Signal denoising through topographic modularity

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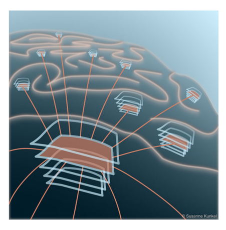
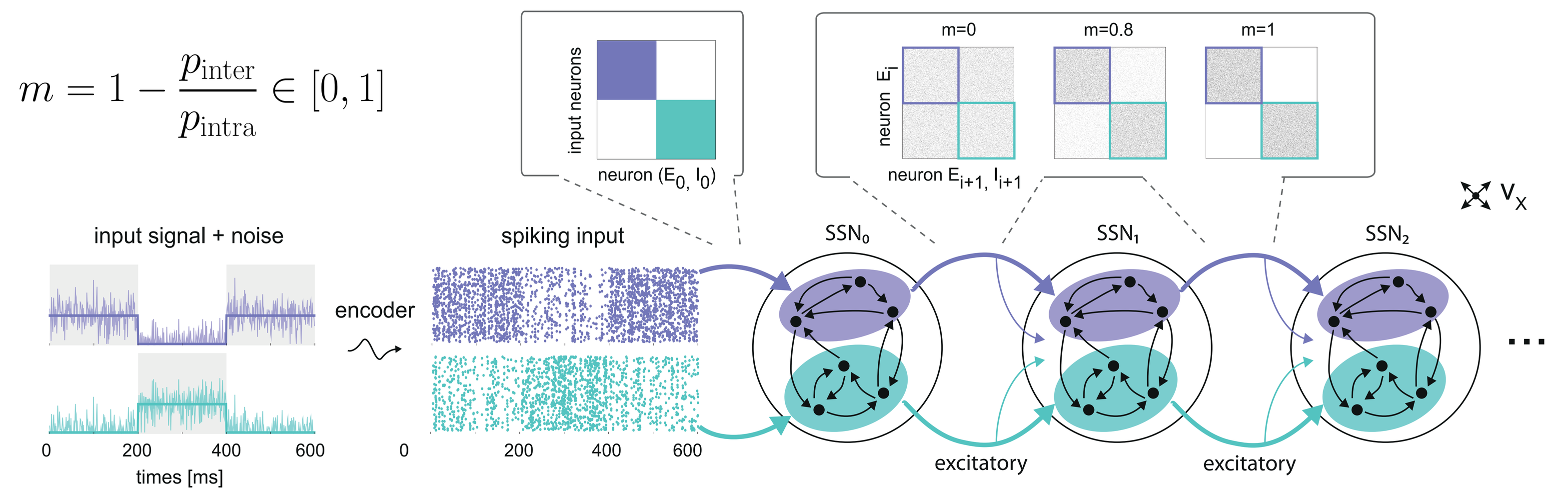


1. Introduction

- Sensory inputs arriving at the cortical circuitry are often ambiguous, noisy and imprecise
- These are typically mapped onto tuned populations and processed through a series of topographic maps [3], comprising ordered projections among distinct neuronal populations
- Accurate sensory perception requires that external stimuli are encoded and propagated through different processing stages in a manner that minimizes signal degradation
- Here we hypothesize that stimulus-specific pathways akin to cortical topographic maps may provide the structural scaffold for such signal routing
  - ➔ Model: large modular circuit of spiking neurons comprising multiple sub-networks
  - ➔ Modular topographic precision can instantiate a effective denoising auto-encoder
  - ➔ Stimulus representation improves with network depth
  - ➔ Theory predicts that denoising may be a universal, system-agnostic feature of such maps

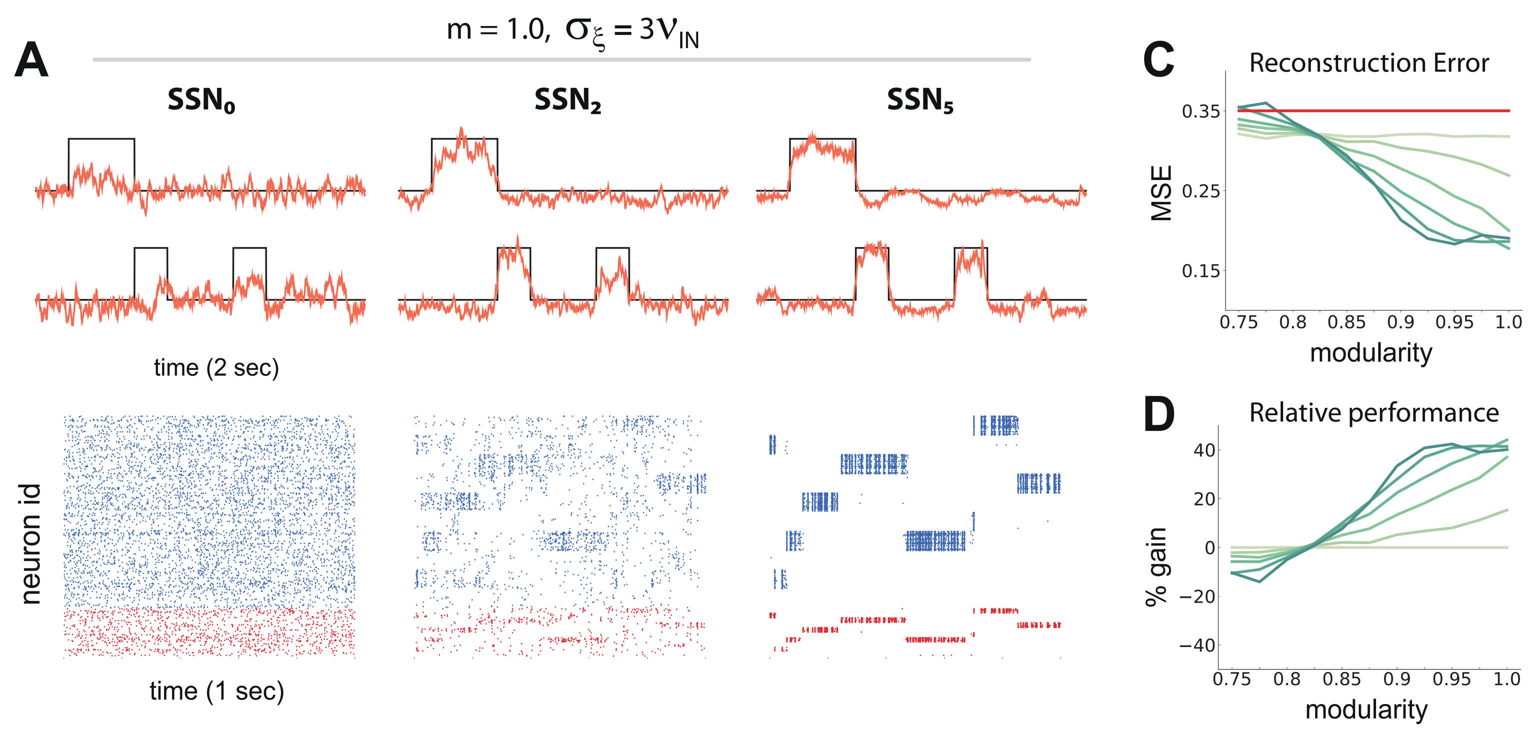
2. Network architecture & task

$$m = 1 - \frac{p_{\text{inter}}}{p_{\text{intra}}} \in [0, 1]$$



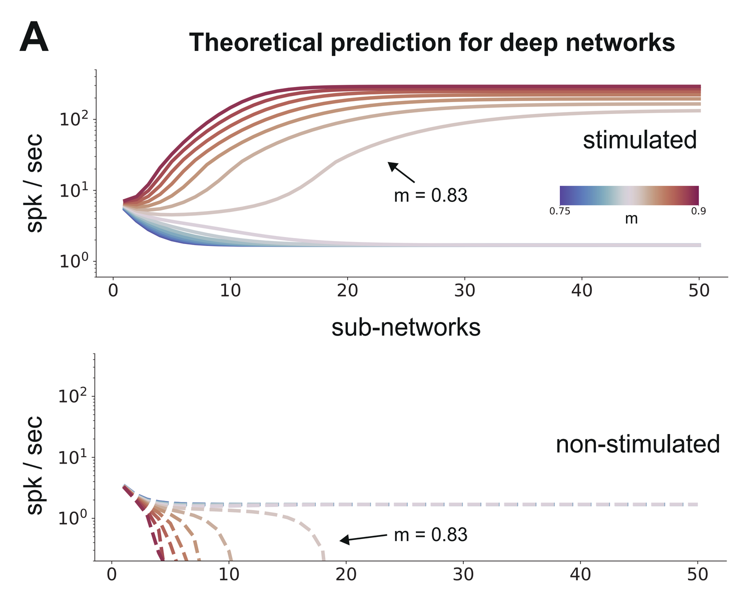
- Sequentially connected balanced random networks of LIF neurons (6 sub-networks, SSNs)
- Structured stimuli drive specific neuronal clusters in SSN_0, building a topographic map
- Task: reconstruct continuous signal corrupted by Gaussian noise, using Reservoir Computing [2]

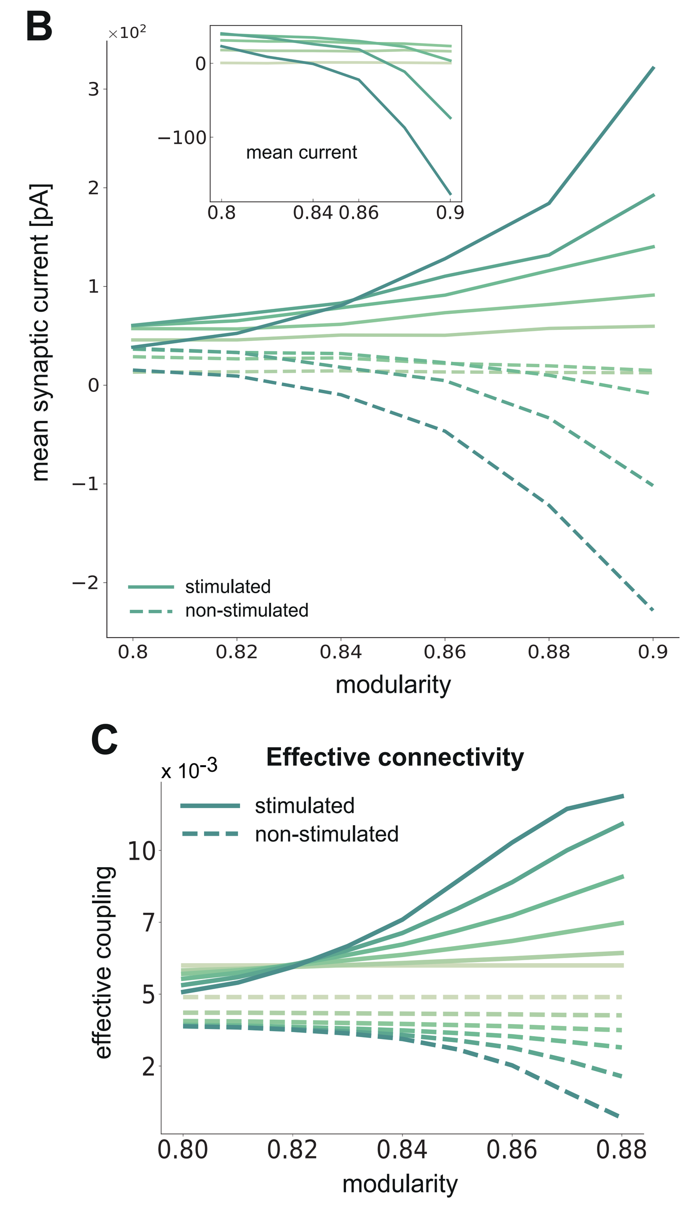
3. A de-facto denoising auto-encoder



- Structured projections are essential for accurate signal reconstruction (see also [1])
- Beyond $m \approx 0.83$, the system behaves as an effective denoising auto-encoder
  - performance improves with network depth
- Modularity gradually sharpens population responses and encoding through spatial segregation
  - this results in both *noise suppression* and *response amplification*

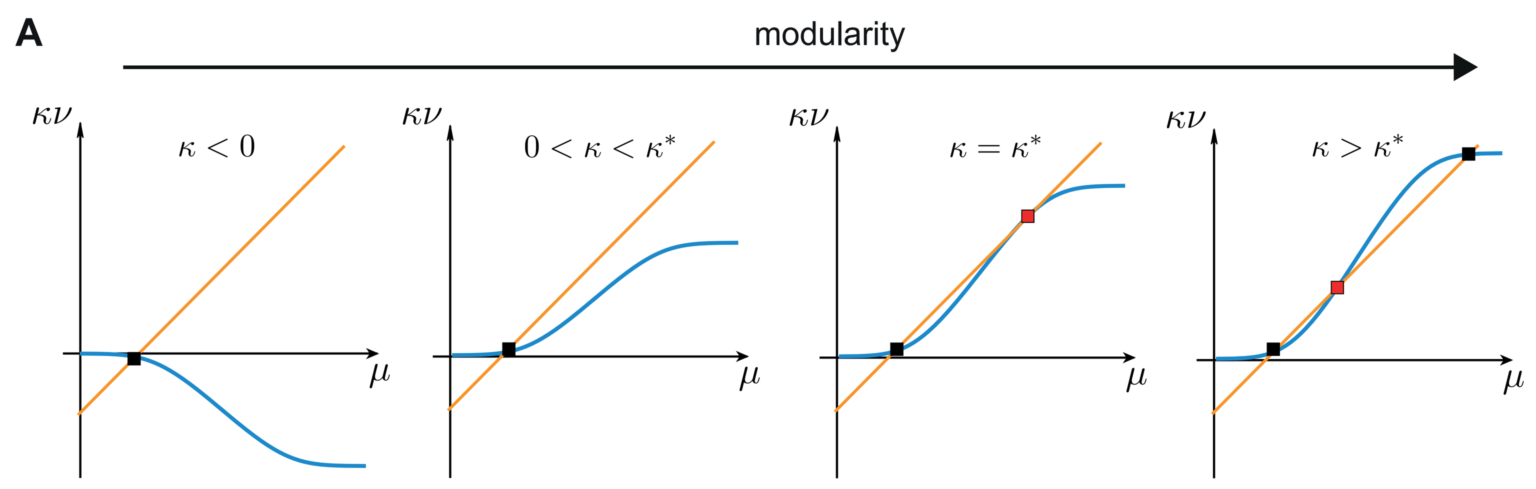
4. Asymmetric coupling and E/I balance

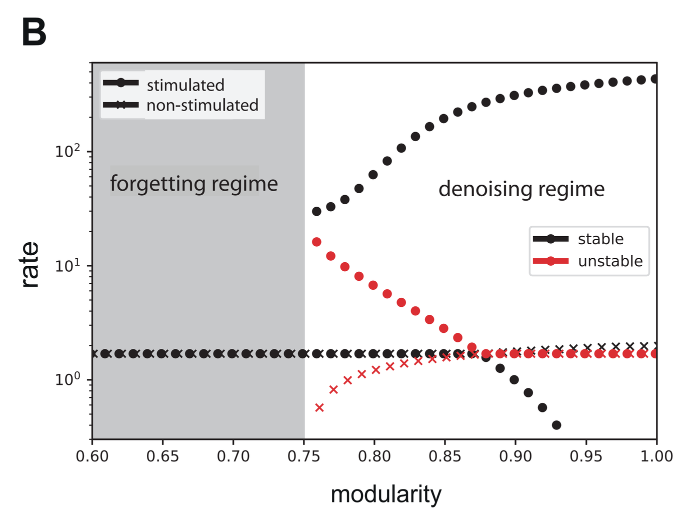




- Firing rates of the stimulated (non-stimulated) clusters increase (decrease) with m
- For very deep networks, these appear to converge to some stationary values
- E/I balance is disrupted (global inhibition)
- Effective coupling becomes asymmetric with increasing modularity and network depth
- Denoising → transient, stimulus-specific change in effective connectivity

5. Fixed point analysis



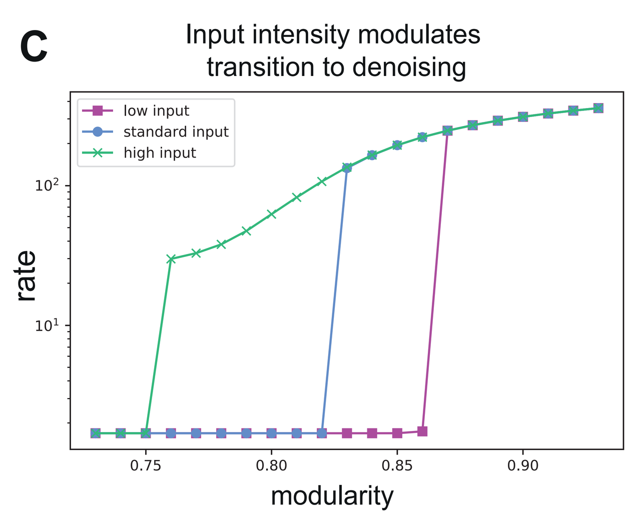


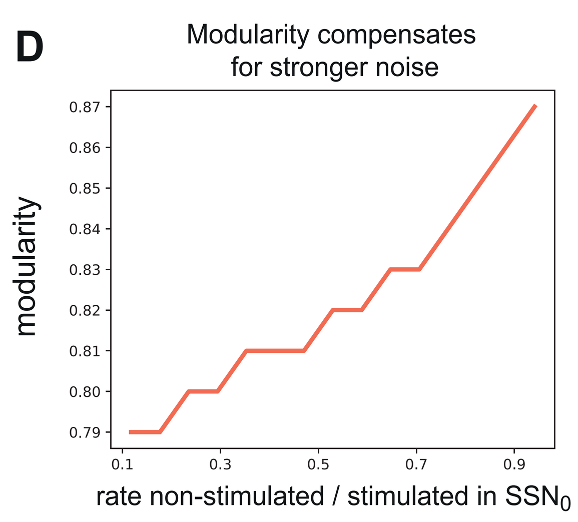
- Linear approximation of the mean input:

$$\kappa\nu = \mu - I$$

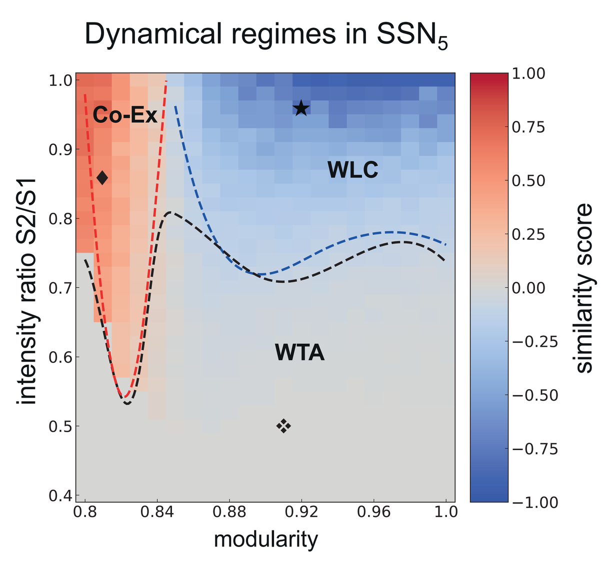
- For a stationary state, modularity of feed-forward projections enters self-coupling term κ
- In the stimulated clusters, sign of κ switches to positive for large m → multiple fixed points

- Denoising effect: successively drive the rates of the stimulated (non-stimulated) clusters to the stable high-activity (low-activity, near zero) fixed point
- Switching point (m) is determined by stimulus intensity and input noise in SSN_0

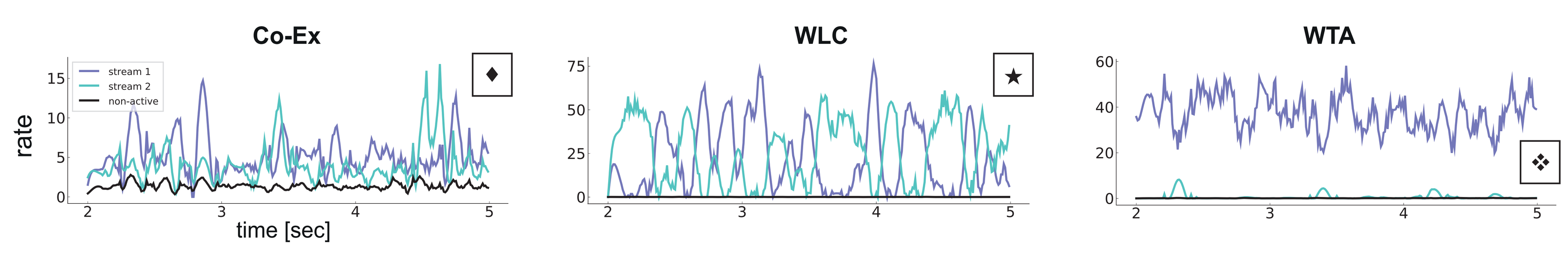




6. Multiple dynamical regimes



- Topography induces behaviorally relevant dynamical regimes in deeper sub-networks (2 stimuli):
  - **Co-Ex**: multiple stimuli decodable
  - **WTA**: one stimulus dominates (winner-take-all)
  - **WLC**: stochastic switching (winnerless-competition)
- Correlation-based similarity score between the firing rates of the stimulated clusters
- Co-Ex vanishes for very deep networks
- (?) Fixed-point landscape: 2 attractors (wells, min.)
  - modularity and input control "well depth"



Discussion

- We show, in biologically plausible setting, that the experimentally observed topographic maps may serve as a structural denoising mechanism for sensory stimuli
- Modularity changes the fixed point landscape, leading to bistable operating regimes
- Robust, general structural property (also for conductance-based synapses and rate networks)
- May explain multiple phenomena: pop-out effect, perceptual bistability

? Impact of different architectures: a) feedback projections; b) shared inhibition?

? Relation to other modular networks, e.g., clustered sub-populations within a local network?

References

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