MORPHOGENETIC "NEURON-FLOCKING":
DYNAMIC SELF-ORGANIZATION
OF NEURAL ACTIVITY
INTO MENTAL SHAPES

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MORPHOGENETIC “NEURON-FLOCKING”

physical space view:
mega-MEA raster plot = activity of $10^6$-$10^8$ neurons

phase space view:
complex spatiotemporal pattern = mental shape

emergence?  structure?  properties?
persistence?  learning?  storage?  compositionality?
MORPHOGENETIC "NEURON-FLOCKING"

Temporal Code, Patterns

Waves, Chains, Phase Shapes

Compositionality

Emergent Neurodynamics

Complex Systems Levels
1. Cognitive Architectures in the Tower of Complex Systems

The emergence of neural/mind states on multiple levels of self-organization

- From agents to collectives, via local interactions
  - From neurons to brain (anatomy)
  - From potentials to fMRI (physiology)
  - From connections to cognition (models)
1. The Tower of Complex Systems

Emergence on multiple levels of self-organization

complex systems:

a) a large number of elementary agents interacting locally
b) simple individual behaviors creating a complex emergent collective behavior
c) decentralized dynamics: no master blueprint or grand architect
1. The Tower of Complex Systems

- From genotype to phenotype, via development

- ecosystems
- groups, societies
- organisms
- cells
- macromolecules
- atoms, metabolites

- DNA, proteins
- gene regulatory networks, cells
- development
- phenotypic traits
1. The Tower of Complex Systems

- From pigment cells to coat patterns, via reaction-diffusion
1. The Tower of Complex Systems

- From social insects to swarm intelligence, via stigmergy
1. The Tower of Complex Systems

- From birds to flocks, via flocking

- ecosystems
- groups, societies
- organisms
- cells
- macromolecules
- atoms, metabolites

- separation
- alignment
- cohesion
1. The Tower of Complex Systems

- All agent types: molecules, cells, animals, humans & tech
1. The Tower of Complex Systems

- From neurons to brain, via neural development (anatomy)
1. The Tower of Complex Systems

- From potentials to fMRI, via synaptic transmission (physiology)

- full brain imaging (fMRI)
- large fields (V-sensitive dyes)
- population code (multielectrode)
- individual potential (electrode)

- groups, societies

Animation of a functional MRI study (J. Ellermann, J. Strupp, K. Ugurbil, U Minnesota)

Dynamics of orientation tuning: polar movie
Sharon and Grinvald, Science 2002

Raster plot of of a simulated synfire braid, Doursat et al. 2011

Action potential propagation
1. The Tower of Complex Systems

- From connections to cognition, via correlations (modeling)

- groups, societies
- cognition
- complex mental shapes
- spatiotemporal patterns (STPs)
- neuron models
- macromolecules

- "John gives a book to Mary" ⇒ "Mary is the owner of the book"

- Dynamics (stability, chaos, regimes, bifurcations)

- Bumps, blobs

- BlueColumn
- Synfire chains
- IR/regular A/sync activity

- Markram (2006)
- Izhikevich (2006)

- Polychronous groups
- Morphodynamics

- Petlott, Doursat (1997, 2005)
- Vogels & Abbott (2006)

- ex: Freeman (1994)
- ex: Amari (1975)

- Hebb STDP LTP/LTD
- McP HH I&F Osc
1. Cognitive Architectures in the Tower of Complex Systems
The emergence of neural/mind states on multiple levels of self-organization

2. The Mind as a Pattern Formation Machine

Neural correlations: The glue of spatiotemporal patterns (STPs)
- The importance of temporal coding
- Pattern formation
- “Neuron flocking”
The importance of temporal coding

✓ more than mean rates → **temporal correlations** among spikes

\[ \langle x_1(t) \rangle = \bullet \text{ high activity rate} \]
\[ \langle x_2(t) \rangle = \bullet \text{ high activity rate} \]
\[ \langle x_3(t) \rangle = \bullet \text{ high activity rate} \]
\[ \langle x_4(t) \rangle = \bigcirc \text{ low activity rate} \]
\[ \langle x_5(t) \rangle = \bigcirc \text{ low activity rate} \]
\[ \langle x_6(t) \rangle = \bigcirc \text{ low activity rate} \]

**temporal coding**

\[ \langle x_1(t) x_2(t) \rangle \gg \langle x_1(t) x_3(t) \rangle \]
\[ \langle x_4(t) x_5(t - \tau_{4,5}) x_6(t - \tau_{4,6}) \rangle \]

**rate coding**

- zero-delays: synchrony
  (1 and 2 more in sync than 1 and 3)
- nonzero delays: rhythms
  (4, 5 and 6 correlated through delays)
2. A Pattern Formation Machine

Historical motivation for rate coding

- Adrian (1926): the firing rate of mechanoreceptor neurons in frog leg is proportional to the stretch applied
- Hubel & Wiesel (1959): selective response of visual cells; e.g., the firing rate is a function of edge orientation

→ rate coding is confirmed in sensory system and primary cortical areas, however increasingly considered insufficient for integrating the information

Temporal coding pioneers of the 1980-90’s

- von der Malsburg (1981): theoretical proposal to consider correlations
- Gray & Singer (1989): stimulus-dependent synchronization of oscillations in monkey visual cortex
- O'Keefe & Recce (1993): phase coding in rat hippocampus supporting spatial location information
- Bialek & Rieke (1996, 1997): in H1 neuron of fly, spike timing conveys information about time-dependent input
The “binding problem”: using temporal code

- how to represent relationships?

2. A Pattern Formation Machine

- feature cells

- stimulus or concept

- circular symbol

- triangular symbol

- red symbol

- green symbol

- binding problem
More generally: feature binding in cell assemblies

- unstructured lists or “sets” of features lead to the “superposition catastrophe”
“Grandmother” “Jennifer Aniston” cells... really?

→ one way to solve the confusion: introduce overarching hypercomplex detector cells
“Grandmother” “Jennifer Aniston” cells... really?

... however, this soon leads to a combinatorial explosion
2. A Pattern Formation Machine

- Instead: relational representation → graph format
  - a better way to solve the confusion: represent relational information with **graphs**
2. A Pattern Formation Machine

- Idea: relational information can be encoded *temporally*
  - back to the binding problem: a solution using temporal coding

![Diagram showing stimulus or concept and feature cells](image)

[Diagram text: after von der Malsburg (1981, 1987)]
Beyond small graphs → large “spatiotemporal patterns”

- **STPs**: large-scale, localized dynamic cell assemblies that display complex, *reproducible* digital-analog regimes of neuronal activity

- these regimes of activity are supported by specific, *ordered* patterns of recurrent synaptic connectivity

- toward a “mesoscopic neurodynamics”: construing the brain as a (spatio-temporal) *pattern formation machine*
2. A Pattern Formation Machine

- Biological development is about pattern formation
  - multicellular patterning
  - ... the brain is no different

- ocular dominance stripes (Hubel & Wiesel, 1970)
- orientation column "pinwheels" (Blasdel, 1992)
- Dynamics of orientation tuning: polar movie (Sharon and Grinvald, Science 2002)
2. A Morphogenetic Machine

➢ ... but beyond pattern formation: complex morphogenesis

“I have the stripes, but where is the zebra?” OR
“The stripes are easy, it’s the horse part that troubles me”
—attributed to A. Turing, after his 1952 paper on morphogenesis
2. A Morphogenetic Machine

- ... but beyond pattern formation: complex morphogenesis

- STPs are not just random, repetitive patterns but mostly complex, composite shapes endowed with a specific structure
1. Cognitive Architectures in the Tower of Complex Systems
The emergence of neural/mind states on multiple levels of self-organization

2. The Mind as a Pattern Formation Machine
Neural correlations: The glue of spatiotemporal patterns (STPs)

3. Example Model: Wave-Based Shape-Matching
Coding coordinates by phases, and shapes by waves

- **Lattices**: group sync, waves, 2D shapes
- **Synfire chains**: wave storage, retrieval
- **Synfire braids**: shape storage, matching
3. Wave-Based Shape-Matching

- Wave-based pattern retrieval and matching
  - **Lattices of coupled oscillators** (zero delays)
    - group synchronization
    - traveling waves
    - 2D wave shapes
    - shape metric deformation
  - **Synfire chains** (uniform delays)
    - wave propagation
    - chain growth
    - pattern storage and retrieval
  - **Synfire braids** (transitive delays)
    - shape storage and retrieval
    - 2D wave-matching
3. Wave-Based Shape-Matching – Lattice

- Lattice of coupled oscillators – *group sync, phase-tagging*

  ✓ the base of many perceptual segmentation models in the 1990’s


    - oscillatory or excitable units as an abstraction of excit↔inhib columnar activity
    - 2D lattice coupling as an abstraction of topographically organized visual cortex

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3. Wave-Based Shape-Matching

➢ Stochastic excitable units

 ✓ ex: Bonhoeffer-van der Pol (BvP) oscillator’s two main regimes:

\[ z > z_c \quad a) \quad \text{sparse, stochastic} \rightarrow \textit{excitable} \]
\[ z_c = -0.3465 \]

\[ z < z_c \quad b) \quad \text{quasi-periodic} \rightarrow \textit{oscillatory} \]

\[
\begin{align*}
\frac{du_i}{dt} &= c \left( u_i - \frac{u_i^3}{3} + v_i + z \right) + \eta \\
\frac{dv_i}{dt} &= \frac{1}{c} \left( a - u_i - bv_i \right) + \eta
\end{align*}
\]

(a) 

(b) 

\[ \begin{align*}
a &= 0.7 \\
b &= 0.8 \\
c &= 3
\end{align*} \]
3. Wave-Based Shape-Matching – Lattice

- Lattice of coupled oscillators
  - \( i \leftarrow j \) coupling features
    - isotropic
    - proportional to the \( u \) signal difference
      - only in spiking domain \( u < 0 \)
    - positive connection weight \( k_{ij} \)
    - possible transmission delay \( \tau_{ij} \)
      - here zero delays \( \tau_{ij} = 0 \)

\[
\begin{align*}
\frac{du_i}{dt} &= c(u_i - \frac{u_i^3}{3} + v_i + z) + \eta + K_i + I_i \\
\frac{dv_i}{dt} &= \frac{1}{c}(a - u_i - bv_i) + \eta
\end{align*}
\]

\[
K_i(t) = \sum_{\substack{j=1 \\text{under } u_j(t-\tau_{ij})<0}}^{N} k_{ij}(u_j(t-\tau_{ij}) - u_i(t))
\]
3. Wave-Based Shape-Matching – Lattice

Lattice of coupled oscillators – *group sync, phase-tagging*

\[ z = -0.336 \]
\[ k = 0.10 \]
\[ I = -2.34 \]


(illustration by Doursat & Sanchez 2011)
3. Wave-Based Shape-Matching – Lattice

Lattice of coupled oscillators – *traveling waves*


3. Wave-Based Shape-Matching – Lattice

Lattice of coupled oscillators – *traveling waves*

- Random propagation
  - $z = -0.346$, $k = 0.04$, $I = 0$

- Circular wave generation
  - $z = -0.29$, $k = 0.10$, $I = -0.44$ (point stimulus)

- Planar & mixed wave generation
  - $z = -0.29$, $k = 0.10$, $I = -0.44$ (bar stimulus)
3. Wave-Based Shape-Matching – Lattice

The “morphodynamic pond”: a neural medium at criticality

- upon coupling onset and/or stimulation → emergence of a wave
- quick transition to ordered regime (STP): reproducible succession of spike events \((t^1, t^2, \ldots)\)

- the structure of the STP is a trade-off between
  - endogenous factors: connectivity (structural bias), attractors (preferred activation modes)
  - exogenous factors: stimulus (perturbation), binding (composition with other STPs)
3. Wave-Based Shape-Matching – Lattice

- Lattice of coupled oscillators – 2D wave shapes
  - coding coordinates with phases
  - the salient “feature-detecting” units of an object can participate in 2 different STPs by propagation of 2 different waves
  - similar to buoys floating on water
  - these 2 STPs form a 2D constellation or “shape” in virtual phase space (timings)
3. Wave-Based Shape-Matching – Lattice

- Lattice of coupled oscillators – *2D wave shapes*
  - coding coordinates with phases
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3. Wave-Based Shape-Matching – Lattice

- Lattice of coupled oscillators – 2D wave shapes
  - the final shape in virtual phase space depends on
    - the physical position of the feature units on the lattice
    - the form and direction of the two waves, itself depending on:
      - endogenous factors: connectivity and weight distribution
      - exogenous factors: stimulus domains
  - ex: no deformation
    - planar & orthogonal waves
      - uniform weights on $P_X$ and $P_Y$
      - orthogonal full-bar stimuli
    → shape = physical positions

uniform weight distribution: $k = 0.09$
3. Wave-Based Shape-Matching – Lattice

- Lattice of coupled oscillators – *shape metric deformation*
  - wave detection and velocity measure based on control units
    - the probability of wave generation increases with $z \downarrow$ and $k \uparrow$
    - the velocity of the generated wave increases with $z \downarrow$ and $k \uparrow$

\[ T \sim \frac{1}{T} \]
3. Wave-Based Shape-Matching – Lattice

Lattice of coupled oscillators – *shape metric deformation*

- ex: “shear stress” deformation
  - vertical wave + horizontal wave
    - $Y$-gradient of weights on $P_Y$
    - orthogonal full-bar stimuli

- ex: “laminar flow” deformation
  - laminar wave + vertical wave
    - $Y$-gradient of weights on $P_X$
    - orthogonal full-bar stimuli
3. Wave-Based Shape-Matching – Lattice

- Lattice of coupled oscillators – *shape metric deformation*
  - ex: irregular deformation
    - heterogeneous waves
      - random weight distribution (bumps & dips) on $P_X$ and $P_Y$
      - orthogonal full-bar stimuli
  - various weight combinations
3. Wave-Based Shape-Matching

_wave-based pattern retrieval and matching_

✓ **Lattices of coupled oscillators** (zero delays)
  - group synchronization
  - traveling waves
  - 2D wave shapes
  - shape metric deformation

✓ **Synfire chains** (uniform delays)
  - wave propagation
  - chain growth
  - pattern storage and retrieval

✓ **Synfire braids** (transitive delays)
  - shape storage and retrieval
  - 2D wave-matching
3. Wave-Based Shape-Matching – Chains

- Synfire chains – *definition*
  - A synfire chain (Abeles 1982) is a sequence of synchronous neuron groups $P_0 \rightarrow P_1 \rightarrow P_2 \ldots$ linked by feedforward connections that can support the propagation of waves of activity (action potentials).

- Synfire chains have been hypothesized to explain neurophysiological recordings containing statistically significant delayed correlations.

- The redundant divergent/convergent connectivity of synfire chains can preserve accurately synchronized action potentials, even under noise.
3. Wave-Based Shape-Matching – Chains

- **Synfire chains – typical example studies**
  - 1-chain propagation viability
  - 1-chain self-organized growth
  - 2-chain binding (→ see Section 4.)
  - N-chain storage capacity
    - Bienenstock (1995) *A model of neocortex*
    - Trengove (2007) *Storage capacity of a superposition of synfire chains using conductance-based I&F neurons*

Synfire chains potential fill all the requirements for a mesoscopic world of mental shapes.
3. Wave-Based Shape-Matching – Chains

- Synfire chains – self-organized growth

1. Hebbian rule
   \[ \Delta W_{ij} \sim x_i x_j \]
   \[ \sum \Delta W_{ij} \sim 0 \]

2. Sum rule

network structuration by accretive synfire growth

3. Wave-Based Shape-Matching – Chains

Synfire chains – *self-organized growth*

- A special group of \( n_0 \) synchronous cells, \( P_0 \), is repeatedly (not necessarily periodically) activated and recruits neurons “downstream” if \( j \) fires once after \( P_0 \), its weights increase and give it a 12% chance of doing so again (vs. 1.8% for the others).

  - If \( j \) fires a 2nd time after \( P_0 \), \( j \) has now 50% chance of doing so a 3rd time; else it stays at 12% while another cell, \( j' \), reaches 12%.

- The number of post-\( P_0 \) cells (cells with larger weights from \( P_0 \)) increases and forms the next group \( P_1 \).

  - Once it reaches a critical mass, \( P_1 \) also starts recruiting and forming a new group \( P_2 \), etc.

- Wave-Based Shape-Matching – Chains
  - Synfire chains – self-organized growth
3. Wave-Based Shape-Matching – Chains

Synfire chains – *pattern mix and selective retrieval*

- random renumbering and uniform rewiring (column→column probability \( p \))

![Diagram](image)

- layout A w/ weights A
- layout B w/ weights B
- layout A w/ mixed weights A + weights B

### High Specificity of Synfire Stimulus

- unlike the “sensitive” isotropic lattice, not any input pattern will trigger a wave
- a synfire chain needs a “critical seed” of \( N \) stimulated neurons at the right place

- **endo**: connectivity, attractors
- **exo**: stimulus, binding

![Diagram](image)
3. Wave-Based Shape-Matching – Chains

- Synfire chains – *pattern mix and selective retrieval*
  - statistics of selective retrieval depending on input size (in first pool)
3. Wave-Based Shape-Matching

- Wave-based pattern retrieval and matching
  - Lattices of coupled oscillators (zero delays)
    - group synchronization
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    - 2D wave-matching
Synfire braids – **definition**

- synfire braids (Bienenstock 1991, 1995) are generalized STPs with longer delays among nonconsecutive neurons, without distinct synchronous groups
- they were rediscovered later as “polychronous groups” (Izhikevich 2006)

- in a synfire braid, delay transitivity $\tau_{AB} + \tau_{BC} = \tau_{AD} + \tau_{DC}$ supports incoming spike coincidences, hence stable propagation of activity
- synfire braids can also grow in a network with nonuniform integer-valued delays $\tau_{ij}$ and inhibitory neurons
3. Wave-Based Shape-Matching – Braids

- Synfire braids – *pattern mix and selective retrieval*
  - same layout, same shape, different wiring (wrap-around)

- $\tau = 10$
- $\tau = 15$
- $\tau = 5$
- $\tau = 10$
- $\tau = 15$

- $z = -0.28$
- $k = 0.016$

- $N_A = 11$
- in ‘A’ sequence

- $N_B = 11$
- in ‘B’ sequence

- $N = 11$
- simultaneously → no wave

- high stimulus specificity
  - to generate a wave, a synfire braid needs a minimum of $N$ neurons stimulated in a sequence ("sub-STP") compatible with the delays
3. Wave-Based Shape-Matching – Braids

- Synfire braids – *pattern mix and selective retrieval*
  - statistics of selective retrieval depending on input size (in sequence)
  - statistics of selective retrieval depending on input size and $p$ or $\tau$

![Graphs showing statistics of selective retrieval](image1)

- statistics of selective retrieval depending on input size and $p$ or $\tau$
3. Wave-Based Shape-Matching – Braids

Synfire braids – *shape mix and selective retrieval*

- same layout, different shape

![Diagram of synfire braids](image)

- to generate a wave, a synfire braid needs a minimum of $N$ neurons stimulated in a sequence (“sub-STP”) compatible with the delays

- $N_A = 11$ in ‘A’ sequence
- $z = -0.28$
- $k = 0.016$

- $N_B = 11$ in ‘B’ sequence

- $N = 11$ simultaneously → no wave


3. Wave-Based Shape-Matching – Braids

- Synfire braids – wave-matching

- check

  - graph-matching implemented as dynamical link matching between two pairs of STPs

\[
\begin{align*}
\frac{du_i}{dt} &= c(u_i - \frac{u_i^3}{3} + v_i + z) + \eta + K_i \\
\frac{dv_i}{dt} &= \frac{1}{c}(a - u_i - bv_i) + \eta + W_i
\end{align*}
\]

\[
W_i = \sum w_{ii'} (u_{i'} - u_i)
\]
3. Wave-Based Shape-Matching – Braids

- **Synfire braids – wave-matching**

- Additional coupling term: 
  \[ W_{i}^{Xx}(t) = \sum_{j=1}^{N} w_{ii'}(t) \left( u_{i'}^{x}(t) - u_{i}^{X}(t) \right) \]

- Where \( w_{ii'} \) varies according to
  
  1. Hebbian-type synaptic plasticity based on temporal correlations
     
     \[ \Delta w_{ii'}(t) = \alpha \left( -w_{ii'}(t) + w_{0} f(s_{ii'}^{Xx}(0)) \right) \quad \text{with} \]
     
     \[ s_{ii'}^{Xx}(0) = \langle u_{i}^{X}(t') u_{i'}^{x}(t') \rangle_{t-T_{s}}^{t} \quad \text{and} \quad f(s) = \left( 1 + e^{-\lambda(s-s_{0})} \right)^{-1} \]

  2. competition: renormalize efferent links
     
     \[ w_{ii'} \rightarrow \frac{w_{ii'}}{\sum_{j} w_{ji'}} \]

  3. label-matching constraint

\[ \text{STP 1x} \rightarrow \rightarrow \text{STP 2x} \]
3. Wave-Based Shape-Matching – Braids

- Synfire braids – 2D wave-matching

- Hebbian rule in 2D: \( \Delta w_{ii'}(t) = \alpha (-w_{ii'}(t) + w_0 f\left(\sqrt{s_{ii'}(0)s_{ii'}(0)}\right)) \)
3. Wave-Based Shape-Matching – Braids

- **Synfire braids – 2D wave-matching**
  - to drive the system to the best match (global minimum), internal coupling \( k \) in graph-2 layer is regularly lowered and increased again
    - if match is weak, this will perturb STP 2 and undo matching links
    - if match is strong, this will not perturb STP 2 because it will be sustained by matching links \( \rightarrow \) resonance between links and STPs

Global “correlation” order parameter \( S \):
\[
S(t) = \frac{1}{N(N-1)} \sum_{i \neq j} \langle u_i(t') \ u_j(t' - \tau_{ij}) \rangle_{t-T_s}^t
\]

Global “synchronicity” order parameter \( C \):
\[
C(t) = \frac{1}{N(N-1)} \sum_{i \neq j} \cos \left( \frac{2\pi}{T} (t_i(t) - t_j(t) - \tau_{ij}) \right)
\]

Weak (mis)match \( \rightarrow \) undone by uncoupling

Strong match \( \rightarrow \) resistant to uncoupling
1. Cognitive Architectures in the Tower of Complex Systems
   The emergence of neural/mind states on multiple levels of self-organization

2. The Mind as a Pattern Formation Machine
   Neural correlations: The glue of spatiotemporal patterns (STPs)

3. Example Model: Wave-Based Shape-Matching
   Coding coordinates by phases, and shapes by waves

4. Shape-Based Compositionality
   STPs: The building blocks of mental shapes
(a) John gives a book to Mary.
(b) Mary gives a book to John.
(c)* Book John Mary give.
(a) John gives a book to Mary.
(b) Mary gives a book to John.
(c) *Book John Mary give.
4. Shape-Based Compositionality

- From temporal binding to shape-based composition

✔ Language as a construction game of “building blocks”
4. Shape-Based Compositionality

- From temporal binding to shape-based composition

 ✓ language as a construction game of “building blocks”
4. Shape-Based Compositionality

- From temporal binding to shape-based composition

- language as a construction game of “building blocks”
4. Shape-Based Compositionality

- From temporal binding to shape-based composition

(language, perception, cognition are a game of building blocks)

- mental representations are internally structured

- elementary components assemble dynamically via temporal binding

Ex: synfire patterns can *bind*, i.e. support compositionality

- Cognitive compositions could be analogous to conformational interactions among proteins...
- In which the basic “peptidic” elements could be *synfire chain* or *braid* structures supporting traveling waves
- Two synfires can bind by synchronization through *coupling links*

→ *molecular metaphor*

*after Bienenstock (1995) and Doursat (1991)*
Sync & coalescence in a “self-woven tapestry” of chains

- multiple chains can “crystallize” from intrinsic “inhomogeneities” in the form of “seed” groups of synchronized neurons

- concurrent chain development defines a \textit{mesoscopic scale of neural organization}, at a finer granularity than macroscopic AI symbols but higher complexity than microscopic neural potentials

- on this substrate, the dynamical binding & coalescence of multiple synfire waves provides the basis for compositionality and learning

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STPs: The building blocks of mental shapes

5. Toward Emergent Neurodynamics
Leaving "signal processing" for dynamic self-assembly
The naive engineering paradigm: “signal processing”

- **feed-forward** structure – activity literally “moves” from one corner to another, from the input (problem) to the output (solution)

- **activation** paradigm – neural layers are initially silent and are literally “activated” by potentials transmitted from external stimuli

- **coarse-grain** scale – a few units in a few layers are already capable of performing complex “functions”
It is not because the brain is an intricate network of microscopic causal transmissions (neurons activating or inhibiting other neurons) that the appropriate description at the mesoscopic functional level should be “signal / information processing”.

This denotes a confusion of levels: mesoscopic dynamics is emergent, i.e., it creates mesoscopic objects that obey mesoscopic laws of interaction and assembly, qualitatively different from microscopic signal transmission.
The emergent dynamical paradigm: excitable media

- **recurrent** structure – activity can “flow” everywhere on a fast time scale, continuously forming new patterns; output is in the patterns

- **perturbation** paradigm – dynamical assemblies are already active and only “influenced” by external stimuli and by each other

- **fine-grain** scale – myriads of neurons form quasi-continuous media supporting structured pattern formation at multiple scales
Tenet 1: mesoscopic neural pattern formation is of a fine spatiotemporal nature

Tenet 2: mesoscopic STPs are individuated entities that are
a) endogenously produced by the neuronal substrate,
b) exogenously evoked & perturbed under the influence of stimuli,
c) interactively binding to each other in competitive or cooperative ways.
5. Toward Emergent Neurodynamics

a) Mesoscopic patterns are endogenously produced

✓ given a certain connectivity pattern, cell assemblies exhibit various possible *dynamical regimes*, modes, patterns of ongoing activity

✓ the underlying connectivity is itself the product of *epigenetic* development and *Hebbian* learning, from activity

→ the identity, specificity or stimulus-selectiveness of a mesoscopic entity is largely determined by its internal pattern of connections
b) Mesosopic patterns are exogenously influenced

✔ external stimuli (via other patterns) may *evoke & influence* the pre-existing dynamical patterns of a mesoscopic assembly

✔ it is an indirect, *perturbation* mechanism; not a direct, activation mechanism

✔ mesoscopic entities may have stimulus-specific *recognition or “representation”* abilities, without being “templates” or “attractors” (no resemblance to stimulus)
Mesoscopic patterns interact with each other

- populations of mesoscopic entities can **compete & differentiate** from each other to create specialized recognition units
- and/or they can **bind** to each other to create composed objects, via some form of temporal coherency (sync, fast plasticity, etc.)
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