

Bridging the Mind-Brain Gap by Morphogenetic “Neuron Flocking”: The Dynamic Self-Organization of Neural Activity into Mental Shapes

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Abstract

This short position paper claims that computational neuroscience should refocus on the study of multiscale *spatiotemporal shapes* (STS) of activity in large neural populations. Instead of naive engineering metaphors, which view the brain as a signal-processing channel traversed by “information”, or neo-Behaviorist probabilistic frameworks, where it is a “gray box” tuned by environmental distributions, new theories should resolutely promote mechanistic, *complex systems* models. In this paradigm, massively recurrent networks should support the spontaneous (and triggered) emergence of intrinsic dynamical regimes, made of myriads of correlated electrophysiological signals—not unlike other collective biological phenomena such as bird flocks, insect constructions, or morphogenesis. “Neuron flocking”, for its part, must happen in *phase space* and across a complex network topology: Can we characterize the “shapes” and composition laws of these mind states, upon which high-level symbolic computing can ultimately rest?

Toward a Mind-Brain “Modern Synthesis”, via Complex Systems

The foundational thesis of cognitive science is that the mind relies on internal dynamical “states”, “regimes” or “representations” that correspond to (and are triggered by) states of the external world. It operates by creating, assembling, and transforming these states under the constraints and meanders of its own internal dynamics, and under the influence of external stimuli. The nature and structure of these brain states, however, is still an open question, in particular their embodiment in the *neural code*, i.e. the laws of organization of electrophysiological signals. When trying to bring an answer to this deep problem, however, the multidisciplinary nature of cognitive science appears to be more of an obstacle than an advantage. According to Bechtel, Graham, and Balota (1998, p3): “Cognitive science is the multidisciplinary scientific study of cognition and its role in intelligent agency”, and the same authors ask: “Do [these disciplines] interact substantively—share theses, methods, views—or do they simply converse?”. Currently, this field can only be defined extensionally as a vast federation of disciplines (psy-

chology, AI, linguistics, logic, neuroscience, neural modeling, robotics, etc.) with widely different viewpoints fundamentally lacking a “central theory” to unify them around a common set of laws—as was the case, for example, when molecular biology provided the missing connection from the level of physics and chemistry to that of genetics and evolution. In many languages, cognitive science is designated in the plural, such as *sciences cognitives* in French.

Moreover, across these various cognitive disciplines, theoretical models are broadly divided into a formal logic camp, or “cognitivism”, and a dynamical camp, or “connectionism”. Similarly to the epistemological scale where physics, chemistry and biology describe different levels of organization of the matter and their emergent phenomena (particles → atoms → proteins → cells → organisms → ecosphere), cognitive science could also be viewed along a vertical axis, where dynamical systems occupy the bottom levels (networks of neuronal activities) and formal systems occupy the top levels (psychological concepts and linguistic symbols). Toward the top of this axis, we find logical models that define high-level symbols and formal grammars, but do not possess the microstructure needed to account for the fuzzy complexity of perception, memory or learning (Smolensky 1988). Conversely, toward the bottom, we find dynamical models whose function is a direct product of neural networks and low-level activation equations, but lack the macroscopic level supporting the compositional and syntactic abilities of language and reasoning (Fodor and Pylyshyn 1988). In the middle, between symbol-based AI architectures and node-based neural computation, there is a lingering theoretical gap. Bridging this mind-brain gap will require a *mesoscopic* scale of description of cognitive functions, one that must offer finer granularity than symbols but larger structural complexity than small artificial neural networks. This challenge can be approached from two complementary directions.

Top-down approach: Discovering the underlying microstructure of symbolic systems

When DNA, RNA, proteins and other molecular components of the cell were discovered, evolution and genetics became united into biology’s Modern Synthesis. In other terms: by elucidating the mesoscopic level of life’s complex self-organization (molecular and cell biology), macroscopic emergent phenomena (heredity, speciation) could finally be

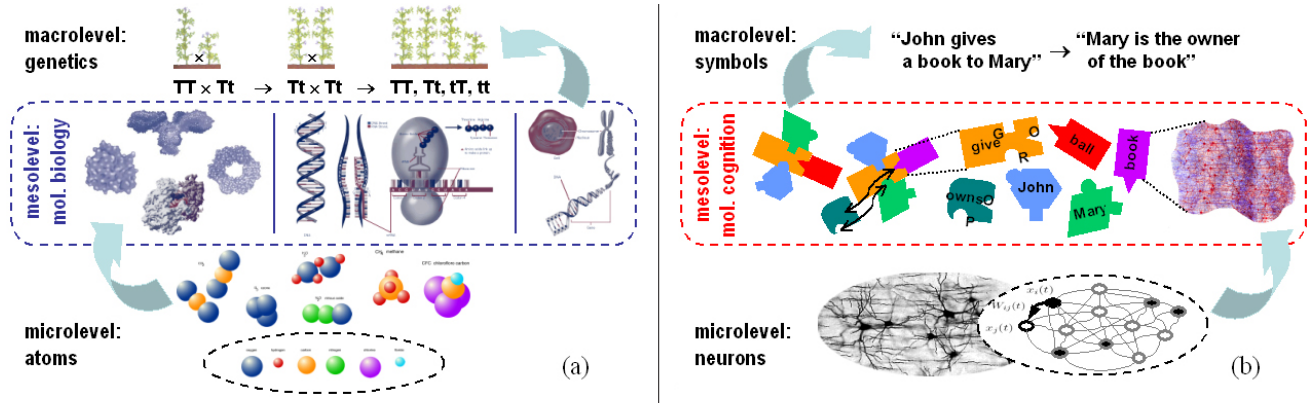


Figure 1: Metaphorically (and summarily), one could say that cognitive science in the 21st century (right: b) faces the same challenge as biology in the 20th century (left: a). Between the microscopic level (a: atoms \Leftrightarrow b: neurons) and the macroscopic level (a: genetics \Leftrightarrow b: symbolic abilities), there remains to discover central mechanisms and a unified theory (a: DNA/proteins \Leftrightarrow b: ???) at an appropriate mesoscopic level of description. The missing “Mind-Brain Modern Synthesis”, so to speak, would need to establish a proper microstructure for the symbolic level (top-down in b), while at the same time providing a complex systems perspective for the elements (bottom-up in b). Inspired by Bienenstock (1996), this particular illustration suggests that this could hinge on compositional “building blocks” made of spatiotemporal shapes (STS) of neural activity (red frame in b).

explained on the basis of microscopic elements (atoms and small molecules; Fig. 1a). By contrast, the inner structure of the mind’s representational states is not yet known. Psychology, AI or symbolic grammars do not yet possess the explanatory foundations that a truly dynamic level of cognition would offer. Therefore, after Bienenstock (1995, 1996), one should speculate about a new discipline of “molecular cognition” (Fig. 1b) to provide the fine-grained neuronal basis of the laws of perception and language. What could be the candidate “molecular” objects of this future Mind-Brain Modern Synthesis of cognitive science? The field of *cognitive linguistics* (Talmy 2000; Langacker 1987; Lakoff 1987; Jackendoff 1983; Croft and Cruse 2004) constitutes an original first candidate toward answering this question. Its typical *iconic grammars* are a unique attempt at digging under the expression surface in search of protosemantic elements. For example, the verbal schema ‘give’ involves three participants: a subject, an object, and a recipient, which have the potential to interact and bind in a topological-temporal space (creating a transfer between domains of ownership, etc.). Thus it is much more than a node in a syntactic parsing tree.

Bottom-up approach: Harnessing the emergent macrostructures of dynamical systems

At the other end of the spectrum reside neuroscience and neurally inspired dynamical systems. These physicalist or “dynamicist” approaches, which bear no resemblance to logical-combinatorial systems (van Gelder and Port 1995), start with the neurons and attempt to derive their collective behavior analytically and numerically. Yet, despite a relative success, they were criticized (Fodor and Pylyshyn 1988) for not explaining the higher properties of *constituency* and *compositionality* (Bienenstock 1996). For classical cognitivism and AI, intelligence relies on symbols (constituents) that can be assembled (composed) by syntactic rules in a systematic and generative way—whereas mainstream con-

nectionism has focused on memory, learning and perception, through chiefly associationist models (a group of cells activates another group of cells). An alternative and promising school of neural modeling, however, has promoted *temporal correlations* (von der Malsburg 1981) between neural activities as the solution to the “binding problem” (reviewed in Roskies 1999) and the basis of the brain’s code, both in theoretical and experimental studies. This hypothesis launched a new series of models looking at *synchronization* among coupled excitable or oscillatory units (König and Schillen 1991; Campbell and Wang 1996; Buzsáki and Draguhn 2004; Wang 2005). Such phenomena on the larger population scale hold a great potential for supporting the microstructure of symbolic and combinatorial systems.

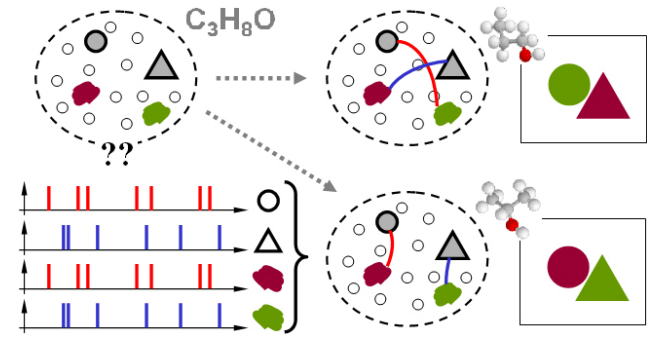


Figure 2: Solving the binding problem through temporal correlations. Just as an ambiguous molecular formula is resolved by revealing its internal bond structure, an ambiguous rate-coding representation (in which four feature detectors, ‘red’, ‘circle’, ‘green’ and ‘triangle’ are simultaneously active) is resolved by revealing its internal spatiotemporal structure. In the bottom configuration, ‘red’ and ‘circle’ are bound by synchronization between their spike trains.

In sum, the overall objective of the new line of research advocated here is to span a bridge between these two opposite ramps, prepared by cognitive linguistics on the one hand and temporally correlated neural networks on the other hand. Today's machines, which surpass humans in heavy calculations, are still surpassed by children in simple scene recognition, story understanding, or interactive tasks. The likely reason for this persistent hiatus is that most artificial systems are engineered on a single scale either as symbolic machines (macroscopic level) or associationist/reactive systems (microscopic level) but never contain the sort of intermediate "building blocks" that the mind must be using at a subsymbolic/supraneuronal *mesoscopic* level. Yet, these blocks are the key to a true representational invariance, based on cognitive schemas, categories and constituents, and I claim they can be uncovered only by complex systems modeling—not informational, thermodynamical, or metaheuristic shortcuts.

From Rate Coding to Temporal Coding to Spatiotemporal Shapes

As mentioned above, there is yet a finer split within the connectionist/dynamicist school. Traditionally, the great majority of neural models proposed by theoretical and computational neuroscience over the last decades have followed an overly literal, and somewhat naive, "signal processing" paradigm originating from classical engineering. In this perspective, pioneered by cybernetics and later reestablished by artificial neural networks in the 1980's, a few coarse-grain units are able to perform high-level, meaningful functions, such as feature detection or concept representation. Units are organized into hierarchical, multilayered architectures, where activity is actually "flowing" from the input (i.e. the "problem" at a sensory level) to the output (i.e. "the solution" at a motor level) through successive transformations—for example in visual perception (Serre et al. 2007). These architectures are also entirely stimulus-driven, i.e. neural layers are silent by default and wait to be activated.

Recently, however, entirely new ways of construing complex neural systems have been gaining ground toward a more genuinely complex and emergent view of neural activity. In particular, documentation of (a) pervasive lateral and *feedback connectivity* (Binguier et al. 1999) and (b) *persistent* (Wang 2001; Wang et al. 2006) or *ongoing activity* (Kenet et al. 2003; Fox and Raichle 2007) in the absence of explicit input both challenge the traditional view that "upstream" areas are necessary to activate "downstream" areas, or that there is any fixed hierarchy of "receptive fields". Instead, the emphasis is now put on *myriads* of fine-grain neurons interacting through dense *recurrent* connections. In this new schema, external stimuli are no longer an essential driving force but only play a secondary role of "perturbation" or "influence" affecting already active ensembles (Llinás 2001; Harris 2005)—possibly poised at "criticality", i.e. ready to switch quickly between states: whether evoked, bound and composed, unbound and competing, or dismissed. Shifting this paradigm further, it is proposed here that such complex neuronal systems form the substrate of "excitable media" capable of producing endogenous activity in the form of

dynamic, transient *spatiotemporal patterns* (STP) (Bienenstock 1995) and, from there, *shapes* (STS). In short: it is not because the brain is an intricate network of causal signal transmissions from neuron to neuron at the micro-scale, that the appropriate functional description at the meso- and macro-scales should also resemble a directed signal processing flow. This is an unjustified conflation of levels.

The importance of temporal coding

The structure and properties of representational states has often been debated since the beginnings of modern neuroscience but it was generally admitted that the *mean firing rate* constituted an important part of the neural code, since it was observed in the neuromuscular junction. In short, the classical view holds that mental entities are coded by "cell assemblies" (Hebb 1949), which are spatially distributed sets of average activity—one of the objects reviewed by Ermentrout (1998). In contrast, following von der Malsburg's "Correlation theory of brain function" (1981) and his pioneering work with Willshaw (1976) and Bienenstock (1986), we need to focus on another format of representation that involves higher-order moments, or multiple *temporal correlations* among neuronal activities (Bienenstock and Doursat 1990). Here, mental representations are not just based on individual rates $\langle x_i(t) \rangle_t$, but pairwise correlations $\langle x_i x_j \rangle$ and even more generally order- N events $\langle x_{i_1} x_{i_2} \dots x_{i_N} \rangle$.

Traditional mean-rate coding received strong support from classical observations in the primary sensory areas (e.g. visual cortex), where cells seem to possess selective response properties. From these experiments, it was inferred that one neuron or cortical column could individually and independently represent one specific type of stimulus (e.g. an edge orientation). Then, to obtain the global representation of an object, these local features should be integrated. The problem is that this integration is unlikely to be achieved by highly specialized cells sitting at the top of a hierarchical processing chain (the conjectural "grandmother" cells that fire only when you see your grandmother). Equally unlikely would be for the assembly of feature-coding cells to remain in a distributed state because of the impossibility to co-evolve two such states without mixing them—the so-called *superposition catastrophe*. According to this well-known objection (von der Malsburg 1987), if two cells coding for 'red' and 'circle' are active, and two other cells coding for 'green' and 'triangle' also become active, then the global set activation is nonrelational, i.e. unable to distinguish the original composition 'red circle & green triangle' from an alternative composition 'red triangle & green circle' (Fig. 2b).

For this reason, it is likely that feature integration requires higher-order codes to be able to represent *relationships* between elementary components that are initially uncorrelated (in the above example the spike trains of 'red' and 'circle' are synchronous and out of phase with those of 'green' and 'triangle'). These correlation events bring to the representation format a *structure* that is fundamentally missing from mean-rate cell assemblies. To pursue the chemical metaphor, one could say that feature lists are to molecular formulas (e.g. C_3H_8O) what correlations are to structural line-bond diagrams (e.g. 1-propanol vs. 2-propanol; Fig. 2).

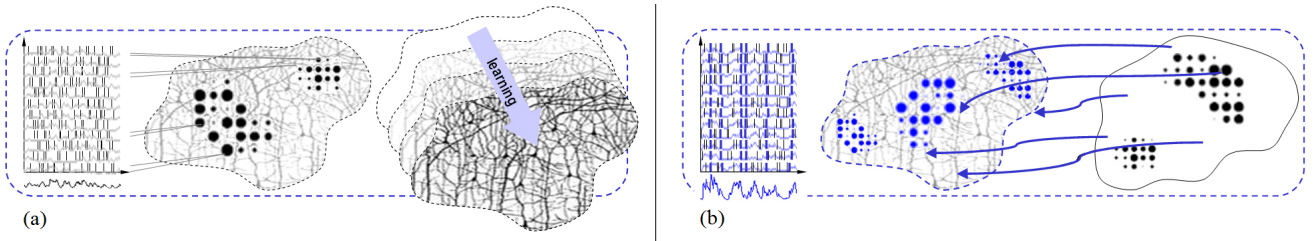


Figure 3: Schematic illustration of mesoscopic shape dynamics. (a) Shapes are endogenously produced. Left: raster of spikes; center: a spatiotemporal shape (STS) of neural activity; right: evolution of the underlying synaptic connectivity by learning. (b) Shapes are exogenously influenced. Right and center: stimulus shape impinging on previous shape; left: in this case, the effect was to enhance an alignment of spikes, revealed by a greater oscillatory amplitude of the mean field potential (bottom).

Complex spatiotemporal shapes

Generalizing from pairwise feature binding, it is further hypothesized that temporal coding and synaptic plasticity could be used by the brain as the fundamental “glue” *in phase space* holding together large-scale, multi-neuron electrophysiological states. In our molecular analogy, these mechanisms are comparable to chemical bonds, whether long-term, strong “covalent” bonds to maintain the cohesiveness and stability inside one STS, or short-term, weaker “ionic/hydrogen” bonds to quickly assemble and disassemble different STS. More formally: if $x_i(t)$ is the time-varying potential of neuron i , then the postulated “cognitive molecules” could be implemented by dynamic cell assemblies $\{x_1(t), \dots, x_n(t)\}$ able to (re)produce specific STS, each denoted by lists of spike timings $\{t_{11}, t_{12}, t_{13}, \dots, t_{n1}, t_{n2}, \dots\}$ (where t_{im} is the m -th instant at which i fires). These STS are characterized by many high-order statistical moments $\langle x_i(t)x_j(t-\tau_{ij})x_k(t-\tau_{ik}) \dots \rangle$ reaching their maxima when delays τ_{ij} coincide with firing time lags, i.e. $\forall i, j, \exists m, m': \tau_{ij} \approx t_{im} - t_{jm'}$. Typically, if $\tau_{ij} = 0$, these moments reveal *synchrony*; if $\tau_{ij} > 0$, they show “rhythms” and *waves*. Both are carried by a specific underlying connectivity. Hence, like proteins, STS should be able to interact in several ways and “assemble” at several levels, forming a hierarchy of complex structures in a modular fashion. In short, by relying on temporal coding, STS might constitute the building blocks of intelligent behavior.

Rebuilding Compositionality Bottom-Up

Following Bienenstock, this paper argues that we must model complex spatiotemporal phenomena in large-scale neural populations for their ability to implement the sought-after mesostructure of symbolic and combinatorial systems. It is conjectured that representational objects are embodied in discrete, bounded STS which are (1) endogenously produced by the neuronal substrate, (2) exogenously influenced by stimuli and (3) interacting with each other.

1. Mesoscopic shapes are endogenously produced

(Fig. 3a) Given a certain connectivity, a dynamic cell assembly can exhibit various STS. Conversely, the “identity” (i.e. shape) of a mesoscopic entity is constrained, but not completely determined by the underlying connectivity. The distribution of synaptic weights forming this connectivity is itself the product of epigenetic

development and Hebbian/STDP learning by feedback from activity (success/failure of spike transmission).

2. Mesoscopic shapes are exogenously influenced

(Fig. 3b) External stimuli may evoke, select and modify the pre-existing dynamical shapes of a mesoscopic assembly. They constitute an indirect perturbation mechanism, not a direct activation mechanism (Harris 2005). Mesoscopic entities may have stimulus-specific recognition or representation abilities without necessarily bearing a geometrical resemblance to the stimulus.

3. Mesoscopic shapes interact with each other

(Fig. 5b) On the developmental time scale, mesoscopic entities compete and differentiate from each other to create a diversified population of specialized cognitive units. On the psychological time scale, they can bind to, or detach from each other to create and undo composite objects, via the temporal coherency “glue” based on synchronization, delayed correlations and fast synaptic plasticity.

Populating the Mesoscopic Level with Models of Complex Neurodynamics

In summary, while individual firing rates $\langle x_i \rangle$ have traditionally dominated neuroscience, alternative theories (von der Malsburg 1981; Abeles 1982) have also long proposed temporal structures and higher-order correlations as the basic code used by the brain to represent mental entities. The correlation theory led to experiments and models investigating the finer temporal structure of neural signals, in particular their intrinsic irregularity and collective a/synchrony (Brunel 2000). Today, these new studies are broadly called *spiking neural networks* (SNN).

Unraveling the laws of (induced) self-organization of neural signals should now become the main focus of a future discipline of *mesoscopic neurodynamics* (Freeman 2000). In recent years, encouraged by multi-electrode recordings, brain imaging and increased computing power, this endeavor has progressed through the large-scale modeling and simulation of biologically realistic SNN (Brette and others 2007). Taking into account the fine timing of membrane potentials has revealed a great diversity of possible and plausible regimes of cortical activity in large cell populations, such as phase locking (Campbell and Wang 1996), synfire chains (Abeles 1982; Bienenstock 1995; Diesmann and oth-

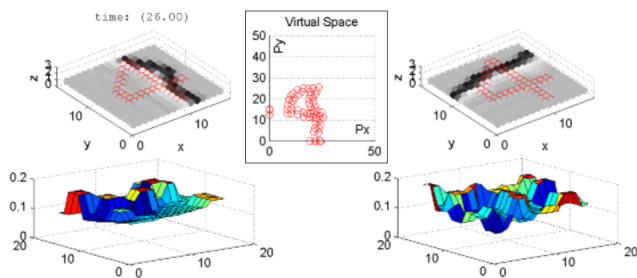


Figure 4: Example of mesoscopic neurodynamic entities (WaveMat project). Top: A pair of irregular traveling waves can represent a 2D shape in phase space (center) if time lags are interpreted as coordinates. Bottom: the heterogeneous landscapes of connection weights giving rise to the waves (simulations: Carlos Sánchez Quintana, Univ. of Málaga).

ers 1999; Doursat and Bienenstock 2006), regularity and chaos (Brunel 2000), cortical columns (Markram 2006), polychronous groups (Izhikevich 2006), and so on. These different SNN models have focused on different classes of neuronal dynamics at various levels of biological detail: conductance-based, integrate & fire, pulsed, oscillatory, excitable, rate-coded, binary, etc. They have also explored different forms of temporal order binding these neurons together: synchronization, delayed correlations, rhythms, resonance, or traveling waves (Doursat and Petitot 2005).

These theoretical entities are all candidates to a framework supporting the mesoscopic level of cognition needed to solve perceptual and linguistic problems. In this domain, mathematical and computational inventiveness should also be deemed more important than fidelity to measurements and data analysis, which are still too lacunary to provide reliable designs. This is especially the case in AI and engineering goals, as opposed to biological modeling goals.

Example: Wave-Based Storage and Matching

For instance, I propose in a study called WaveMat (publication in preparation) that nonzero phase-locking among coupled stochastic oscillating units, i.e. traveling waves, could be exploited to code for metric relationships among the features of an image. Briefly put, the main idea is that: *if spike timings can be interpreted as coordinates, then a pair of STS can represent a 2D visual pattern* (Fig. 4). The dynamics of visual perception likely involves two complementary processes: “bottom-up” self-organization, where features spontaneously group according to low-level cues, and “top-down” template matching, where global segmentation is completed by schemas previously stored in memory. Accordingly, there are two components in the schematic recognition task modeled by this study: the input image and the stored shape, each represented by a pair of STS relying on a common metric formed by accurate spatiotemporal relationships among action potentials. In sum, it is a model of dynamical matching between lattices of excitable units. The interaction between the input form and the schema form, formally interpreted as a graph-matching task, is implemented by the growth of dynamical links between two pairs of STS.

Future Directions

The goal of mesoscopic neurodynamics is to transition from a classical view (Fig. 5a) to a “complex systems” view (Fig. 5b), and reinterpret neural networks along several axes:

- **From coarse grain to fine grain:** Instead of a few units each capable of performing complicated functions → myriads of neurons forming an “excitable medium”.
- **From hierarchical, multilayered architectures to recurrent architectures:** Instead of signal processing from input (problem) to output (solution) → distributed activity dynamically creating and erasing transient shapes.
- **From input-driven activity to endogenous activity:** Instead of initially silent neural layers waiting to be activated → already active cell assemblies modified under the influence of external stimuli (and each other).
- **From atomistic hierarchies to compositional hierarchies:** Instead of specialized integrator “grandmother” cells → modular binding of dynamic cell assemblies.
- **From statistical uniformity to shapes:** Instead of homogeneous dynamic regimes (synchronized or chaotic) → heterogeneous, complex spatiotemporal objects.

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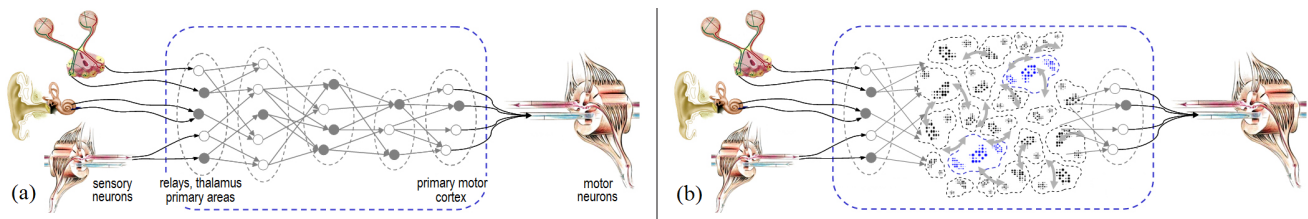


Figure 5: Paradigm shift from traditional neural networks to complex neurodynamics. (a) The classical paradigm is literally copied from the engineering notions of “transmission of information” and “signal processing”. It assumes feed-forward structures with relatively few coarse-grained, high-level units, generally organized into layers (standing for cortical areas). The network is silent by default and must be activated by external stimuli. The flow of neural activity is unidirectional from sensory inputs to motor outputs. (b) By contrast, the “emergentist” paradigm of complex systems envisions myriads of fine-grained neurons forming a quasi-continuous excitable substrate. The network structure is fundamentally recurrent (without any global chain of causality) and constantly, and spontaneously, generates multiple STS on a fast time scale, which can bind to each other and form composite entities. These dynamical assemblies are already active, and only selected or modified by external stimuli.

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