



1. Introduction

What would AI/ML look like if it had to evolve within the physical and energetic limitations of real hardware, without access to cloud resources or labeled data?

The brain learns without labels, all without a global orchestrator.

Canonical AI assumes centralized training signals

Constraint	Canonical AI/ML	Hardware reality	Biological parallel
Local Autonomy	Global objective	Bandwidth constraint / Congestion	Neurons learn locally (bAP)
Template autonomy	Requires Labels / Targets	No labels on edge	No external template. Everything input-driven.
Clock autonomy	Scheduled steps, Backprop. (Forward/Backward)	Global training clock -> pipelining (Design is costly - OoO is hard)	Dynamics are asynchronous .

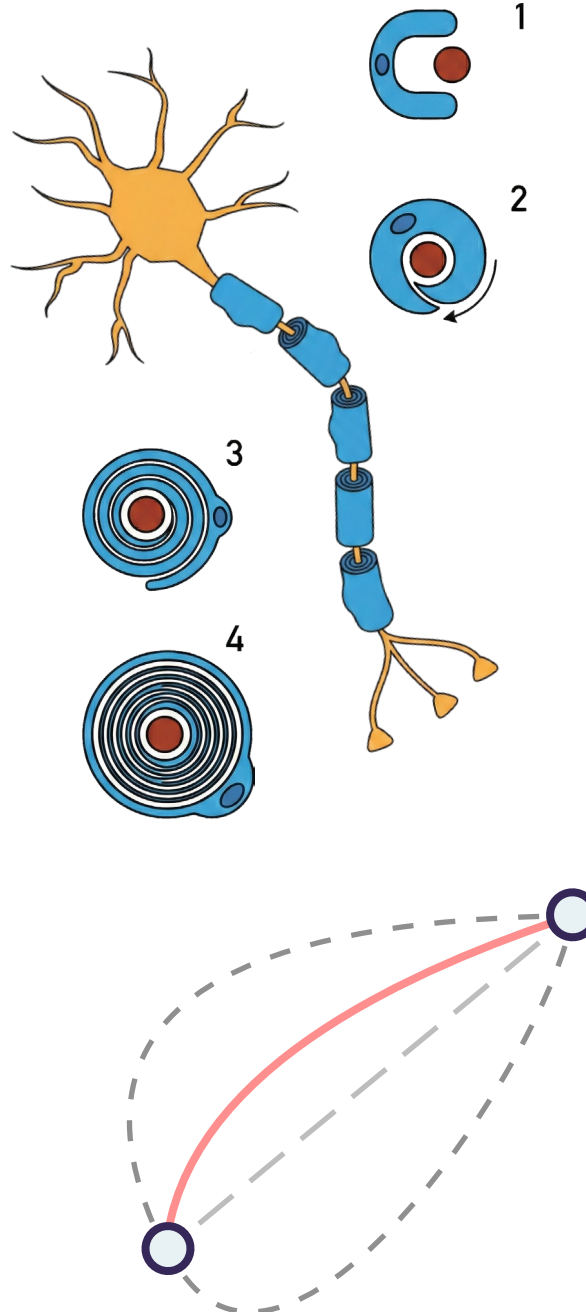
The ideal autonomous self-learning hardware

Local learning (No global knowledge)	Target-free (No explicit labels)	Asynchronous (Local evolution)	Thermodyn. constrained (Energy efficient)
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2. Neurobiological inspiration

The **autopoietic** [1] frame: each cell/compartiment as an independent agent under metabolic pressure. Learning is an emergent property of survivability.

- Metabolic constraints: **Limited energy limits computation** [2]
- Glial support and activity reward:
 - Astrocytes couple **synaptic activity** to **metabolism** [3,4]
 - Oligodendrocytes (**Myelination investment**) metabolically support and **enable long-range communication** [5].
 - Energy delivery is **integrated** with **neural signaling** and tracks computation [6].
- Dynamical neurons:
 - Brains self organize: **Neural avalanches** [7] and criticality are the fingerprints of **complexity** and emergence.
 - Oscillations and resonance: **Rich firing patterns** can emerge from low-dimensional **continuous time dynamics** [8, 9].



Normative framing:

- Least action principle**: Conservation laws and symmetries in real-life commonly make dynamical systems follow the path of least action.

$$\delta S = \delta \int_t L dt = 0$$

3. The \mathcal{NRCSTK} framework

Cost of existing - Mass as a proxy for commitment

- Neurons carry a metabolic mass m_k which has to be sustained with q_k
- Dynamical properties (ω_k, γ_k) are modulated by mass m_k
- More mass = more capability \rightarrow **Learning as an allocation problem.**

A competitive metabolic market

- Global metabolic flux Q is split into per-branch shares $\pi_k \rightarrow q_k = \pi_k Q$
- Branches **compete for share**: useful branches grow; redundant starve.
- Signal entanglement as reward deservability \rightarrow **100% local learning.**

Emergent learning (specialization + synchronization)

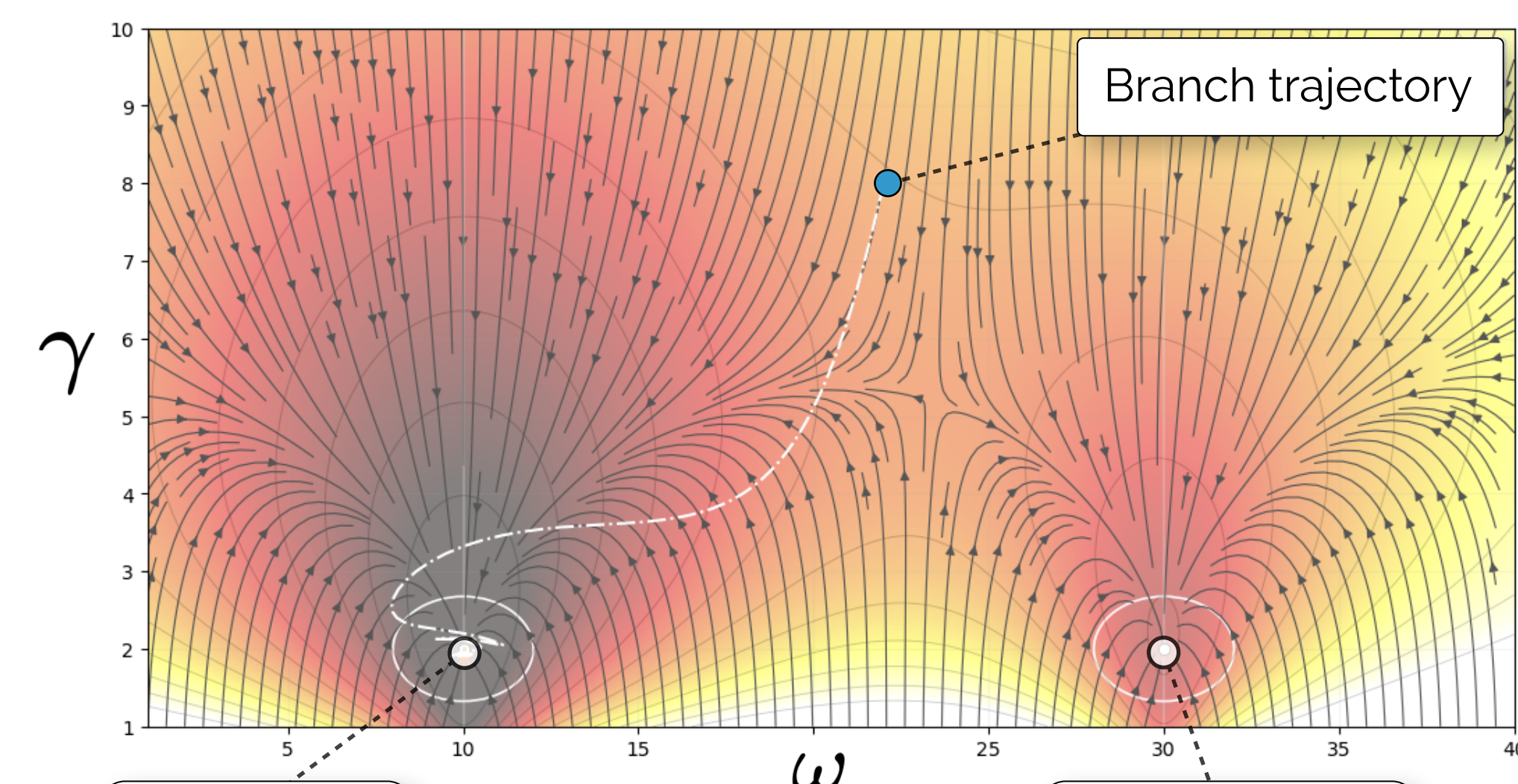
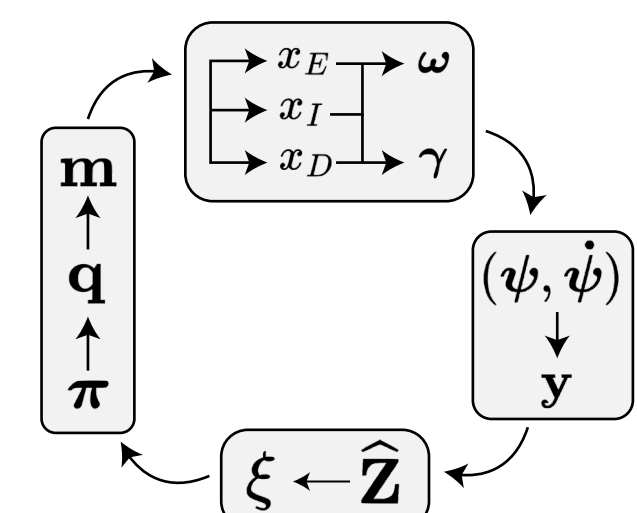
- Branch dynamics drive **spectral specialization**.
- Deflation encourages branches to tune to explained components ξ
- Competition produces **repulsion**
- Synchronization** emerges as stable point.

$$\begin{bmatrix} x_I \\ x_E \end{bmatrix} = m \begin{bmatrix} c_I & 0 \\ 0 & c_E \end{bmatrix} \begin{bmatrix} 1-\eta & \eta \\ \eta & 1-\eta \end{bmatrix} \begin{bmatrix} s \\ 1-s \end{bmatrix} \quad x_D = c_D m \delta$$

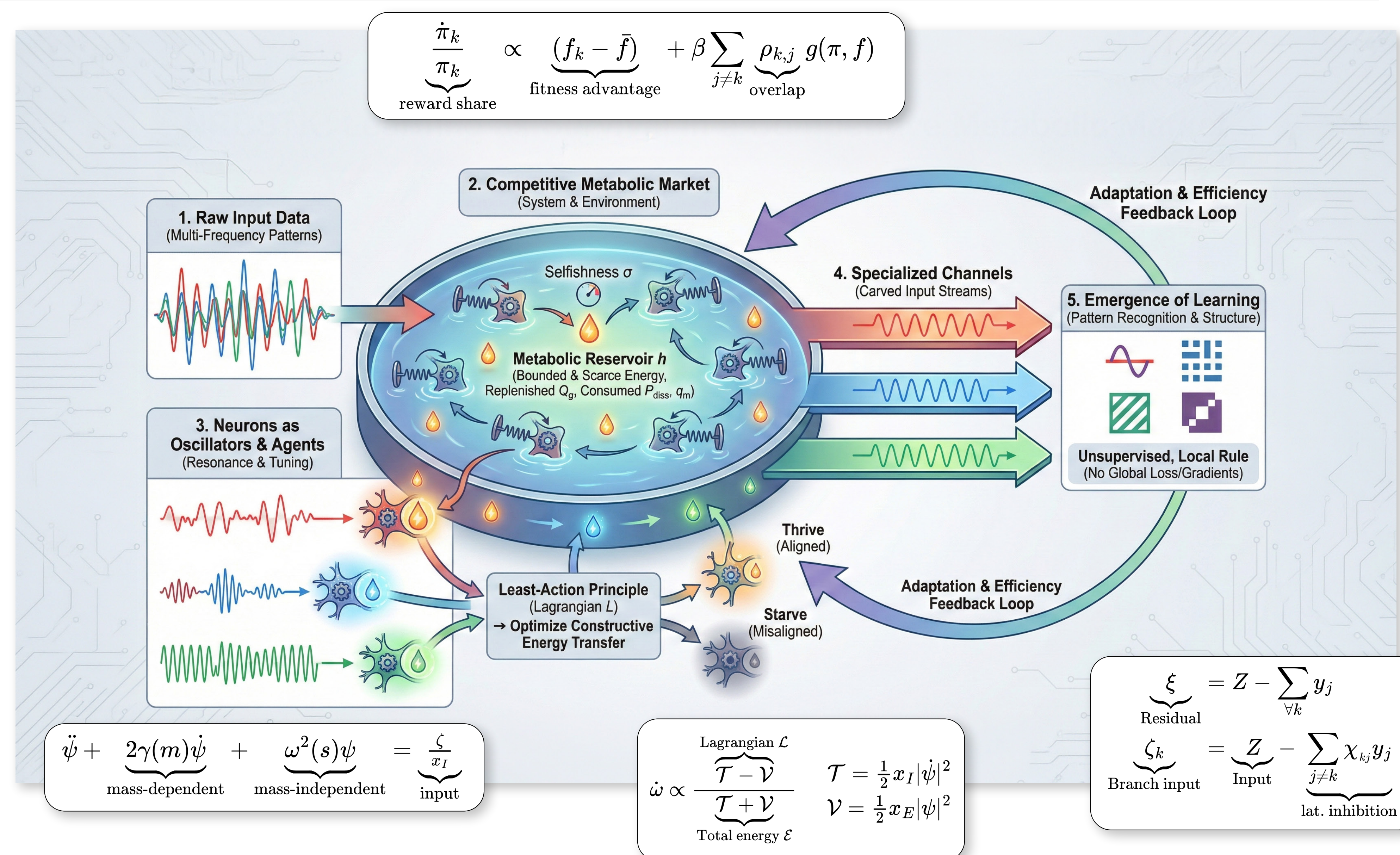
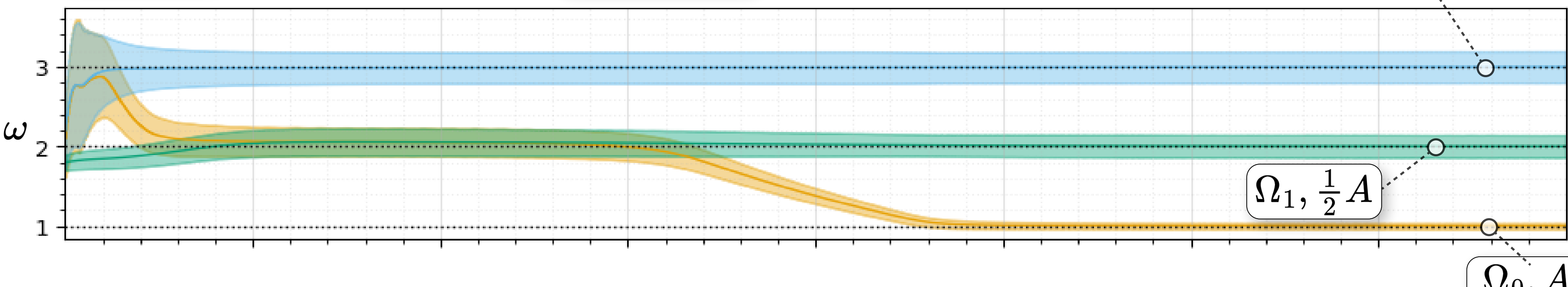
$$x_I \ddot{\psi} + x_D \dot{\psi} + x_E \psi = \zeta \quad \dot{m} = \mu^+ q - \mu^- m$$

4. Spectral predation ecology and self organization

- Residual/deflation**: Each branch focuses on a spectral band ζ_k
- Bigger branches **predate** smaller branches share q_k
- Positive feedback** reinforces spectral decomposition.



Ω_0, A Loud tone $\Omega_1, \frac{1}{2}A$ Quiet tone



$$\frac{\dot{\pi}_k}{\pi_k} \propto \underbrace{(f_k - \bar{f})}_{\text{fitness advantage}} + \beta \sum_{j \neq k} \underbrace{\rho_{k,j}}_{\text{overlap}} g(\pi, f)$$

$$\ddot{\psi} + \underbrace{2\gamma(m)\dot{\psi}}_{\text{mass-dependent}} + \underbrace{\omega^2(s)\psi}_{\text{mass-independent}} = \frac{\zeta}{x_I} \text{input}$$

$$\omega \propto \frac{\text{Lagrangian } \mathcal{L}}{\mathcal{T} - \mathcal{V}} \quad \mathcal{T} = \frac{1}{2} x_I |\dot{\psi}|^2$$

$$\mathcal{V} = \frac{1}{2} x_E |\psi|^2 \quad \text{Total energy } \mathcal{E}$$

$$\xi = Z - \sum_{\forall k} y_k$$

Residual

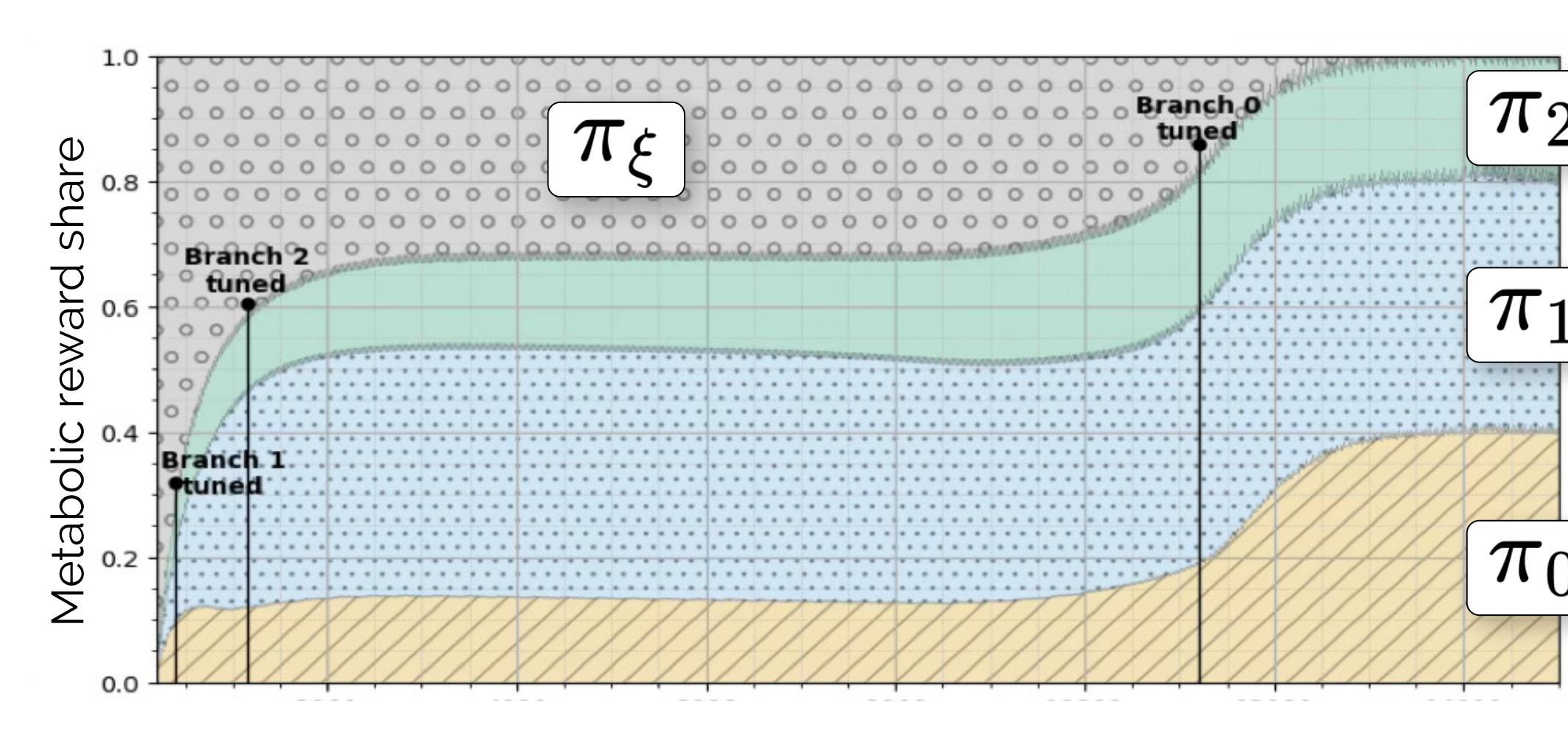
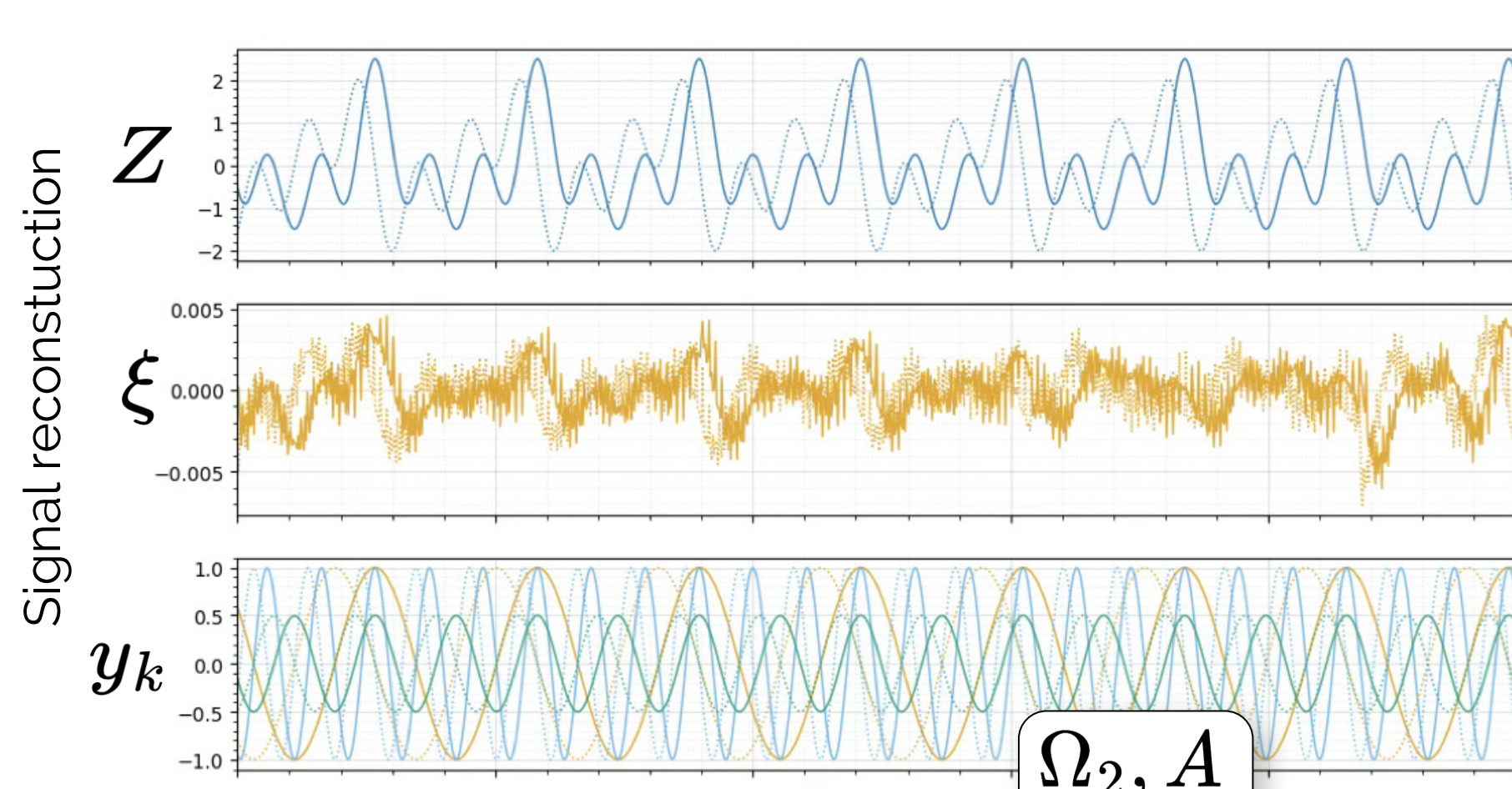
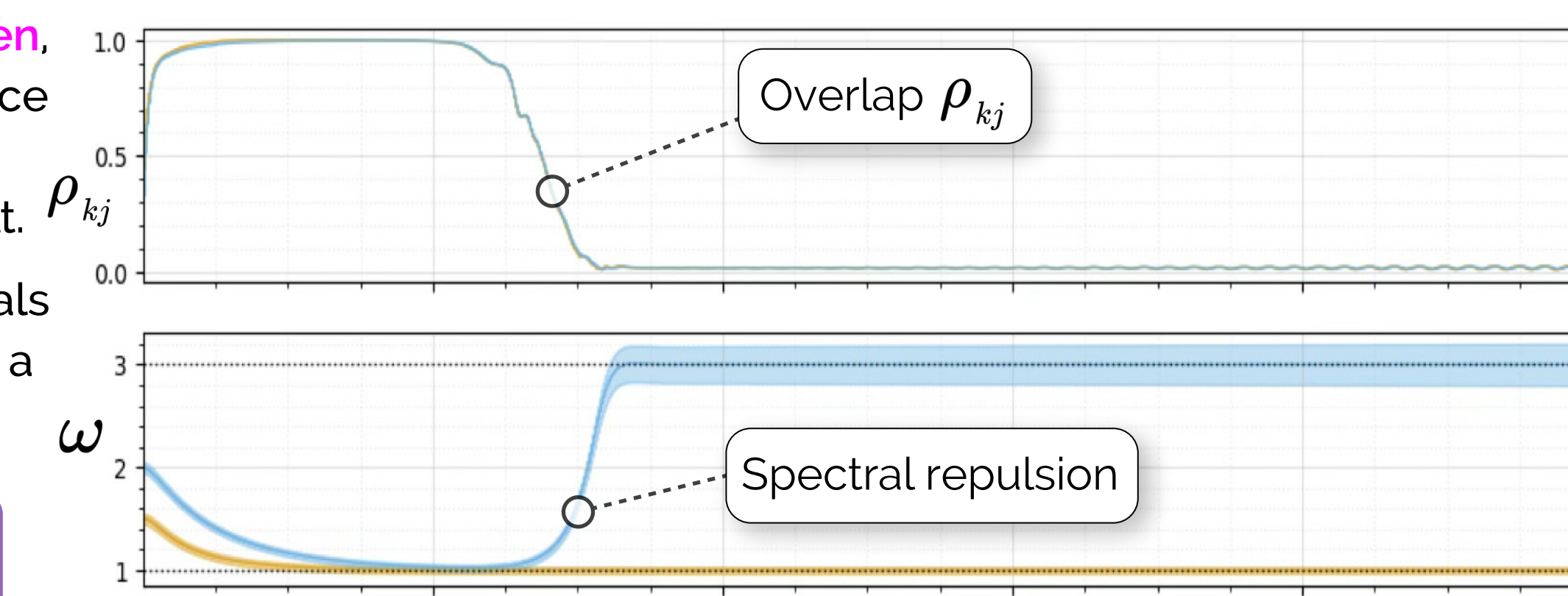
$$\zeta_k = Z - \sum_{j \neq k} x_{kj} y_j$$

Branch input Input lat. inhibition

5. Results and Future work

- We presented the \mathcal{NRCSTK} framework: a **metabolism-driven, locally self-tuning ecosystem** where **competition** over scarce resources **makes spectral decomposition** of inputs the optimal learning strategy. **Synchronicity** emerges as a result.
- Under investigation**: map \mathcal{NRCSTK} state variables and signals onto **concrete electrical circuit components** and prototype a minimal \mathcal{NRCSTK} neuron ASIC demonstrator.

\mathcal{NRCSTK} puts us on a credible path toward one of the first **self-tuning, metabolically driven on-hardware learning**.



References and Acknowledgements

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