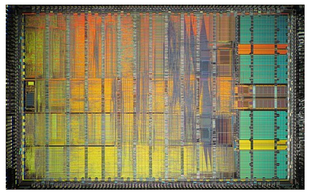
Reflections on Neurocomputing

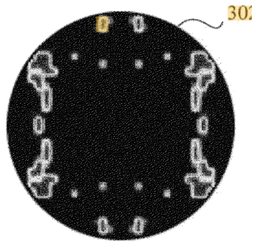
Maps of the possible, territories of practice

David DeMaris 11/10/2026

Maps

- Is the field coherent? Could we construct dimensions of theory to locate (embed) a paper?
- Brief history of research community forking
- What part of the space of neural theories has been explored in neuromorphic computing?





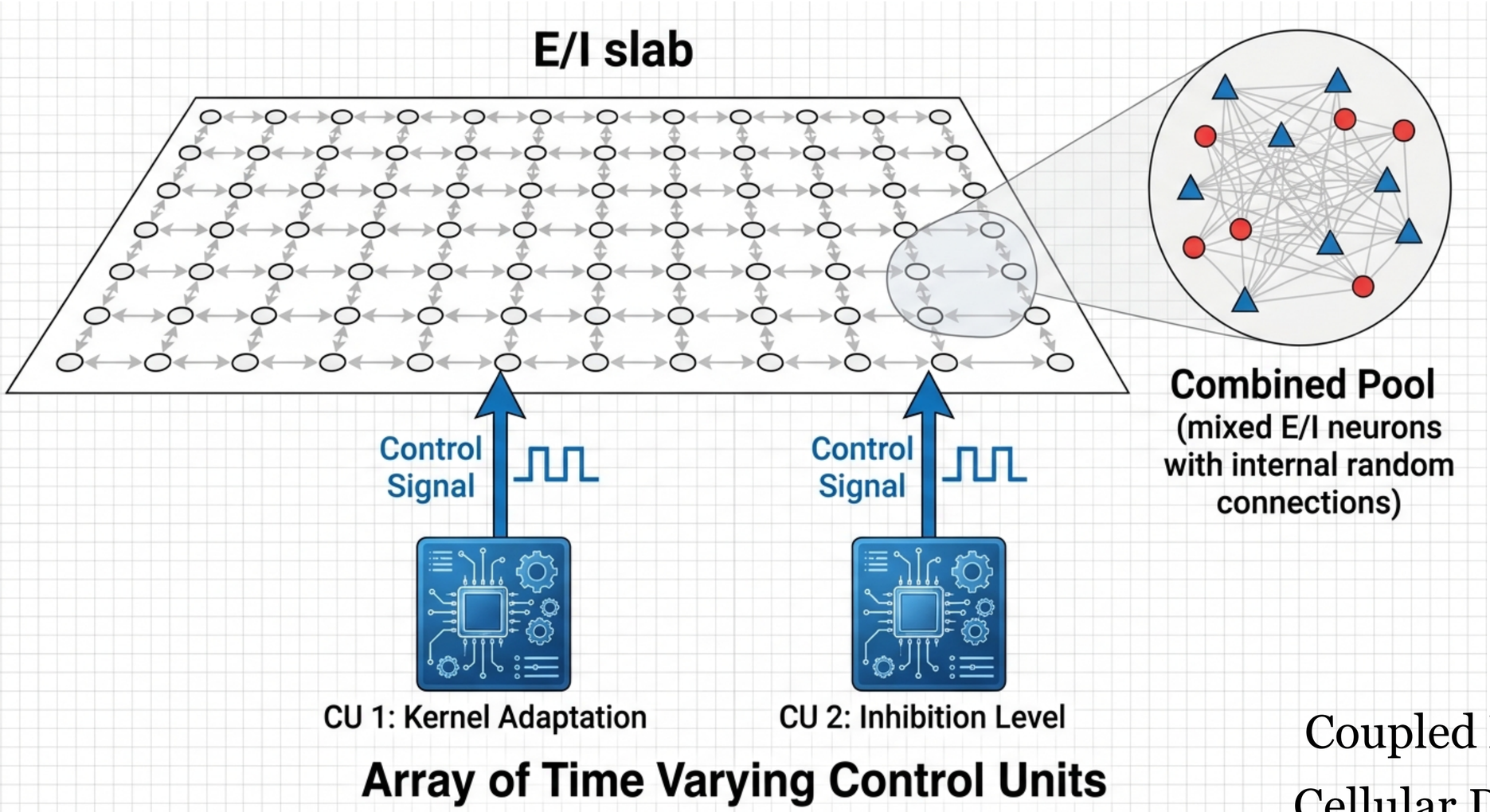
My background

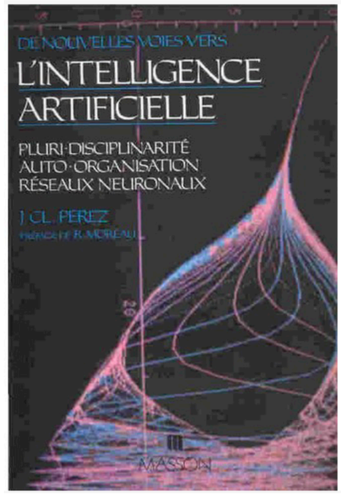




- Small town IL, also birthplace of William Jennings Bryan and Bill Laswell.
- Read Shelley's Frankenstein at age 6, Phillip K. Dick at 8
- 32 years in semiconductors, design automation, design process integration for sub-wavelength lithography at IBM, 15 years 'gigs': entertainment robotics, journalism tools, opera, jazz piano
- 1980 U. Illinois Urbana, EE: encountered chaos in perturbed coupled oscillators.
- UT Austin 1992-2001; recurrent convolutional networks, neural field theory, unsupervised and semi-supervised learning for 2 and 3D vision, ambiguous percepts, semi-supervised learning, few shot learning, contrastive learning, similarity hashing
- Neuroscience: criticality, transients of chaotic dynamics, spatio-temporal oscillations and cross-frequency coupling, coarse grained representation spaces, wave computing,
- Co-developed (w/G. Werner) UT course Neurodynamics 2000; student G. Aggarwal went on to publish in Science on decoding mouse position from spatiotemporal oscillations

Recurrent convolutional network (CML)



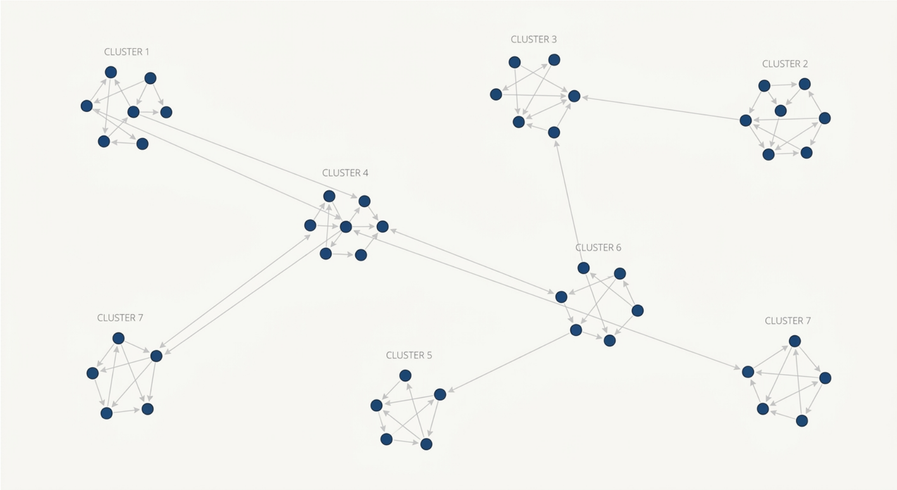


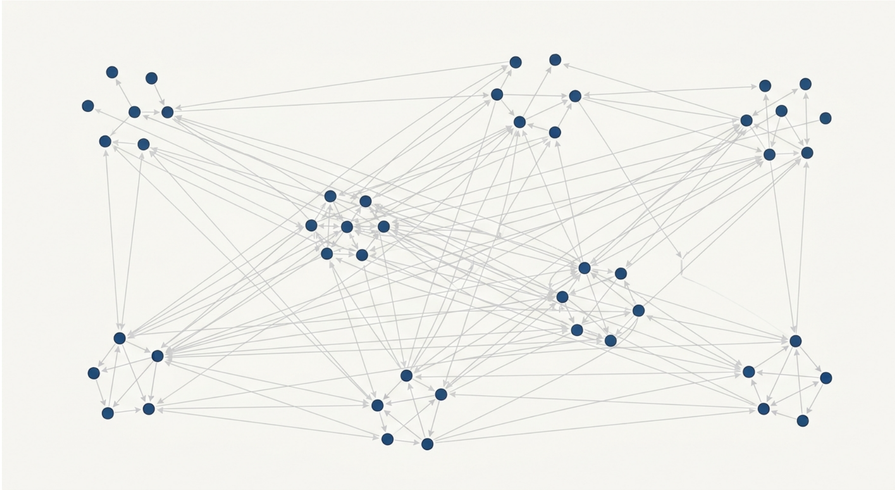
Coupled Map Lattice (Kaneko),
Cellular Dynamata (Abraham),
Fractal Chaos Network (Perez)

How can we think about a vast research topic

How can it be made coherent?

Think of research paper citations as a graph





Incoherent : most references

Near in theory dimensions /scale

Incoherent : balance of references

Near/ distant in theory dimensions /scale

How can we approach a vast topic?

Slicing Neuroscience Literature by dimensions

Slicing a theory space by dimensions

- Imagine we want to locate (embed) scientific / engineering work in a field
- The typical modern approach to extract topics or organize documents
  - “embedding in a space” where the axes of a space are some kind of measurable point in opposing poles
- I asked some Language models what they would choose for axes, as a contrast to mine.
  - See supplementary pdfs for the eplanations

Dimensions of Neural Computation

Qwen 3.8 32G dense

Ten Axes for Classifying Neuroscience Research (Qwen 3.8 32G dense)

1. **Granularity — Molecular / Genetic ↔ Societal / Behavioral**
2. **Causal Power ↔ Descriptive Adequacy — Interventionist (perturb, manipulate) ↔ Observational (measure, image, model)**
3. **Mechanism ↔ Function / Teleology — "How does it work?" ↔ "What is it for?"**
4. **Substrate-Bound ↔ Substrate-Transcendent — Neurobiologically specific ↔ Computationally / information-theoretically abstract**
5. **Static Architecture ↔ Dynamic Process — Structure at $t = 0$ ↔ Plasticity, development, trajectory**
6. **Universal Law ↔ Particular Instance — Canonical brain, general invariance ↔ Context-dependent, individual-specific**
7. **Compositional ↔ Emergent / Relational — Understand the parts, reassemble ↔ System-level properties irreducible to components**
8. **Descriptive ↔ Normative / Optimal — "The brain does *X*" ↔ "The brain approximates the optimal solution to *Y*"**
9. **Inductive / Data-Driven ↔ Deductive / First-Principles — Patterns discovered in data ↔ *A priori* physical / information-theoretic constraints**
10. **Encapsulated ↔ Embedded / Extended — Cognition is the brain / organism ↔ Cognition is distributed across body, environment, tools, and agents**

Dimensions of neural computation: chatGPT

Visual overview

These are the ten axes condensed into a classification matrix:

#	Pole A	Pole B
1	Reductionism	Holism
2	Localization	Distributed processing
3	Bottom-up	Top-down
4	Nature	Nurture
5	Static	Dynamic
6	Descriptive	Mechanistic
7	Correlational	Causal
8	Computation	Biology
9	Universal	Individual-specific
10	Basic science	Translational

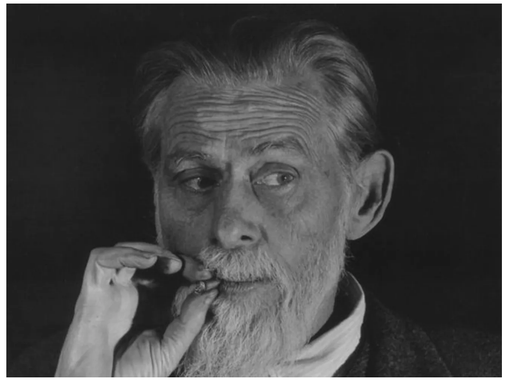
Dimensions of Neural Computation: Gemini 11/26

Axis	Left Pole (Reductionist / Structural / Passive)	Right Pole (Systemic / Functional / Active)
1. Spatial Scale	Microscopic (Reductionist)	Macroscopic (Systemic)
2. Temporal Dynamics	Static Anatomy (Structural)	Real-Time Kinetics (Functional)
3. Investigation Paradigm	Observational Correlative	Interventional Causal
4. Primary Driver	Data-Driven Exploration	Hypothesis-Driven Testing
5. Theoretical Orientation	Computational / Abstract	Biological / Biophysical
6. Development & Plasticity	Hardwired Innateness (Nature)	Experience-Dependent Plasticity (Nurture)
7. Cognitive Architecture	Modular Localization	Distributed Emergence
8. Organismal Context	Isolated Circuitry	Embodied / Enactive Systems
9. Mental State Orientation	Objective Behavior	Subjective Experience
10. Research Translation	Basic Discovery	Clinical Application

Dimensions of neural computation

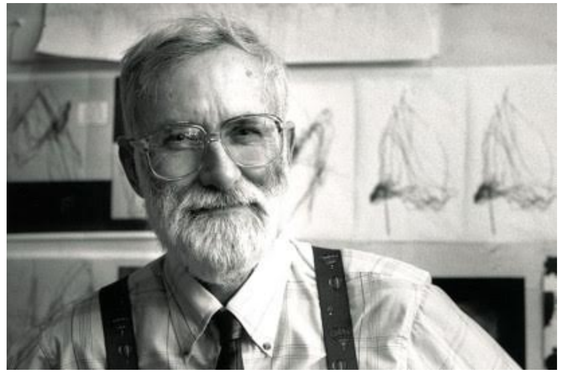
My version

- **Brain Inside Out** (reservoir) vs. Tabula Rasa (deep networks, transformers)
- Circuits vs **Fields**
- Competitive **vs Cooperative**
- Spikes vs **Oscillations**
- Oscillations as gain modulators vs **Nested Oscillations**
- **Training/inference** vs Continual Learning vs Insight learning
- **Event processing** vs Perturbation and response
- Feed forward vs **Recurrence** (Predictive Processing)
- **Individual** vs Social
- **Single Scale vs Multi Scale** (Circular Causality)



Warren McCullough



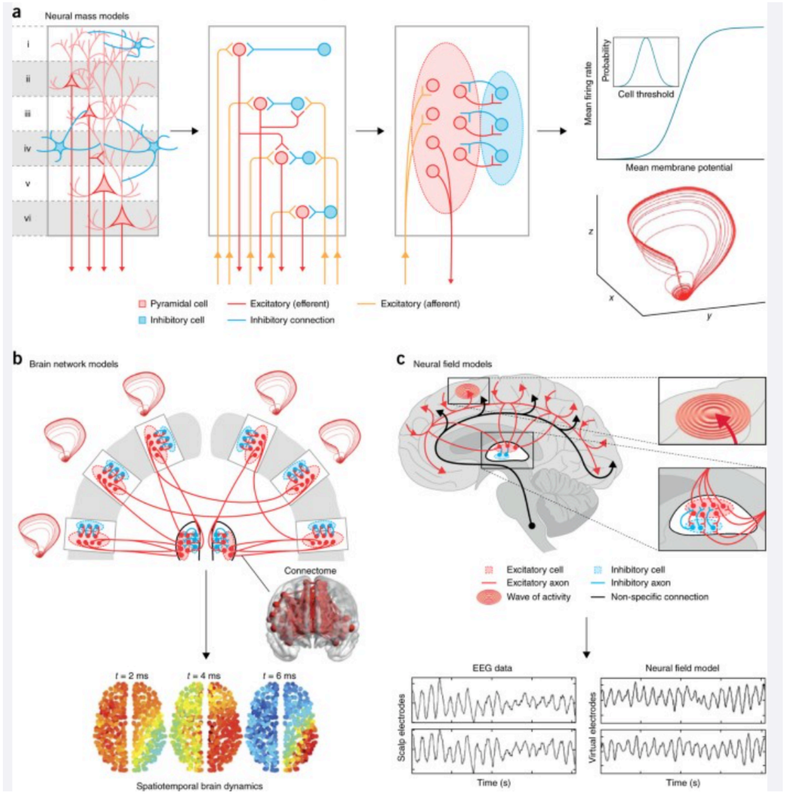


Walter J. Freeman III

Neural Networks: Types

- Feedforward neural networks (FNN)
- Multilayer perceptrons (MLP)
- Convolutional neural networks (CNN)
- Recurrent neural networks (RNN)
- Long short-term memory networks (LSTM)
- Transformers
- Generative adversarial networks (GAN)
- Radial basis function (RBF) networks
- Self-organizing maps (SOM)
- Autoencoders

Syracuse University
School of Information Studies



Dynamic models of large-scale brain activity

- Michael Breakspear

The Dual-Track Timeline of Mind and Brain Sciences

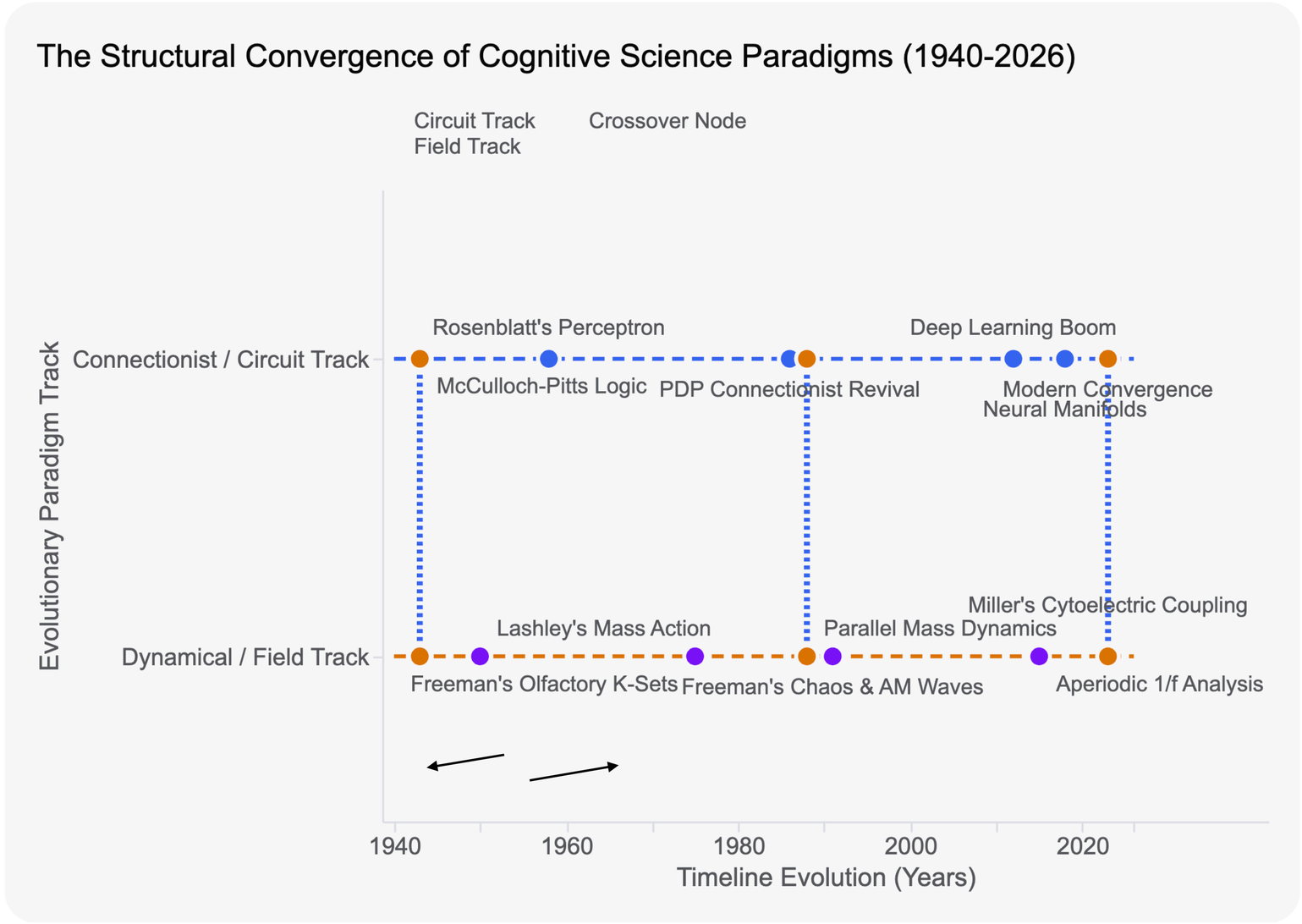
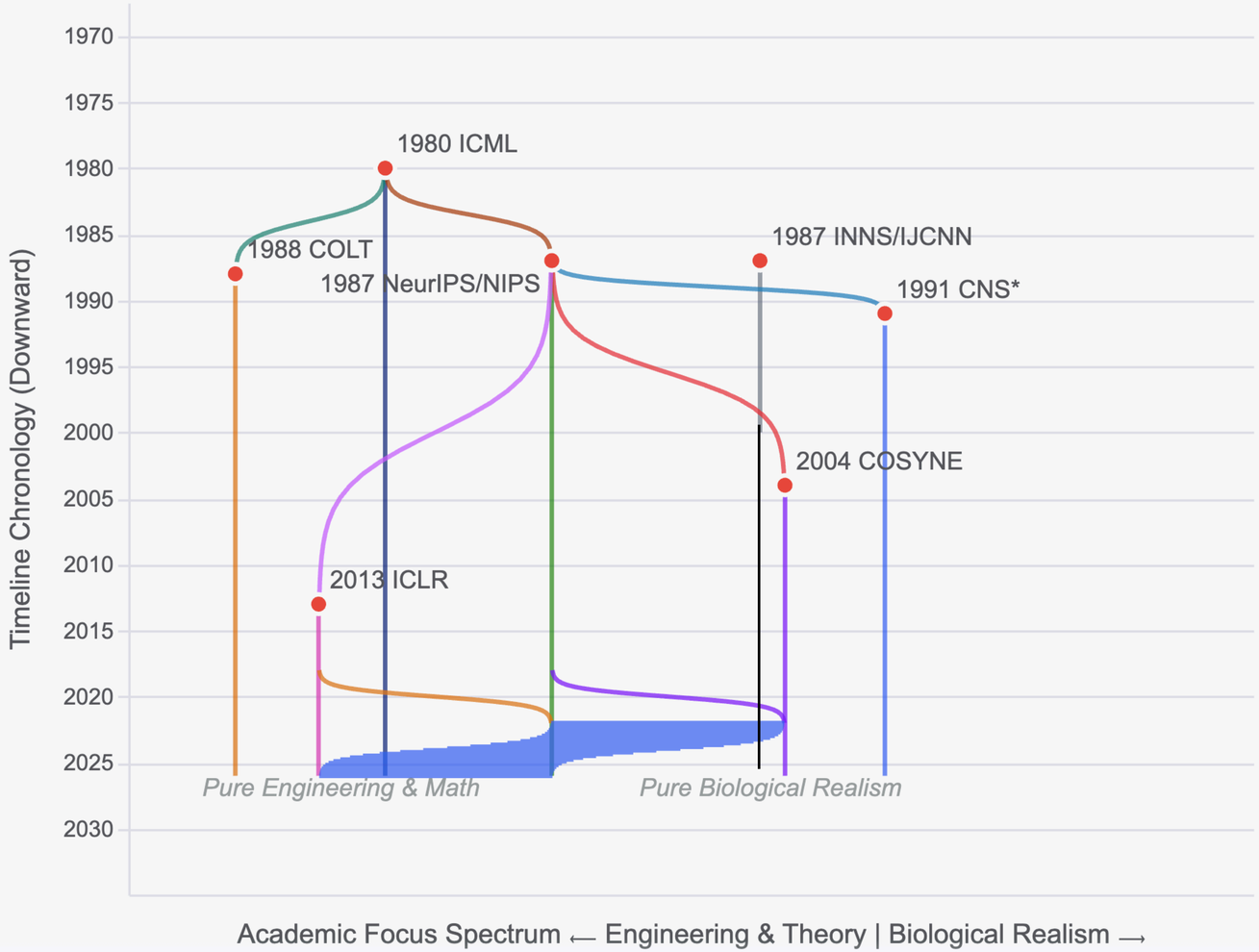


Diagram summary of a history chat with Gemini (see pdf supplement); Earl K. Miller is a prominent advocate for primacy of fields / waves as more than “exhaust fumes” of neural circuits

Evolution and Lineage of Machine Learning & Neuroscience Conferences (1980-2026)

Tracking historical tracking forks, academic schisms, and the modern Neuro-AI convergence loops



The Territory: 20 years of neuroscience advances not in AI

Updated Comparison: Biology vs. Modern AI

Biological Mechanism (Last 20 Years)	Status in Mainstream AI/ML	Why it is ignored / Current Bottleneck
Glial Cell Modulation	**Non-existent**	**Adds massive computational overhead; mathematically complex to model alongside standard nodes.**
Volume Transmission	**Absent** (except for highly abstract RL rewards)	**Backpropagation relies on precise, differentiable mathematical paths, not diffuse chemical clouds.**
Adult Neurogenesis	**Absent**	**Machine learning architectures require fixed-dimension matrices and weights for tensor processing.**
Dendritic Computation	**Absent**	**Point-nodes are highly optimized for GPU hardware; shifting to sub-structural computing breaks current hardware efficiency.**
Ephaptic Coupling	**Absent**	**Digital architectures enforce absolute separation between memory addresses; there is no natural "leakage" or ambient field effect to exploit mathematically.**
Traveling Waves	**Absent**	**AI relies on static spatial representations or discrete temporal tokens, lacking the fluid, continuous mechanics required to simulate macro-wave propagation.**

(Gemini Free LLM prompted Oct 2026)

Scales and Multiscale

Synthese (2022) 200:129
https://doi.org/10.1007/s11229-022-03551-y

ORIGINAL RESEARCH

Descriptive multiscale modeling in data-driven neuroscience

Philipp Haueis[1]

Received: 31 May 2020 / Accepted: 6 January 2022 / Published online: 11 April 2022
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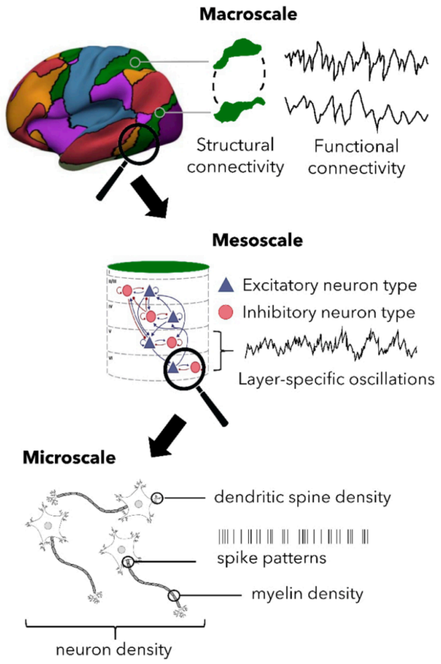


Fig. 3 Scales of brain organization in multiscale connectomic modeling. *Top*: parcellation of the brain into seven networks (visual, somatomotor, dorsal attention, salience, limbic, control and default mode network, adapted from Wang et al., 2019). *Middle*: canonical microcircuit model. (adapted from Beul & Hilgetag, 2015). *Bottom*: schematic drawing of neurons, Creative Commons CC0 1.0

A common assumption in connectomics is that structural connectivity patterns constrain the functional connectivity patterns observed with fMRI, but it is largely unknown how these macroscale patterns are related to mesoscale circuit dynamics and microscale spiking patterns. To investigate these relationships, Deco et al. developed the multiscale modeling schema shown in Fig. 4.

The microscale model in this schema is the *full spiking model*, which describes brain dynamics in terms of individual spiking neurons with three receptor types at the

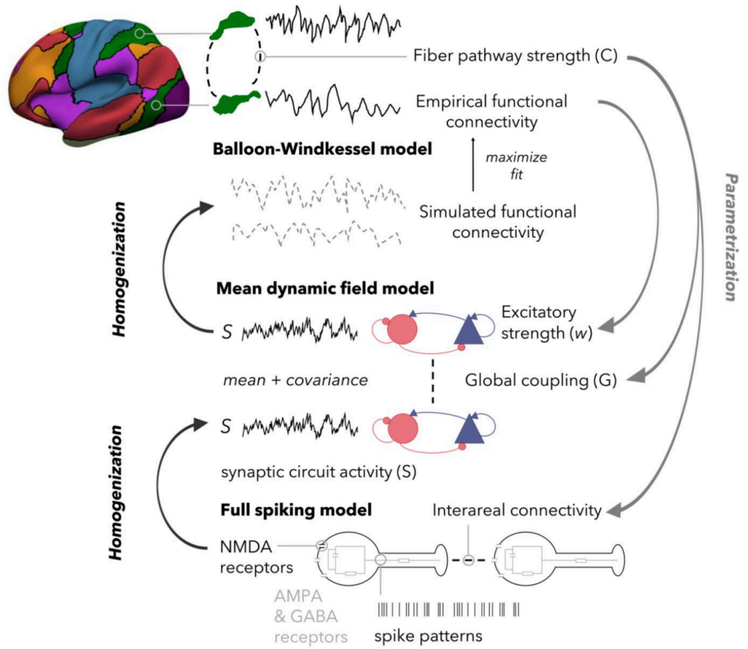


Fig. 4 Multiscale modeling schema developed by Deco et al. (2013). For explanation of model parameters, see text

Scales and Multiscale

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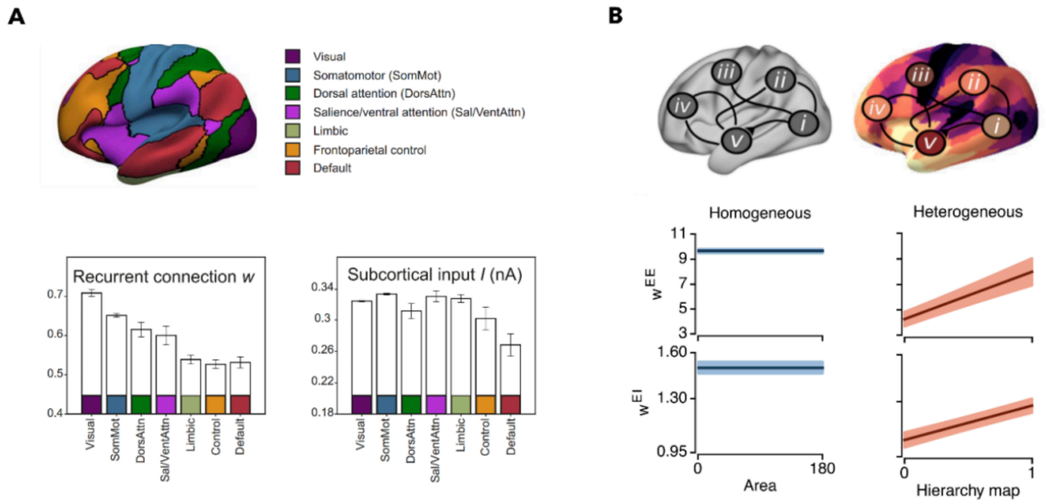


Fig. 5 Two parametrizations for multiscale modeling of cortical gradients. **A***Top*: Same macroscale network parcellation as shown in Figs. 3 and 4. *Bottom*: Parametrization results in high *w* values in sensory and low values in association areas; *I* values show the inverse pattern. Adapted from Wang et al., (2019, Fig. 2). **B.** Same network parcellation as in Wang et al., (2019) plus auditory network, five circled regions are shown to illustrate circuit differences across the brain. *Left*: A homogenous parametrization assigns uniform parameter values (y-axis) across 180 brain areas (x-axis) *Right*: A heterogenous parametrization based on MRI contrast values across the brain (x-axis) assigns low *w* values to primary sensory areas (dark colors in the brain map) and high values in association areas (bright colors). Adapted from Demirtaş et al., (2019, Figs. 1 and 2)

CFC or Nested Oscillations

Cross-frequency coupling (CFC) is a neurophysiological mechanism in which activity across different frequency bands of the brain's electrical rhythms interacts and coordinates with one another

While different neural assemblies oscillate at distinct speeds—such as slow waves carrying global context across long distances, and fast waves handling localized, high-speed computation—CFC bridges these scales.

Types of Cross-Frequency Coupling

Researchers generally categorize CFC into four main types based on what properties of the two rhythms interact: [1, 2]

- **Phase–Amplitude Coupling (PAC):** The most studied form. The phase (position in the wave cycle) of a slow oscillation (e.g., delta or theta) modulates the amplitude (power/volume) of a faster oscillation (e.g., gamma or beta). For example, tiny bursts of high-frequency gamma activity "ride" on top of specific phases of a slower theta wave. [1, 2, 3]
- **Phase–Phase Coupling (PPC):** A constant phase-locking relationship or ratio is maintained between two different frequency bands (e.g., a 2:1 or 3:1 integer relationship). [1]
- **Amplitude–Amplitude Coupling (AAC):** The power envelope fluctuations of a slow rhythm correlate directly with the power envelope fluctuations of a faster rhythm. [1, 2]
- **Phase–Frequency Coupling:** The phase of a slow rhythm influences the instantaneous frequency shift of another oscillation. [1, 2]

Functional Role in Cognition and Disease

- **Cognitive Processing:** PAC helps bind sensory information, manage working memory (e.g., theta organizing gamma to hold items in mind), focus attention, and facilitate long-range communication across brain regions. [1, 2, 3]
- **Pathology:** Abnormal or disrupted CFC patterns are tied to neurological and psychiatric conditions such as Parkinson's disease, epilepsy, schizophrenia, and social anxiety disorder.

Does anyone do neuromorphic neural field theory?

Direct corporate commercialization of hardware explicitly named after Neural Field Theory (NFT) or Dynamic Field Theory (DFT) is almost non-existent. Instead, companies operating in this domain position their technology under the broader banners of neuromorphic computing, analog-mixed-signal AI accelerators, or wetware computing. [1, 2, 3]

NFT and DFT model the brain's electrical activity as continuous, self-organizing spatial-temporal fields rather than discrete point-to-point digital connections.

Continuous field equations (like partial differential equations) are notoriously inefficient to run on standard digital GPUs, a few hardware startups and major tech labs are building chips specifically designed to natively run these field-based, fluid dynamics. [1, 2]

Neuromorphic Field Theory Computing

(NFT)

Startups Building Field-Based & Continuous Dynamics Hardware

- **Trauth Research**
  - **Approach:** Field-based neural architectures.
  - **Technology:** Developed the *T-Zero Field Generator*.
  - **Objective:** Embeds a self-organizing resonance field directly into the neural topology. It treats optimization as a fluid field interaction, reducing GPU power draw and thermal load by up to 70% under full load. [1]

- **Unconventional AI**
  - **Approach:** Nonlinear material physics over digital abstractions.
  - **Technology:** Founded by Naveen Rao, this $4.5B startup builds brain-inspired silicon.
  - **Objective:** Rather than forcing silicon to emulate rigid 1s and 0s, their chips exploit the inherent continuous, nonlinear dynamics of the material. This provides a direct physical substrate for continuous field-like interactions. [1]

- **Cortical Labs**
  - **Approach:** True biological "Wetware" computing.
  - **Technology:** Created the *CL1* biological computer.
  - **Objective:** Integrates live, lab-grown human neurons onto custom silicon. Biological brain tissue naturally processes information using local field potentials and continuous spatial-temporal waves, which makes this the ultimate substrate for NFT principles. [1, 2]

Major Tech Giants and Their Near-Field Analogs

While major tech companies rarely frame their products in pure NFT language, their advanced hardware designs are the primary engines researchers use to test these theories.

- **Intel**
  - **Hardware:** Loihi 2 / Hala Point.
  - **NFT Alignment:** Loihi's architecture natively handles asynchronous, continuous spatial-temporal patterns. While technically a Spiking Neural Network (SNN) platform, it excels at the macro-level wave propagation modeling fundamental to Neural F
- **IBM**
  - **Hardware:** TrueNorth / NorthPole.
  - **NFT Alignment:** IBM focuses heavily on in-memory computing crossbar arrays and continuous analog-mixed-signal chips. These chips eliminate the separation between memory and processing, allowing global patterns to self-organize through lo
    2, 3]

Hardware Substrates Supporting NFT Mechanics

When analyzing these hardware companies, look closely at the underlying components they design. True neural field simulation relies heavily on three core physical architectures:

1. **Memristor Crossbar Arrays:** (Pursued by startups like *Axelera AI* and *Mythic*) These components naturally handle continuous, field-like mathematical equations using Ohm's and Kirchhoff's laws. [1, 2]

3. **Analog Photonic/Optical AI Chips:** (Pursued by *Lightmatter* and *Luminous*) Utilizing light waves instead of electricity allows signals to naturally interact as interfering waves, mimicking mathematical field overlays. [1]

5. **Resonance Architectures:** Emerging microcontrollers that utilize structural energy retention rather than clock-cycled execution, letting the chip's internal physics serve as the "field" itself. [1]

Remains poorly understood



David DeMaris
@DavidDeMaris1

Even if we measure the footsteps of the goddess, note their frequency and average length, we are still far from the secret of her instantaneous grace - Valery, Problems of Poetry

From the last time I was tempted to use the phrase, which evidently has some history.

>  **Kevin Mitchell** @WiringTheBrain · Apr 22, 2021
> I swear if I have to read the phrase "...remains poorly understood" in another paper abstract I'm gonna lose it...

Puzzling Evidence

Are we close to understanding the brains operating principles?

- Representational Drift (decoder stops working)
- Functional Reorganization (compensation after injury)
- Data Efficiency (few shot learning)
- Role of sub-threshold activity (70% of local field, means neurons that didn't fire)
- **In the News**, last couple of months
  - Mice with no Neo-cortex or Hippocampus learn a maze
  - Mice synapses shrink and regenerate after hibernation
  - Human binocular rivalry task represents conscious/unconscious in rapid alternation in same neurons

Looking for a Certain Ratio

Warren McCullough, 1965

Embodiments of Mind, MIT Press

That man, like the beasts, lives in the world of relations rather than in a world of classes or propositions seems certain. He does not know the relative size of two cubes from a measurement of the lengths of their edges, or even from the area of their faces. If he can just detect a difference of one part in twenty of a length, he can do the same for areas and also for volumes. I happen to have spent two years in measuring man's ability to set an adjustable oblong to a preferred shape, because I did not believe that he did prefer the golden section or that he could recognize it. He does and he can'! On repeated settings for the most pleasing form he comes to prefer it and can set for it. The same man who can only detect a difference of a twentieth in length, area, or volume sets it at 1 to 1.618, not at 1 to 1.617 or 1 to 1.619. So the aesthetic judgment bespeaks a precise knowledge of certain – shall I say privileged? – relations directly, not compounded of the simpler perceptibles. A sculptor or painter has sometimes told me he had added enough to a

If you take a line divided into two segments A and B so that A/B is the golden ratio, and then form a rectangle with sides $A + B$ and A, then this rectangle is called a *golden rectangle*.



A golden rectangle is made up of a square (white) and a smaller rectangle (grey). The smaller rectangle is also a golden rectangle.

https://plus.maths.org/myths-maths-golden-ratio

Attempts to replicate this work are inconsistent, i.e. some but not all people are more accurate

Claude on the golden mean winding ratio of circle maps and transition to chaos *

The setup: the circle map

The standard model is the sine circle map:

$\theta_{n+1} = \theta_n + \Omega - (K/2\pi) \sin(2\pi\theta_n) \pmod 1$

Ω is a bare driving frequency and K is the nonlinearity strength. The **rotation number** is the average advance per iteration:

$W = \lim (\theta_n - \theta_0) / n$

For $K = 0$, $W = \Omega$, so an irrational Ω gives quasi-periodic motion that never closes up and fills the circle densely.

Mode locking

For $K > 0$, the nonlinearity makes W "stick" at rational values p/q over whole intervals of Ω. These intervals are the **Arnold tongues**. Plotting W against Ω gives a devil's staircase: flat plateaus at every rational, with quasi-periodic motion living only on the leftover Cantor-like set. As K increases the tongues widen, and at $K = 1$ (the critical line) they fill up the whole Ω axis except for a set of measure zero, with fractal dimension about 0.87. Beyond $K = 1$ the map becomes non-invertible and chaos is possible.

Why the golden mean

A rotation number is hardest to mode-lock when it is poorly approximated by rationals. The golden mean

$W^* = 1/\phi = (\sqrt{5} - 1)/2 \approx 0.618034$

has the continued fraction [0; 1, 1, 1, ...], which is the slowest-converging one possible. Its rational approximants are ratios of consecutive Fibonacci numbers: 1/1, 1/2, 2/3, 3/5, 5/8, 8/13, ... Since no rational approximates it unusually well, it is the "most irrational" number. Its quasi-periodic motion is the last to be destroyed as nonlinearity grows, and it is the standard choice for studying the transition to chaos.

Universality at the golden-mean critical point

At $K = 1$, the golden-mean orbit sits right at the edge of breakdown, and the dynamics are self-similar under rescaling by Fibonacci steps. A renormalization-group analysis (Feigenbaum, Kadanoff, and Shenker; Ostlund, Rand, Sethna, and Siggia, 1982-83) gives universal constants for circle maps with a cubic inflection point, analogous to the period-doubling constants:

- **$\delta \approx -2.8336$**, the parameter-space scaling for successive Fibonacci rotation numbers F_{n-1}/F_n
- **$\alpha \approx -1.2886$**, the scaling of spatial structure on the circle

These are a different universality class from $\delta = 4.6692\ldots$ and $\alpha = 2.5029\ldots$ of the period-doubling route.

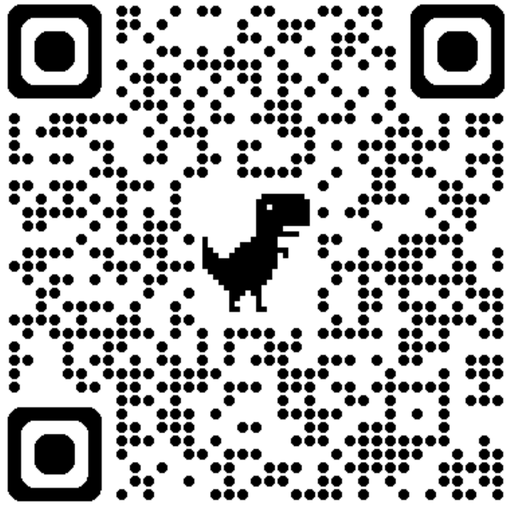
The Hamiltonian cousin

The same idea appears in area-preserving maps, such as the Chirikov standard map. The golden-mean KAM invariant curve is the last to survive, breaking at $K \approx 0.9716$ (found by Greene's residue criterion), and its destruction shows the same kind of Fibonacci-based renormalization scaling. This is where "golden mean" and "transition to chaos" are connected in a precise, testable way.

* Claude knows a lot but I knew this already

Slides and background docs

Thanks !




Neural Conchlier of Music
Artificial Life Models
Generative Music Model
Artificial Life Models
Generctive Music Theory