The Self-Organized Growth of Synfire Patterns

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1. Rate vs. Temporal Coding
- \(z_1(t)\) = \(z_2(t)\) = \(z_3(t)\) = \(z_4(t)\) = \(z_5(t)\)

2. The Binding Problem
- \(\text{supposition catastrophe: no relational information in rate coding}
- \(\text{but rather than creating more 'grandfather' cells to fix the problem, feature combinations are better coded temporally, e.g., by synchrony}

3. The Compositionality of Cognition
- \(\text{language, perception, cognition are a game of building blocks}
- \(\text{mental representations are internally structured}
- \(\text{elementary components assemble dynamically via temporal binding}

4. Spatiotemporal Pattern Binding
- \(\text{cognitive compositions might be analogous to conformational interactions among proteins}
- \(\text{the basic 'peptidic' element might be a synfire braid structure supporting a traveling wave, or spatiotemporal pattern (STP)}
- \(\text{two STPs can synchronize via coupling links}

5. Neocortical Growth by Focusing
- \(\text{we propose a model of synfire pattern growth akin to the epigenetic structuration of cortical areas via interaction with neural signals}
- \(\text{from an initially broad and diffuse (immature) connectivity, some synaptic contacts are reinforced (selected) to the detriment of others}

6. Rule A – Neuronal Activation
- \(\text{we consider a network of simple binary units obeying a LNP spiking dynamics on the 1ms time scale (similar to fast McCulloch & Pitts)}

7. Rule B – Synaptic Cooperation
- \(\text{the weight variation depends on the temporal correlation between pre and post neurons, in a Hebbian or binary STDP fashion}

8. Rule C – Synaptic Competition
- \(\text{to offset the positive feedback between correlations and connections, a constant preserves weight sums at } a_{ij} \text{ (different) and } a_{ij} \text{ (different)}

9. Development by Aggregation
- \(\text{a special group of } s \text{ synchronous cells, } P_1 \text{ is repeatedly (yet not necessarily periodically) activated and recruits neurons downstream}

10. A Chain Grows like an Offshoot
- \(P_0 \text{ becomes the root of a developing synfire chain } P_0, P_1, P_2, \ldots \)
- \(\text{where } P_1 \text{ itself might have been created by a seed neuron sending out strong connections and reliably triggering the same group of cells}

11. Numerical Simulation of a Chain
- \(\text{after 4000 iterations, a chain containing 11 groups has developed}

12. Evolution of Total Activity
- \(\text{global activity in the network, revealing the chain's growing profile}

13. Evolution of Connections
- \(\text{the aggregation of } P_{ij} \text{, by } P_0 \text{, is a form of 'Darwinian' evolution}
- \(\text{in a first phase, noise acts as a diversification mechanism, by proposing multiple candidate neurons that fire after } P_0
- \(\text{in a second phase, competition selects among the large pool of candidates and rounds up a final set of winners } P_{ij} \text{)}

14. Synfire Braids
- \(\text{synfire braids are more general structures with longer delays among nonconsecutive neurons, but no identifiable synchronous groups—}
- \(\text{they were rediscovered as 'polychronous groups' (Izhikevich, 2006)}
- \(\text{in a synfire braid, delay transitivity } \theta_{ij} = \theta_{ik} + \theta_{kj} \text{ of } 0 \text{ to } \theta_{ij}

15. The Self-Made Tapestry
- \(\text{the recursive growth of a chain from endogenous neural activity is akin to the accretive growth of a crystal from an inhomogeneity}
- \(\text{if multiple 'seed neurons' coexist in the network (and fire in an uncorrelated fashion), then multiple chains may grow in parallel}

16. Synchronization and Coalescence
- \(\text{on this substrate, the coalescence of synfire waves via dynamical link binding provides the basis for compositionality and learning}

\(z_1(t)\) = \(z_2(t)\) = \(z_3(t)\) = \(z_4(t)\) = \(z_5(t)\)

\(\text{temporal coding: spike correlations}

\(\text{rule coding: average spike frequency}

\(\text{there is more to neural signals than mean activity rates — synchronization and delayed correlations among spikes (but not necessarily oscillatory)}\)