

Reprogramming the sensory cortex for adaptive task learning

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Animals adapt their behaviour in response to variable changes in reward reinforcement. How animals employ specific behavioural strategies while learning tasks and how the prefrontal areas of the mammalian neocortex, especially the orbitofrontal cortex (OFC), contribute to such strategy-based learning remain understudied. Using a tactile flexible learning task, longitudinal 2P-Ca²⁺ imaging and tensor component analysis combined with a novel method of temporal decoding, we revealed the crucial contribution of OFC and its interactions with hierarchically organised sensory areas. In my talk/poster, I will highlight neural circuit interactions between lateral OFC (lOFC) and a small ensemble of outcome/value-selective neurons in the primary somatosensory cortex (S1) during task reversal in mice (Nature 2020) and briefly discuss similar circuits in operation in cognitive tasks combined with fMRI/EEG measurements in humans (Nat. Comm. 2023; In prep). By implementing a Bayesian evidence accumulation model to analyse behavioural learning data in mice, we revealed multiple exploratory strategies animals employ during key task-learning phases. Silencing lOFC impairs strategy deployment during behavioural flexibility, highlighting the role of lOFC in leveraging prior knowledge supporting reward and error-guided learning (In prep). Furthermore, I will show evidence of how disinhibitory VIP interneurons in the OFC encode a context-prediction error signalling a loss of confidence that is mirrored in top-down signals modulating apical activity S1 pyramidal neurons. A proposed theoretical model will explain how contextual changes are detected in the brain and how a hierarchy of prediction errors in different cortical regions interact to reshape and update the sensory representation (Under review, Nat. Neurosci. 2024). Finally, I would argue that such feedback circuits would also be key targets for behavioural inflexibility seen in neurodevelopmental disorders (In prep). Taken together, our experiments shed light on the circuit mechanisms underlying predictive ‘teaching signals’ that drive adaptive changes in sensory cortices and in behaviour.

Emergence of a state of coherent bursting and power-law distributed avalanches when excitation is balanced by adaptation

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Spontaneous brain activity contains rich dynamical structures such as neuronal avalanches with power-law duration and size distributions. Despite extensive studies, the underlying mechanism of these dynamical patterns remain to be fully understood. Using numerical simulations of networks of adaptive neurons with stochastic input, we find that a state of coherent bursting and power-law distributed avalanches emerges under suitable conditions. We show that coherent bursting occurs when excitation is sufficiently strong and yet small enough to be balanced by adaptation, and that the power-law distributed avalanches are direct consequences of the time-dependent oscillatory population firing rate due to coherent bursting and stochastic driving. When excitation is too weak, neurons exhibit irregular and independent spiking and when excitation is too strong for the adaptation, neurons exhibit incoherent fast spiking, and in these two states, durations of the avalanches are exponentially distributed. Our work thus shows that the rich dynamical patterns observed in the brain can arise from collective stochastic dynamics of adaptive neurons.

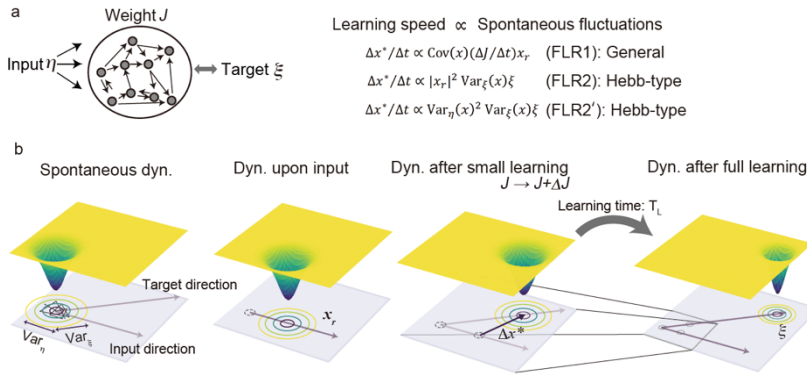
Fluctuation-learning relationship: fluctuation in the spontaneous dynamics determines the learning speed

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Learning speed is shaped by both neural dynamics and task structure, with growing experimental evidence linking variability in spontaneous neural activity before learning to learning performance. However, a unified theoretical framework explaining this relationship has been lacking. In this study, inspired by the fluctuation-response relation in statistical physics, we derive general formulae connecting spontaneous neural fluctuations to learning speed. We show that the initial learning speed is proportional to the covariance between spontaneous activity and the neural response to inputs, independent of the specific learning rule. For Hebbian learning, learning speed further depends on the variance of spontaneous activity along task-relevant directions—specifically, the input and target axes.

These results apply to a wide range of learning paradigms, including associative memory and input/output mapping tasks. Numerical simulations confirm the validity of our theoretical predictions across different network architectures, learning rules, and beyond the linear and full-rank assumptions used in the derivation. As a direct implication, learning is accelerated when task-relevant directions align with the dominant axes of spontaneous fluctuations, consistent with empirical findings from brain-computer interface and behavioral studies.

Our framework provides a unified theoretical basis for understanding how the geometric relationship between pre-learning neural variability and task-relevant directions governs learning efficiency. This insight has broad implications for interpreting variability in neural systems and guiding the design of learning algorithms and neurotechnological interventions.



Neural coding of subthreshold sinusoidal inputs into symbolic temporal spike patterns

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Despite intense research on neural coding, it is still far from understood how sensory neurons encode signal information into spike sequences. Using different neuronal models, we have shown that single and coupled neurons can encode a subthreshold periodic signal (which on its own is incapable of generating spikes) by exploiting noise (stochastic electrical fluctuations that do not encode any information). Using a symbolic time series analysis method, we have found that the relative order of interspike intervals (ISIs) can encode signal information [1].

We have also found that this coding mechanism is plausible for neuronal ensembles, when they all perceive a subthreshold periodic signal [2]. Neuronal coupling is beneficial for signal encoding, since a sufficiently large ensemble is capable of encoding a signal of small amplitude, which could not be encoded when only one or two neurons perceive it. Interestingly, we found that a few random connections can significantly improve signal encoding.

We have also performed experiments with an excitable laser that emits light pulses that have some statistical similarities to neuronal spikes [3], to analyze whether information can be encoded in sequences of optical spikes. Indeed, we found that the laser's ISI sequences recorded under low- or high-frequency modulation tend to be located in different regions of a "feature space" [4] and therefore, information of the frequency of the signal applied to the laser is contained in the sequence of emitted optical spikes, which may be a new approach for spike-based information processing in neuromorphic photonic systems.

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Human perceptual decision making of nonequilibrium fluctuations

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Perceptual decision-making frequently requires accumulating noisy sensory inputs as evidence to execute rapid, reliable choices. Neural recordings from the lateral intra-parietal area in humans and primates performing perceptual decision-making tasks highlight evidence accumulation mechanisms, often modeled as drifted diffusions. In those experiments, participants were exposed to computer-generated randomly fluctuating stimuli whose motion was unrelated to any physical phenomenon. To better characterize the statistical processes underlying decision-making, we performed experiments where human participants visualized fluctuations of physical nonequilibrium stationary states and analyzed responses in the context of stochastic thermodynamics [1]. Forty-five participants viewed hundreds of movies of a particle undergoing drifted Brownian dynamics and were tasked with judging the motion as leftward or rightward in a reliable manner (see Fig. 1). Overall, the results uncover fundamental performance limits consistent with thermodynamic trade-offs [2]; specifically, lower entropy production rates lead to longer decision times. Moreover, to achieve a given accuracy, participants required more time than predicted by Wald’s optimal sequential probability ratio test, indicating suboptimal integration of the available information. Given this suboptimality, we develop an alternative account equipped with non-Markovian evidence integration and a memory time constant, and find tight fits. Our results suggest that humans adapt their memory relaxation time to the dissipation of the observed phenomenon, favouring memory over momentary evidence for effective decisions in scenarios where stimuli are far from equilibrium. Our study illustrates that perceptual psychophysics using stimuli rooted in nonequilibrium physical processes provides a robust platform for understanding how the human brain makes decisions on stochastic information inputs.

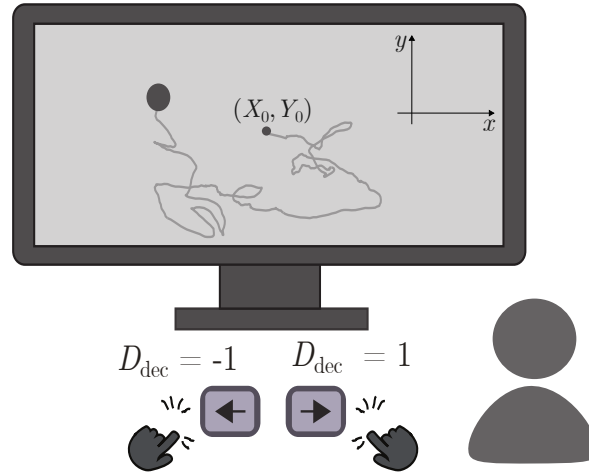


FIG. 1: **Sketch of the experimental setup.** Forty-five human participants were instructed to judge the net motion direction (left versus right) of a moving disk displayed on a computer screen by pressing the right (left) arrow key on a keyboard. The snapshots of the disk’s motion are generated from stochastic simulations of a overdamped Langevin dynamics.

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Abstract for oral presentation in COLLECTIVE DYNAMICS AND INFORMATION PROCESSING IN NEURAL SYSTEMS

30 June - 2 July 2025 · Cà Bottacin, Venice, Italy

Title: Thermodynamic analysis of spontaneous neuronal activity operating in different criticality regimes by maximum entropy modeling

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Abstract:

Spontaneous brain activity organizes into scale-free bursts called “neuronal avalanches”, suggesting that neuronal dynamics are poised near criticality between quiescence and hyperactivity, with deviations from this state associated with pathological conditions. Recently, using maximum entropy arguments, time-averaged experimental neuronal data have been described using Ising-like models at unit temperature, allowing the study of neuronal networks under an analogous thermodynamic framework.

In this work [1], [2], we apply the maximum entropy method to an integrate-and-fire model that simulates neuronal avalanches and can be tuned to subcritical, critical, and supercritical regimes, offering a controlled setting for the application of this method to spontaneous neuronal activity, as opposed to experiments. We show that the network dynamics are well-described by Ising-like models with different distributions of disorder in their parameters, depending on the state of criticality of the networks. By introducing a temperature-like parameter T , we explore the behavior of the Ising-like models in temperature space, finding that for critical and supercritical networks the specific-heat curve has a maximum near $T = 1$ and increases with system size, suggesting a phase transition. We verify that these results are consistent with analogous maximum-entropy analyses on neuronal data from disinhibited rat cortical cultures [2].

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Excitation-inhibition balance controls information encoding in neural populations

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The brain integrates vast environmental information, with cortical encoding relying on interactions between excitatory and inhibitory populations [1, 2]. Understanding how their activity shapes the information-processing capabilities of the brain is a long-standing question in neuroscience. By focusing on a paradigmatic architecture, we show, both analytically in an exactly solvable regime and numerically for a nonlinear scenario, that the mutual information between an external input and the receiving neuronal populations is controlled at various timescales by the balance between the excitatory and inhibitory couplings [3].

We model the activity of an excitatory and inhibitory subpopulation with Langevin equations

$$\tau \frac{dx_\mu}{dt} = -r_\mu x_\mu + \sum_{\nu \in E, I} A_{\mu\nu} f(x_\nu) + h(t) + \sqrt{2D_\mu} \tau \xi_\mu$$

where τ is the neural timescale, r_μ the decay rate, ξ_μ independent white noises, f an activation function, $A_{\mu\nu}$ the synaptic connectivity, and $h(t)$ the external input.

At long timescales, the mutual information $I_{\mathbf{x},h}$ vanishes for fast switching inputs ($\tau_{\text{input}} \ll \tau$) but is bounded for slow inputs ($\tau_{\text{input}} \gg \tau$) as $I^{(b)}(\eta/4) \leq I_{\mathbf{x},h} \leq I^{(b)}(\eta)$, where $I^{(b)}(\eta) = -\sum_{i=0}^M \pi_i^{\text{st}} \log \left[\sum_{j=0}^M \pi_j^{\text{st}} e^{-(j-i)^2 \eta} \right]$ with π_i^{st} stationary distribution of the switching input and $\eta = \frac{\Delta h^2 [r + w(k - k_c)][2r^2 + (3k - 1)w + (k^2 + 1)w^2]}{4Dr w^2(k - k_c)(2r(k - k_c) + (k^2 + 1)w)}$ depending on excitation (w) and inhibition (k) strength. These bounds tighten near the edge of stability, collapsing to the input's entropy as $k \rightarrow k_c$.

At short times, in the inhibition-stabilized regime ($w > 1$), stronger excitation accelerates response. Sensitivity, defined as: $\chi_{\mathbf{x},h} = \left. \frac{\partial^2 I_{\mathbf{x},h}(t)}{\partial t^2} \right|_{t=t_{\text{stim}}} = \frac{\sigma_h^2 [r + w(k - k_c)][2wk_c^2 + r(k + 1)]}{2D 2r(k - k_c) + w(1 + k^2)}$ peaks at optimal inhibition $k_{\text{max}}(w) > 1$. Since $k_c < k_{\text{max}}(w)$, this reveals a trade-off between encoding speed and accuracy.

Overall, our findings advance our understanding of how connectivity shapes information encoding in neuronal dynamics.

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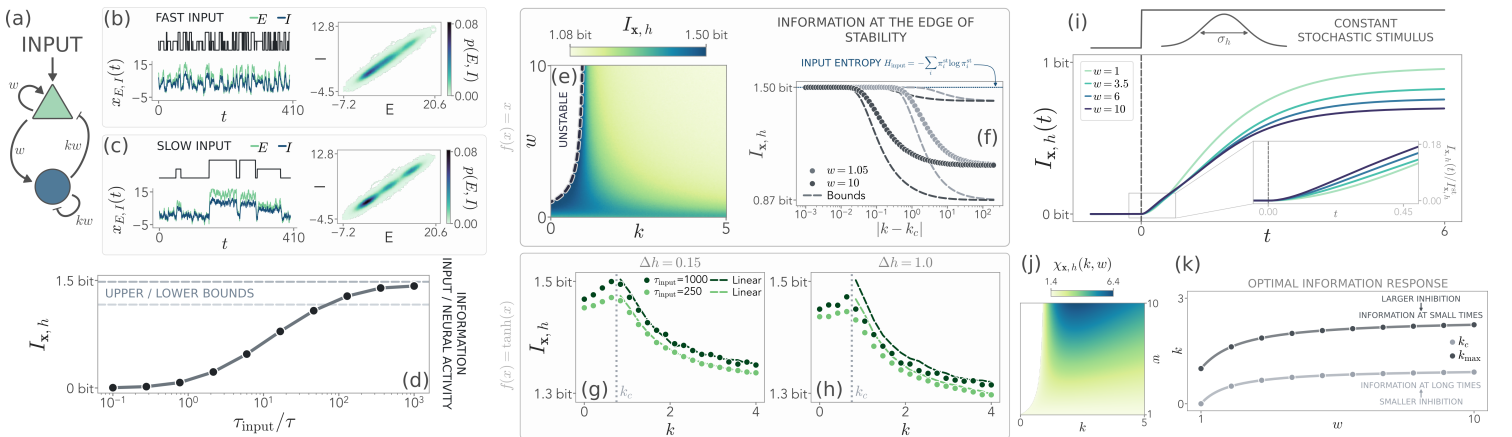


FIG. 1. (a) Sketch of the model with excitatory (E , green) and inhibitory neurons (I , blue). (b-c) A switching input $h_i = i \Delta h$ stimulates the excitatory population over a timescale τ_{input} . For $\tau_{\text{input}} \ll \tau$, neural populations cannot resolve inputs, while for $\tau_{\text{input}} \gg \tau$, activity peaks around different input strengths. (d) Mutual information is zero for fast inputs but increases sharply when $\tau_{\text{input}} \gg \tau$. (e-f) Information is maximized at the edge of stability ($k \rightarrow k_c$), converging to the input entropy H_{input} . (g-h) Nonlinear results align with the linear regime for small Δh but differ at larger values. (i) Dynamics of mutual information with constant stochastic input. (j) Sensitivity peaks at $k_{\text{max}}(w) > k_c$. (k) Greater inhibition (k) enhances short-term response, while long-term information is maximized by reducing k near k_c . Parameters: $D = 1/2$, $r = 1$, $\tau = \tau_{\text{input}} = 1$, $w = 2$, $k = 1.1$, $\Delta h = 2.5$, $\sigma_h = 1$, unless stated otherwise.

A resting-state network of oscillations and avalanches is reinforced after whisker stimulation in the barrel cortex

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Abstract

The cerebral cortex operates in a state of restless activity, even in the absence of external stimuli [1,2]. Collective neuronal activities, such as neural avalanches[3] and collective oscillations[4], are also found under resting conditions, and these features have been suggested to support sensory processing and brain readiness for rapid responses [2]. The rat barrel cortex and thalamus circuit, with its somatotopic organization for processing whisker movements, provides a powerful system to explore the interplay between spontaneous and evoked activities.

To characterize the resting state circuits, we perform multi-electrode recordings in both rats' barrel cortex and thalamus through a neural probe, both during spontaneous activity and activity after controlled whisker stimulation. We decompose the LFP signals into their frequency contents and we analyze avalanches' distributions by detecting events in MUAs activity. We then employ a mesoscopic firing rate model, fitted on real data [5], to understand the observed phenomenology.

During spontaneous activity, we find 10-15 Hz oscillations in the barrel cortex nested with slow 1-4 Hz oscillations, as well as power-law distributed avalanches, modulated by the slow oscillation. We then record neural activity during controlled whisker movements to confirm that the 10-15 Hz barrel circuit is amplified after whisker stimulation. We finally show how the thalamic-driven firing rate model can describe the entire phenomenology observed and predict the response to whisker stimulations.

Our results show that even during spontaneous activity the rat barrel cortex displays a rich dynamical state that includes avalanches and oscillations, that are amplified after the whisker stimulation.

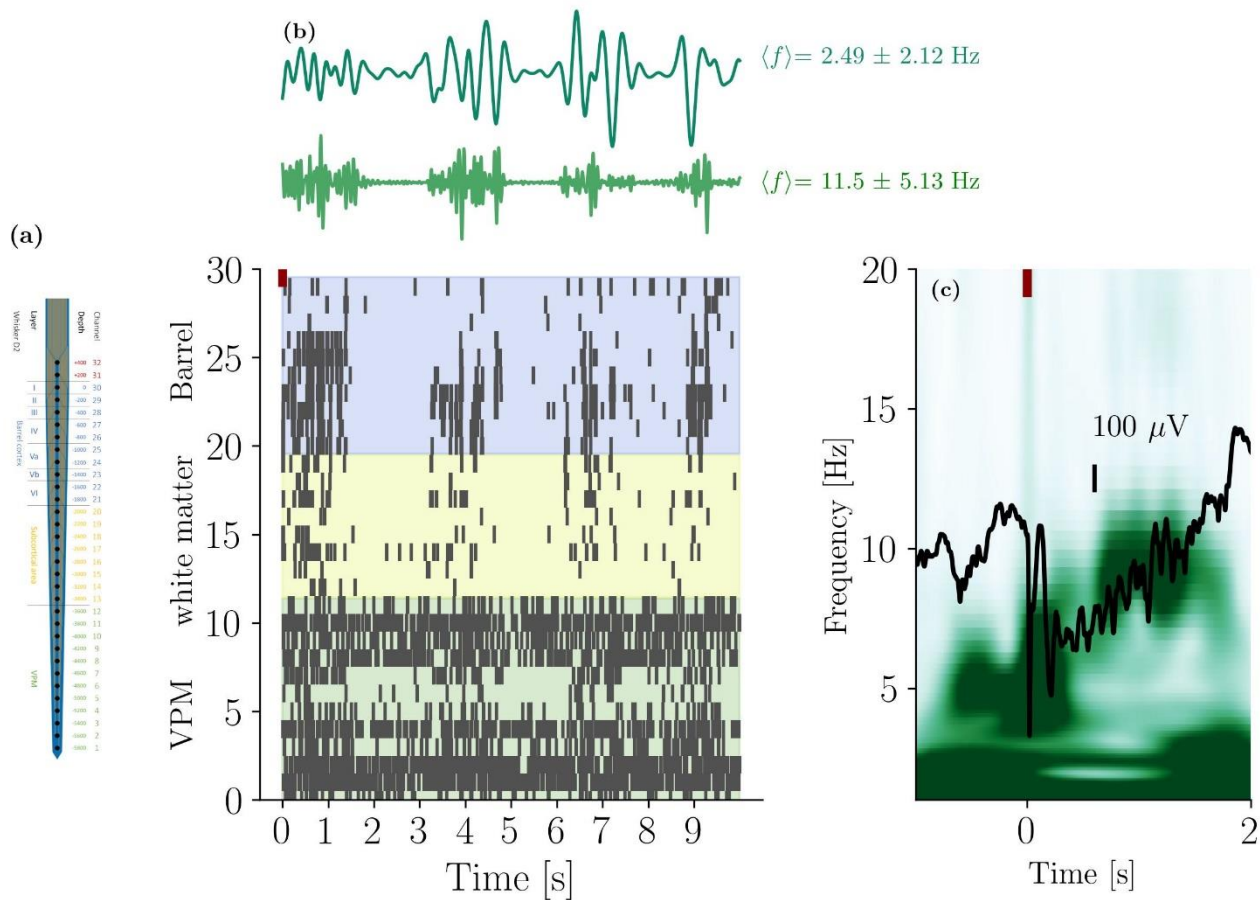


Figure. *Experimental setup and example of the quantities that are analyzed.* (a) Neural probe. The neural probe used is a 32-channel, single shank, linear probe with a pitch between the electrodes of 200 μ m. Among the total 32 channels, 30 are inserted in the brain, spanning a barrel column, a subcortical area, and part of the ventral posteromedial nucleus (BPN) of the thalamus. (b) In the bottom, an example of a 10-second long raster plot (obtained by identifying events in the MUAs activity) is shown; the stimulation of the whisker is at time zero. On the top of the raster plot two main frequency components (intrinsic mode functions (IMF) 2 and 4) that contribute to the local field potentials are shown: the one with frequencies between 1 and 4 Hz and the one with frequencies between 7 and 15 Hz. (c) A time frequency analysis in the barrel cortex after whisker stimulation is shown, averaging over all the trials. Oscillations below 4 Hz appear to be present during the whole recordings, and oscillations around 11 Hz appear after the stimulation.

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Weakly Nonlinear Theory of Echo-State Networks

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Echo-state-networks (ESN) [1,2] are known for their remarkable property of producing prescribed autonomous dynamics by learning a simple feedback to a large recurrent random network. The aim of learning is to obtain a vector of output synaptic weights \mathbf{w} such that the linear combination of network unit rates $z(t) = \sum_j w_j r[x_j(t)]$ reproduces, as best as possible, a desired function $f(t)$. ESN with simple firing rate units serve as useful conceptual models for how the brain produces movement [2] and for the role of the thalamo-cortical loop [3]. However, the principles that underly the seemingly miraculous success of learning remain incompletely understood. Here, we describe a precise theory of learning in the regime where the recurrent network evolution is stable and the feedback $z(t)$ is weak. In this weakly nonlinear regime, we show that learning the output weights \mathbf{w} amounts to i) positioning the eigenvalues of the linear dynamics at locations close to those of the Fourier frequencies of $f(t)$ and ii) constraining the weakly nonlinear dynamics to converge to the correct amplitudes for these Fourier modes. We further provide analytical predictions for when the nonlinear dynamical attractors are stable, corresponding to successful learning that is strongly network size dependent. We expect our theory to be applicable to various generalizations of the simplest setting of randomly connected firing rate units with, for instance, more complex dynamical units, or more structured networks with different unit classes.

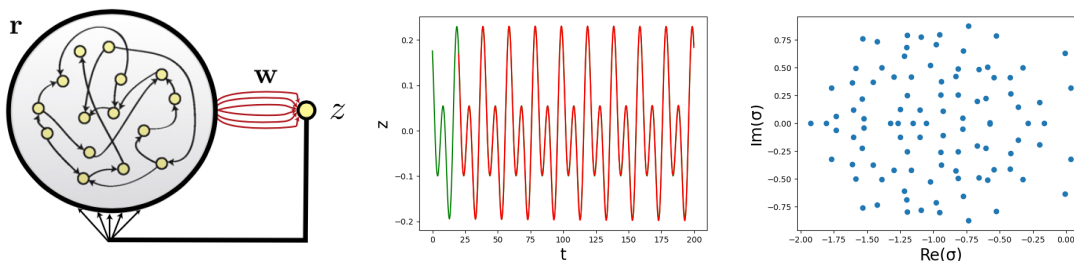


Figure 1. Left: Network schematic (adapted from [2]); (Center) One period of the function f to be learnt (green) and its network approximation z (red); (Right) Spectrum of the linear dynamics after learning showing 4 slow modes ($N=100$).

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The effect of chaotic spiking dynamics on computation through the lens of kernel functions of reservoir computers

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Reliable computation is thought to rely on a robust mapping of input to an output, also in the brain. However, even if in response to a stimulus the firing-rate of neurons in cortex can be relatively robust, both experimental and theoretical arguments suggest that spiking activity in the cortical microcircuit forms a strongly chaotic system. What is the effect of spike-chaos on dynamics and computation? Is spike-chaos "just noise" or altogether different?

We seek to systematically answer this question by casting reservoir computing in the language of kernel regression, and explore the kernel shape in the presence of spike-chaos. This kernel fully determines the effect of chaos at the level of spike-times and firing-rates on the function prior implemented by the reservoir.

For simple random binary- and rate-networks we compute the kernel analytically using a 2-replica dynamical mean-field theory. Spike-chaos leads to a sharp peak in the kernel function, which acts as an effective L2-regularizer. Spiking neurons therefore intrinsically handle outliers in a robust fashion, and this is similar to regularization by noise. However, over short times on the scale of 100ms their chaotic dynamics differs drastically from noisy dynamics: Input representations are expanded rapidly, facilitating fast non-linear computation, as opposed to noisy dynamics which only destroys information. In this way spike-chaos may support rapid computation on the scale of perceptual recognition times, while regularizing the representation similarly to effective noise over longer times.

Critical scaling exponents of hippocampal activity predict spatial memory performance

The critical brain hypothesis suggests that operating at “criticality” would endow the neural substrate with maximal information processing and storage capabilities. Experimental support for this hypothesis is, however, limited, stemming primarily from the power-law distributions in neural activity patterns, neuronal avalanches, and the scaling of coarse grained activity in the recently introduced phenomenological renormalization group. Despite the circumstantial support for the critical brain hypothesis, the functional role of criticality, and critical scaling in particular, remains heavily debated.

In this study, we investigated the potential association between measures of criticality and behaviour using the activity of simultaneously recorded hippocampal CA1 neurons in freely moving rats. Rats performed a spatial learning and recall task interleaved with sleep sessions. This setup allowed us to quantify learning performance and memory retention while, at the same time, measure signatures of criticality, in both sleep and waking sessions. The application of the phenomenological renormalization group to our data showed a collapse of activity distributions, as well as scaling of the covariance matrix spectrum, correlation times, probability of silence and the activity variance. Most importantly, during sleep sessions that followed learning, the scaling exponent for the activity variance was significantly correlated with memory retention. This is the first report experimentally linking critical properties of neural activity during sleep with functionally-relevant behavioral performance. Therefore, our results broadly support and simultaneously sharpen the scope of the brain criticality hypothesis.

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Title:

Computation with heterogeneous neural substrates

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Abstract:

Neurons and the synapses connecting them are inherently heterogeneous in their structure and electrophysiological response properties. To understand how brain function arises from networks of neurons, we must understand how the heterogeneity of neural tissue relates to that function. In this line of work, we provide novel insight into the computational role of neural heterogeneity by directly relating heterogeneity-induced changes in neural dynamics to changes in neural population function.

To this end, we derived a set of mean-field equations for spiking neural networks which allows us to determine a direct relationship between the heterogeneity of spike thresholds and the resulting low-dimensional network dynamics (Gast et al. 2023 PRE). Building on this model, we found that the heterogeneity of inhibitory interneurons plays a crucial role in shaping the dynamic regimes of neural circuits: heterogeneous inhibitory interneuron populations preserve the dynamic repertoire of local excitatory populations, whereas homogeneous interneurons overwrite excitatory dynamic repertoires and facilitate synchronized dynamics (Gast et al. 2024 PNAS). Furthermore, we discovered that neural heterogeneity directly controls the encoding capacity of populations of recurrently coupled excitatory neurons by affecting the multistable dynamic regime of the population.

Going beyond our published work, we recently identified opposing roles of synaptic and neural heterogeneity for controlling the dynamical regimes of neural networks (see Fig.1). Using the framework of low-rank RNNs, we discuss how neuromodulatory control of neural vs. synaptic heterogeneity can be leveraged for learning, computation, and task switching.

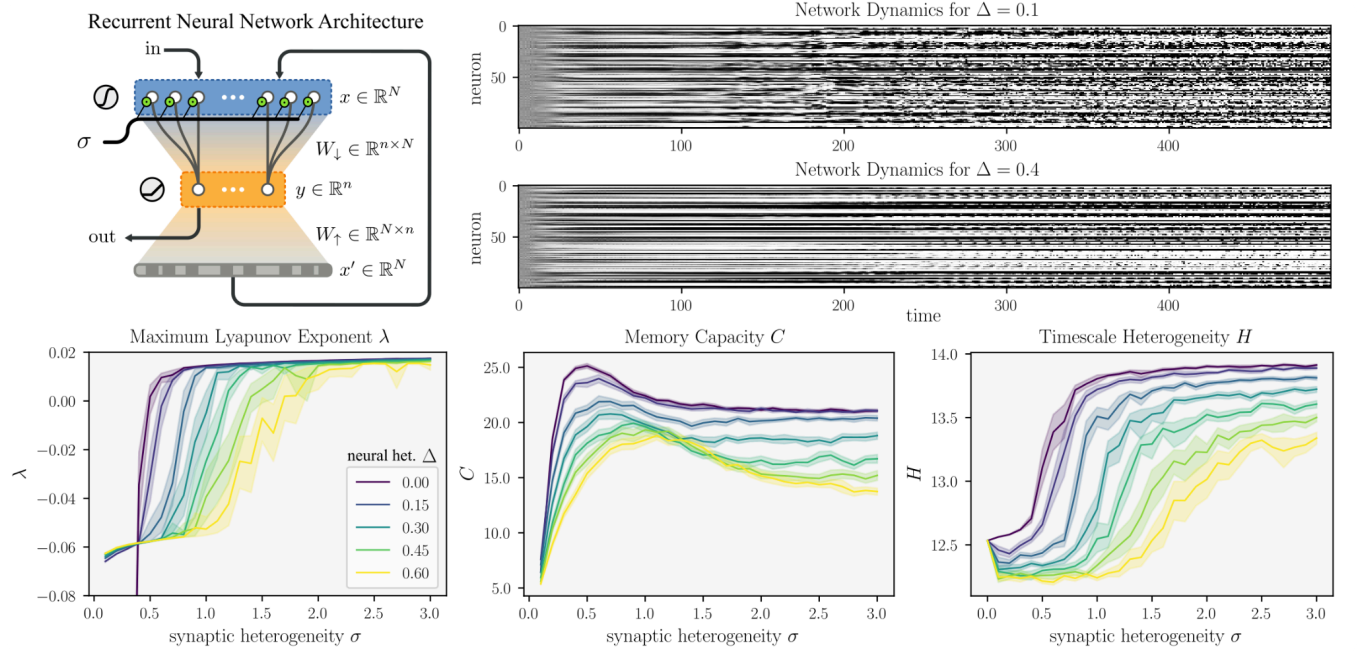


Figure 1: Differential Effects of Neural vs. Synaptic Heterogeneity on Low-Rank RNNs. All results were obtained in randomly initialized RNNs ($N = 2000$ and $n = 200$) subject to white noise input. **Top row:** Exemplary network dynamics were generated for two different levels of neural heterogeneity Δ , where neuromodulatory control of synaptic heterogeneity was slowly increased from $\sigma = 0$ to $\sigma = 3$. **Bottom row:** Synaptic heterogeneity acts as the main control parameter to destabilize RNN dynamics and induce a transition to chaotic dynamics. Neural heterogeneity has a stabilizing effect, making the transition to chaos less abrupt. Neural heterogeneity makes the computational capacity of the system more stable to small changes in synaptic heterogeneity, at the cost of a reduction in the overall computational capacity.