapse in the system. The representations—built layer by layer—are distributed among all the synaptic junctions of all the layers in the network: each layer abstracts features and builds a model of the system of “objects” structured in the layers that feed into it. The “objects” and their meanings as represented in our brains are not atomic in nature but mutually defining spaces in a field. This model of constructing objects within an encompassing structured field is the same as the old structuralist world of “meaning by difference” with which humanists have long been familiar.

III. Neuronal Poststructuralism, or You Know what You Want

By Poststructuralism, I mean a major revision *within* structuralism. In structuralism, the categories of differentiation that bring structure to the system are arbitrary. In poststructuralism, in contrast, the categories of differentiation are not random and instead draw on pre-existing hierarchies of power, desire, and need to generate the system of mutual differentiation. I argue here that the brain, because of its architecture and developmental dynamics, builds the higher order representational structures—and semantic memory in particular—through such a logic of power, desire, and need.

A. Supervised Learning—Defining the System of Needs

To clarify the structural role of desire in the brain, I return to the model of deep belief networks. Although such networks can be trained to extract the features of their input domain through bottom-up learning—called “unsupervised learning”—in most cases, those who are building the

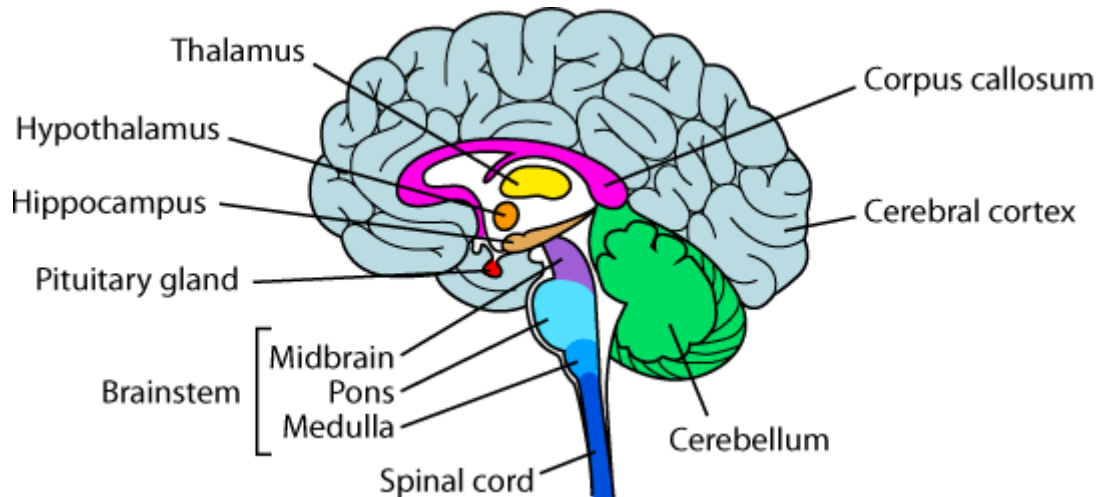
network know the patterns they want the system to capture and correct the synaptic weights in the system to assure the desired results. When researchers at Google trained AlphaGo to play Go, for instance, they trained it to *win*, not just to play. This is “supervised learning.”

Learning in the human brain—especially in infancy—crucially relies on supervised learning. While the basic layers of the sensory cortices in the brain are trained to extract the features of their sensory domain when the child is a neonate, the higher cortical structures that record autobiographical and semantic memory develop later, and the neural networks that underlie these memory systems are shaped through forms of supervised learning. This supervision comes in two forms. The first, which should never be forgotten, is external: an unsupervised infant dies. Thus, a caretaker keeps a child fed, warm (since internal temperature regulation matures after birth), removed from danger, and comforted when in distress. All of these nurturing activities profoundly shape the nature and timing of the sensory input and internal visceral states the infant encounters and from which it extracts its model of itself and the world.

B. Affect as Supervisor: the Neurological Affective System

The second system for supervising the structuring of memory networks is internal. The body has its requirements for survival, or in the language of biology, for maintaining homeostasis, a constant internal environment with acceptable levels of blood sugar, salt, and warmth as well as an absence of pain. All of these bodily parameters must be converted into neuronal inputs accessible for cortical processing. The mechanism for this conversion is the complex of subcortical structures in the brain stem and midbrain.¹³

¹³ Drawing courtesy of Brett Szymik. "A Nervous Journey." ASU - Ask A Biologist. 5 May 2011. <http://askbiologist.asu.edu/parts-of-the-brain>. © Arizona Board of Regents / ASU Ask A Biologist. Published under Creative Commons BY-SA 3.0.



To draw on the language of Jaak Panksepp, these subcortical structures produce *affect*, the brain's primary responses to bodily information. Panksepp divides affect into three types:

1. Sensory affect (sensory input assessed as either pleasurable or unpleasant)
2. Homeostatic affect (hunger, thirst, etc.)
3. Emotional affect (the “emotion actions systems” produced subcortically)¹⁴

Panksepp lists seven basic systems of “emotional” response produced in the brain stem and mid-brain regions: SEEKING, RAGE, FEAR, LUST, CARE, PANIC, and PLAY. He uses capital letters to attempt to clarify that the subcortical systems do not produce what we consciously know as these emotions but instead produce the neurochemical substrates and neural activations transmitted into the thalamus, amygdala, hippocampus and some cortical regions that underlie the development of the complex network of responses that we come to know as emotions.¹⁵ One crucially important aspect of this list of affects is how many of them support the development of specifically *social* emotions: humans have evolved as complexly social animals in ways that

¹⁴ See, for example, Jaak Panksepp, “Cross-Species Affective Neuroscience Decoding of the Primal Affective Experiences of Humans and Related Animals,” *PLOS*, September 7, 2011, p. 3.

¹⁵ Jaak Panksepp, “Cross-Species Affective Neuroscience Decoding,” p. 9

have helped the survival of the group, but the shaping of the subcortical systems inherited from our early primate ancestors work here by very indirect, emergent developmental processes that begin prenatally and take years to complete.

The clusters of nuclei in the brainstem and midbrain that produce primary affective responses initially have no data from the nervous system, no knowledge of the body. Indeed, the crucial connectivity between the brain stem, the midbrain structures and the rest of the body develop in stages during gestation and the early neonatal period.¹⁶ As these connections mature both prenatally and after birth, however, the brain stem and midbrain neural networks build maps of the significant features of the input from the body.¹⁷ In Antonio Damasio's terms, these are the interoceptive and proprioceptive maps that are the basis of emotional responses.¹⁸ Both Panksepp and Damasio tell essentially the same story—with different terminology and focus—of the centrality of the brainstem and midbrain nuclei in the generation of affect. Both stress the midbrain's mapping of the body very early in development and the subsequent mapping of these subcortical systems into the neocortex as the next stage in developing from primary to secondary

¹⁶ “By the 7th gestational month the medulla and pons have nearly completed their cycle of myelination and most of the various descending spinal–motor fiber tracts have reached target tissues and established their synaptic interconnections (Gilles et al., 1983; Langworthy, 1937; Yakovlev & Lecours, 1967). However, because the fetal brainstem matures in a caudal to rostral arc, and as different nuclei mature and myelinate at different rates, fetal brainstem reflexes are initially triggered infrequently or in isolation and thus emerge gradually and in an irregular fashion (Debakon, 1970)... Nevertheless, the brainstem continues to mature well after birth, and, correspondingly, brainstem reflexes emerge and disappear at different time periods over the course of the first 3 to 6 months of postnatal life (Debakon, 1970; see also Capute, Palmer, Accardo, Wachtel, Ross, & Palmer, 1984; Piper & Darrah, 1994). For example, initially, vital functions such as heart rate and respiration are irregular, body temperatures fluctuate, and swallowing is precarious.” R. Joseph, “Fetal Brain Behavior and Cognitive Development,” *Developmental Review* **20**, (2000), p. 85.

¹⁷ Panksepp rightly stresses the crucial point that the mappings of the body in the very earliest stages of the affective system are learned, as in the FEAR system: “FEAR, like every other emotional system, is born essentially ‘objectless’ and, like all other emotional systems of the BrainMind, it becomes connected to the real world through learning.” Panksepp and Biven *The Archaeology of the Mind: Neuroevolutionary Origins of Human Emotions* (New York: Norton, 2012), p. 176.

¹⁸ Damasio describes the interoceptive maps as based on “the functional condition of the body tissues such as the degree of contraction / distension of smooth musculature [and] parameter of internal milieu state,” while the proprioceptive use “images of specific body components such as joints, striated musculature, [and] some viscera.” See Antonio Damasio, *Self Comes to Mind* (New York: Vintage, 2012), p. 80.

affect. These primary and secondary affective systems then play a central role in our manner of engaging the world.

Damasio's abstraction of the secondary affective system (the systems by which the neocortex internally maps the brainstem and midbrain sources of affective response) as a dispositional space offers an elegant way of thinking about the constant, pervasive effect of emotion on our experience:

[I]n addition to the logic imposed by the unfolding logic of events in the reality external to the brain—a logical arrangement that the naturally selected circuitry of our brains foreshadows from the very early stages of development—the images in our minds are given more or less saliency in the mental stream according to the value for the individual. And where does that value come from? It comes from the original set of dispositions that orients our life regulation, as well as from the valuations that all the images we have gradually acquired in our experience have been accorded, based on the original set of value disposition during our past history.¹⁹

Damasio presents a system in which the brain learns by mapping between the early-developing sensory cortices and the “dispositional devices” that are the equally early-developing network of brainstem and midbrain nuclei and their cortical representations (Panksepp's primary and secondary emotional affects). As the association cortices mature, they serve as convergence zones that develop the experiential connections between the affective systems—represented as dispositions—and the sensory data from the environment.²⁰ Our memories, created through

¹⁹ Damasio, *Self Comes to Mind*, p. 76.

²⁰ “The cortical *dispositional space* included all the higher-order association cortices in temporal, parietal, and frontal regions; in addition, an old set of dispositional devices remained beneath the cerebral cortex in the basal

identifying patterns binding dispositional and sensory data, therefore are of inherently “dispositional objects:”

Our memories of things, of properties of things, of people and places, of events and relationships, of skills, of life management processes—in short all of our memories, inherited from evolution and available at birth or acquired through learning thereafter—exist in our brains in dispositional form, waiting to become explicit images or actions.²¹

Damasio writes about our memories for objects. But it remains important to recall that in the brain the neural networks that encode higher-order memories for objects and events remain based on matrix mathematics: the complex “objects” of our experience are arrays of attractor basins in a high dimensional “dispositional space,” and it is a *constructed* space.

C. Developmental Structuring of Supervised Memory

In supervised learning, the “desired” patterns of activations are passed from higher to lower networks and serve as inputs to revise the pattern of synaptic weights in the lower networks. The desired outcome in the *brain* is to “seek the good; avoid the bad,” and the affective system provides this feedback for the perceptual input (which includes the assessment of action scenarios implemented by the sensorimotor networks of the brain). In early infancy the higher-order dispositional space of the association areas in the temporal, parietal, and frontal cortices are weakly functional at best. However, with the progressive myelination of the neural networks as

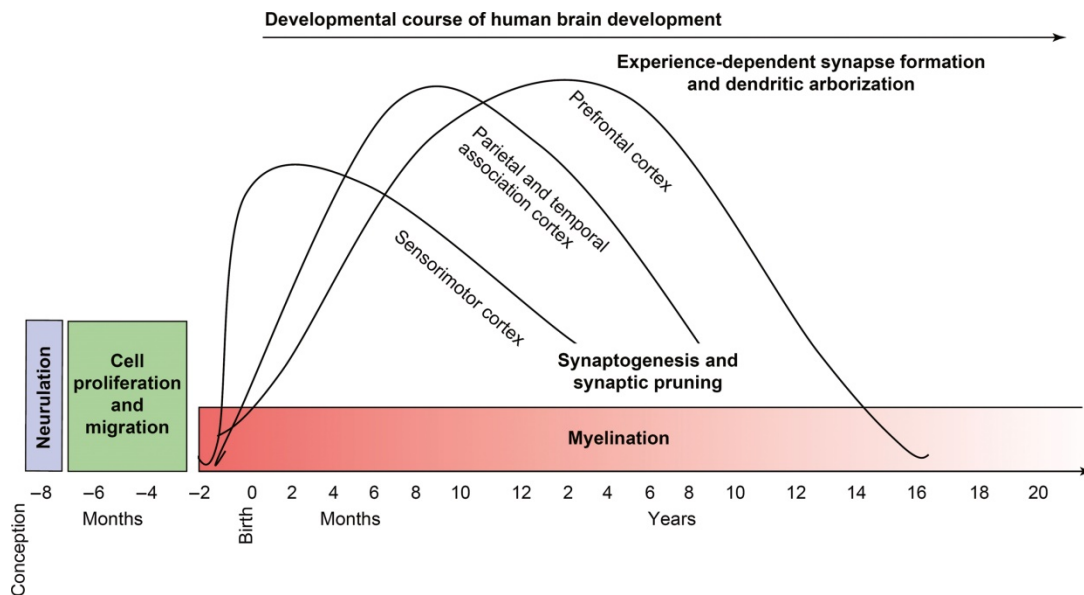
forebrain, basal ganglia, thalamus, hypothalamus, and brain stem.” (Damasio, *Self Comes to Mind*, p. 151.)

²¹ Damasio, *Self Comes to Mind*, pp. 153-54. Panksepp reaches a similar conclusion:

For this reason we prefer to envision emotional systems as ‘attractor landscapes’ (in the lingo of nonlinear dynamic systems theory) that help us make particular connections with our environments both in thought and deed. Thus we envision primary-process emotional systems to be in the ‘cat-bird seat’—having the upper hand—when it comes to how learning controls the formation of memories in our brains

Panksepp and Biven *The Archaeology of the Mind*, p. 237.

the infant matures (proceeding from the rear to the front of the brain), the connections to the affective and sensory systems strengthen, and increasingly complex multimodal assessments mediated by the “working memory” and “attention” systems of the frontal and parietal lobes become possible.²²



While all changes in synaptic weights throughout all the cortical pathways that are maturing are forms of memory formation, what we typically think of as memory—that for objects and events—becomes increasingly possible and stable through the maturation of the hippocampus in particular. Although there are many important categories of memory, I focus here in particular on the episodic, autobiographical, and semantic memory system developed via the hippocampus because these are the forms of memory most important for humanists. The hippocampus is the great integrator of the many modalities of memory that comprise the memory of events.²³ The hippocampus makes possible the encoding of the many types of information

²² Baars and Gage, *Cognition, Brain, and Consciousness*, p. 479, modified from R.A. Thompson and C. A. Nelson, “Developmental science and the media. Early brain development,” *American Psychologist* 56 (2001), 5–15. Source: B. J. Casey et al., “Imaging the developing brain: What have we learned about cognitive development,” *Trends in Cognitive Science* 9.3 (2005), pp. 104-110.

²³ Randall C. O’Reilly, Rajan Bhattacharyya, Michael D. Howard, Nicholas Ketz, “Complementary Learning

that comprise the meaning of an event. In this process of synthesizing memory, many researchers over the years have noted the effect of affective arousal in enhancing hippocampal functioning.²⁴ The role of affect in shaping the neural networks structured by the hippocampus has three components. The first is the immediate influence of neuromodulators produced by the affective midbrain nuclei and the role of the amygdala in strengthening the synaptic changes during the initial moment of the event being remembered. Next, affective recall during the consolidation of the memory through the replaying of the memory enhances those aspects of the episodic memory that have stronger affective valences. The final aspect is the most general, but it remains crucial: the very information being provided to the hippocampus for encoding already is structured by the role of the dispositional space in which the raw sensory and proprioceptive data are synthesized into higher-order structures.

D. From Moving Events to Meaningful Objects

Once the hippocampus and the neocortical regions associated with it have encoded an episodic memory informed by affective responses, the larger order patterns across the episodic encounters with objects and events are then extracted into semantic memory.²⁵ I want to stress that in early infancy in particular, as the initial structure of semantic memory is just forming and the network of attractor basins that define the high-order “objects” is just emerging, the patterns arising in the dispositional space are essentially about the affective significance of sensory and proprioceptive

Systems,” *Cognitive Science* (2011) p. 4.

²⁴ Most research has focused on the role of connections between the amygdala and the hippocampus. But the role of affect is more complex. Todd and Thompson, for example, point to the norepinephrine system of the locus coeruleus in the brainstem. (Rebecca Todd and Evan Thompson, “Strengthening emotion-cognition integration,” *Behavioral and Brain Sciences* (2015), pp. 40-42)

²⁵ “[T]he nature of the memories that become consolidated in the neocortex is significantly different from those that were originally encoded by the hippocampus, by virtue of the complementary nature of these memory systems. Whereas the hippocampus encodes a crisp, contextualized, episodic memory, the neocortex extracts a highly semanticized, generalized ‘gist’ representation that integrates over many different episodes.” O’Reilly et al., “Complementary Learning Systems,” p. 7.

data. The fundamental structure of meaning as it initially forms is a cortical, early experiential articulation of the system of needs and desires provided by the affective system. That is, the infant knows what it wants.

Crucially, this initial structure of meaning in infancy persists at the heart of the adult understanding of the nature of the self and the world. As attachment theory, based on the model of the dyadic emergence of the infant self and the caregiver, becomes increasingly important in psychoanalytic understanding, it becomes ever clearer that the infantile “working model” of the self articulated in the neural networks of memory remains at the core of adult identity.²⁶ These early networks are fundamentally poststructuralist, with their arrays of “objects” as attractor basins differentiated by affective criteria of want and need.

Meaning for both infants and adults is necessarily poststructuralist. This conclusion should matter both to neuroscientists and to humanists. The poststructuralist world is riven by conflict and contradiction, and this is the world that is within us. It is neurobiological in nature, shaped by the developmental logic and basic mathematics of the brain. What clarity neuroscience can bring to this complex, inevitably strife-filled human experience will be to articulate this logic and—therapeutically—underscore the profound importance of early childhood. Humanists in turn need to recognize in these results that neurobiological materialism is not reductionist (or at least should not be) and that we should put aside the idealism of our faith in the infinite regress of meaning and instead look to the richness of the neurobiological model. In the biological model, meaning is individual, since embodied meaning is meaning as encountered through particular bodies and follows the particular trajectory of individual

²⁶ The intersection of developmental neuroscience and attachment theory in psychoanalysis—and the therapeutic implications of the neuroscience—are at the heart of such books as Louis Cozolino, *The Neuroscience of Psychotherapy* second edition (New York: Norton, 2010) and Efrat Ginot, *The Neuropsychology of the Unconscious* (New York: Norton, 2015)

experience. Yet biological meaning also of necessity draws its patterns from individual engagement with an external world of structures, both human and natural. In our explorations of the construction of meaning, we humanists must remember the body and the brain in their biological materiality. We need a conversation with the neuroscientific community to deepen our sense of the dynamics of experience and the *embodied* structure of meaning. And we humanists, for our part, can contribute our reflections on the complexity of living in a poststructuralist world of meaning.