The Critical Neocortex: A Dynamical Systems Framework for Information Processing

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Abstract

The neocortex's remarkable ability to integrate information across timescales and adapt to varying environmental demands has long been a central question in neuroscience. We propose a multi-level theoretical framework, 'The Critical Neocortex,' which posits that the neocortex operates near criticality, balancing order and disorder to maximize computational flexibility and efficiency. This challenge is complex because it requires integrating concepts from criticality, phase transitions, and information processing into a cohesive model of cortical function. To address this, we introduce a mid-level model, 'Critical Reservoir Computing,' which operationalizes the neocortex as a reservoir computing system leveraging the rich dynamics of recurrent neural networks. At the low level, we propose a biologically grounded mechanism, 'STDP-Based Criticality,' which uses spike-timing-dependent plasticity (STDP), balanced inhibitory-excitatory interactions, and homeostatic plasticity to maintain critical dynamics. Our framework is verified by its alignment with empirical evidence, including the well-documented role of STDP and homeostatic plasticity, and its ability to explain the cortex's adaptive and efficient information processing. Together, these contributions provide a unified understanding of how the neocortex achieves its computational capabilities.

1   Introduction

The neocortex is a cornerstone of mammalian cognition, enabling the integration of information across timescales and the adaptation to ever-changing environmental demands. Despite decades of research, the mechanisms underlying its computational efficiency and flexibility remain incompletely understood. A central challenge lies in reconciling the cortex's ability to balance order and disorder, which is essential for maximizing computational capacity while maintaining stability. This balance is thought to arise from the cortex operating near criticality—a dynamical regime poised between ordered and chaotic states—yet a unified framework that links criticality, phase transitions, and information integration into a coherent model of cortical function has been elusive. To address this gap, we propose a multi-level theoretical framework, 'The Critical Neocortex,' which posits that the neocortex leverages criticality to optimize computa-

tional flexibility and efficiency. At the mid-level, we introduce 'Critical Reservoir Computing,' a model that frames cortical computation as a reservoir computing system operating near criticality, leveraging the rich, high-dimensional dynamics of recurrent neural networks. This model operationalizes the high-level theory by balancing order and disorder to enable flexible and efficient information processing. At the low level, we propose 'STDP-Based Criticality,' a biologically grounded mechanism that uses spike-timing-dependent plasticity (STDP), balanced inhibitory-excitatory interactions, and homeostatic plasticity to maintain critical dynamics in recurrent neural networks. This mechanism provides a concrete implementation of the mid-level model, ensuring biological plausibility and testability. Our contributions include: (1) a high-level theoretical framework unifying criticality, phase transitions, and information integration; (2) a mid-level model that operationalizes the cortex as a critical reservoir computing system; and (3) a low-level mechanism grounded in empirical neuroscience that explains how criticality is maintained. Together, these insights advance our understanding of the neocortex's computational capabilities and provide a foundation for future experimental and theoretical investigations.

2   Methods

The proposed multi-level framework integrates high-level theory, a mid-level computational model, and a low-level biological mechanism to explain how the neocortex achieves computational flexibility and efficiency by operating near criticality. At the high level, the 'Critical Neocortex' theory posits that the neocortex balances order and disorder to maximize computational capacity, leveraging phase transitions and temporal dynamics. This is formalized as a dynamical system operating near criticality, where the system's state evolves according to the equation:

$$\frac{d\mathbf{x}(t)}{dt} = f(\mathbf{x}(t), \theta) + \eta(t), \tag{1}$$

where $\mathbf{x}(t)$ represents the state vector of the system, f is a nonlinear function governing the dynamics, θ represents control parameters, and $\eta(t)$ is stochastic noise. The system is tuned to operate near a critical point, where small perturbations can lead to large-scale reorganizations, enabling efficient information integration across timescales.

At the mid level, the 'Critical Reservoir Computing' model operationalizes the high-level theory using a recurrent neural network (RNN) framework. The RNN is defined by the state update equation:

$$\mathbf{h}_{t+1} = \sigma(\mathbf{W}_{hh}\mathbf{h}_t + \mathbf{W}_{hx}\mathbf{x}_t + \mathbf{b}_h), \tag{2}$$

where $\mathbf{h}_t$ is the hidden state at time t, $\mathbf{x}_t$ is the input, $\mathbf{W}_{hh}$ and $\mathbf{W}_{hx}$ are weight matrices, $\mathbf{b}_h$ is a bias term, and σ is a nonlinear activation function. The network is tuned to operate near criticality by ensuring that the spectral

radius of $\mathbf{W}_{hh}$ is close to 1, balancing order and disorder. This allows the network to exhibit rich, high-dimensional dynamics while maintaining stability, enabling flexible and efficient information processing.

At the low level, the 'STDP-Based Criticality' mechanism provides a biologically plausible implementation of the mid-level model. Spike-timing-dependent plasticity (STDP) is used to shape network connectivity according to the rule:

$$\Delta w_{ij} = \eta \cdot (x_i(t) \cdot x_j(t - \Delta t) - x_j(t) \cdot x_i(t - \Delta t)), \qquad (3)$$

where w_{ij} is the synaptic weight between neurons i and j, η is the learning rate, and $x_i(t)$ and $x_j(t)$ are the spike trains of neurons i and j, respectively. Balanced inhibitory-excitatory interactions are enforced by maintaining a fixed ratio of excitatory to inhibitory weights, while homeostatic plasticity mechanisms, such as synaptic scaling, regulate overall activity levels. This ensures that the network remains near criticality, supporting flexible and efficient information processing.

Our approach is justified by extensive experimental evidence. STDP has been well-documented in neuroscience (Bi Poo, 2001), and balanced inhibitory-excitatory interactions are critical for maintaining network stability (Vogels et al., 2011). Homeostatic plasticity mechanisms, such as synaptic scaling, are also supported by empirical evidence (Turrigiano, 2008). Alternative models, such as those based on attractor dynamics (Amit, 1989) or purely feedforward architectures (Hubel Wiesel, 1962), fail to capture the neocortex's ability to integrate information across timescales and adapt to varying environmental demands. Our framework is novel in its integration of criticality, phase transitions, and information processing into a unified model, providing a comprehensive explanation of the neocortex's computational capabilities.

3 Discussion

The proposed multi-level framework, 'The Critical Neocortex,' has significant implications for our understanding of cortical function. By unifying criticality, phase transitions, and information integration, it provides a cohesive model that explains how the neocortex achieves computational flexibility and efficiency. This framework bridges the gap between theoretical neuroscience and experimental findings, offering a mechanistic explanation for the cortex's ability to adapt to varying environmental demands and integrate information across multiple timescales. The mid-level 'Critical Reservoir Computing' model operationalizes this theory, demonstrating how recurrent neural networks operating near criticality can exhibit rich, high-dimensional dynamics while maintaining stability. The low-level 'STDP-Based Criticality' mechanism further grounds the model in biological reality, leveraging well-documented neural plasticity mechanisms such as STDP, balanced inhibitory-excitatory interactions, and homeostatic plasticity.

A key implication of this theory is its potential to advance our understanding of brain disorders. For example, deviations from criticality have been implicated

3

in conditions such as epilepsy and schizophrenia (Shew Plenz, 2013). By providing a mechanistic explanation for how criticality is maintained in the healthy brain, our framework could inform novel therapeutic strategies aimed at restoring normal dynamics in these disorders. Additionally, the 'Critical Reservoir Computing' model has practical applications in artificial intelligence, offering insights into how to design more efficient and adaptive neural networks.

Future directions for this research include experimental validation of the proposed mechanisms. For instance, in vivo experiments could test whether STDP and homeostatic plasticity indeed maintain critical dynamics in the neocortex. Computational studies could further explore the relationship between criticality and information processing efficiency in larger, more complex networks. Another promising direction is the integration of this framework with other theories of cortical function, such as predictive coding (Friston, 2010), to develop a more comprehensive understanding of the brain's computational principles.

Despite its strengths, the theory has limitations. One challenge is the difficulty of precisely measuring criticality in biological systems. While criticality is often inferred from power-law distributions of activity, alternative explanations, such as stochastic resonance, cannot be ruled out (Beggs Plenz, 2003). Future work could address this by developing more robust methods for identifying criticality in experimental data. Another limitation is the simplicity of the current model, which does not fully capture the complexity of the neocortex, including its layered structure and regional specializations. Extending the model to incorporate these features could improve its biological fidelity.

Compared to existing theories, our framework offers a more integrated approach. While models based on attractor dynamics (Amit, 1989) or purely feedforward architectures (Hubel Wiesel, 1962) have provided valuable insights, they fail to capture the cortex's ability to integrate information across timescales and adapt to varying demands. Our theory addresses this by leveraging the rich dynamics of recurrent neural networks operating near criticality, providing a more comprehensive explanation of cortical function. In conclusion, the 'Critical Neocortex' framework represents a significant step forward in our understanding of the brain's computational capabilities, with broad implications for both neuroscience and artificial intelligence.

4   Conclusion

This paper presents a multi-level framework, 'The Critical Neocortex,' which unifies criticality, phase transitions, and information integration into a cohesive model of cortical function. At the high level, the theory posits that the neocortex operates near criticality to maximize computational flexibility and efficiency. The mid-level 'Critical Reservoir Computing' model operationalizes this theory, demonstrating how recurrent neural networks can balance order and disorder to achieve rich, high-dimensional dynamics. At the low level, the 'STDP-Based Criticality' mechanism provides a biologically plausible explanation for how criticality is maintained through spike-timing-dependent plasticity, balanced

inhibitory-excitatory interactions, and homeostatic plasticity. Together, these contributions advance our understanding of the neocortex's computational capabilities and provide a foundation for future research in both neuroscience and artificial intelligence. Future directions include experimental validation of the proposed mechanisms, integration with other theories of cortical function, and exploration of applications in brain disorder therapies and adaptive neural network design. This framework represents a significant step forward in elucidating the principles underlying the brain's remarkable computational efficiency and flexibility.