

The Energy-Minimizing Neocortex: A Self-Organizing Framework for Information Processing

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Abstract

The neocortex is a highly efficient information-processing system, yet the principles governing its ability to balance stability and adaptability remain poorly understood. Here, we propose a unified framework, the Energy-Minimizing Neocortex, which posits that the cortex operates as a self-organizing system that minimizes energy expenditure while maximizing information efficiency. This framework integrates predictive coding, attractor dynamics, and information theory to explain how the cortex dynamically adjusts its processing to optimize predictions, compress information, and maintain robust representations. To operationalize this theory, we introduce the Predictive Energy Minimization model, which frames neocortical computation as a predictive coding process that minimizes energy expenditure by reducing prediction errors, balancing stability and adaptability. At the mechanistic level, we propose an STDP-Based Energy Minimization mechanism, leveraging spike-timing-dependent plasticity (STDP) to minimize prediction errors through synaptic adjustments, supported by balanced inhibitory-excitatory interactions and homeostatic plasticity. This mechanism provides a biologically plausible basis for real-time, energy-efficient learning. The feasibility of our model is supported by its alignment with established principles of predictive coding and attractor dynamics, while the testability of the mechanism is grounded in well-documented neural phenomena such as STDP and synaptic scaling. Together, this multi-level framework offers a cohesive and empirically grounded explanation of cortical function, bridging theoretical insights with biological mechanisms.

1 Introduction

The neocortex is a marvel of biological computation, capable of processing vast amounts of information with remarkable efficiency and adaptability. Despite decades of research, the principles underlying its ability to balance stability and adaptability remain elusive. A key challenge lies in understanding how the cortex minimizes energy expenditure while maximizing information efficiency, a problem that spans multiple levels of analysis—from high-level theoretical

frameworks to low-level neural mechanisms. To address this challenge, we propose the Energy-Minimizing Neocortex framework, which posits that the cortex operates as a self-organizing system that dynamically adjusts its processing to optimize predictions, compress information, and maintain robust representations. This framework unifies predictive coding, attractor dynamics, and information theory into a cohesive model of cortical function, offering a novel perspective on how the brain achieves its computational feats. At the mid-level, we introduce the Predictive Energy Minimization model, which operationalizes this framework by framing neocortical computation as a predictive coding process that minimizes energy expenditure through the reduction of prediction errors. This model integrates attractor dynamics and self-organization to explain how the cortex robustly represents and updates information while maintaining energy efficiency. At the low level, we propose the STDP-Based Energy Minimization mechanism, which leverages spike-timing-dependent plasticity (STDP) to minimize prediction errors through synaptic adjustments, supported by balanced inhibitory-excitatory interactions and homeostatic plasticity. This mechanism provides a biologically plausible basis for real-time, energy-efficient learning, bridging the gap between theoretical models and empirical neuroscience. The significance of this work lies in its ability to unify disparate theories and mechanisms into a coherent framework, offering new insights into the principles of cortical function. Key contributions of this research include: (1) a high-level theory that integrates predictive coding, attractor dynamics, and information theory into a unified model of the energy-minimizing neocortex; (2) a mid-level computational model that operationalizes this theory through predictive energy minimization, balancing stability and adaptability; and (3) a low-level neural mechanism that implements this model using STDP, balanced inhibition, and homeostatic plasticity, grounded in empirical evidence. Together, these contributions advance our understanding of how the neocortex achieves its remarkable computational efficiency and adaptability, providing a foundation for future research in neuroscience and artificial intelligence.

2 Methods

The Energy-Minimizing Neocortex framework is grounded in the principle that the neocortex operates as a self-organizing system that minimizes energy expenditure while maximizing information efficiency. This framework integrates three key theoretical components: predictive coding, attractor dynamics, and information theory. Predictive coding posits that the brain generates predictions about sensory inputs and minimizes the error between predictions and actual inputs. Attractor dynamics describe how neural networks settle into stable states, enabling robust representation of information. Information theory provides a quantitative framework for understanding how the cortex compresses and processes information efficiently. Together, these components form a cohesive model of cortical function that explains how the brain balances stability and adaptability. At the mid-level, the Predictive Energy Minimization model op-

erationalizes this framework by framing neocortical computation as a predictive coding process. The model minimizes energy expenditure by reducing prediction errors, which are defined as the difference between predicted and actual neural activity. Mathematically, the prediction error E is given by:

$$E = \sum_i (y_i - \hat{y}_i)^2 \quad (1)$$

y_i is the actual neural activity and \hat{y}_i is the predicted activity. The model dynamically adjusts neural activity to minimize E , ensuring that the system remains both stable and adaptable. This is achieved through a combination of attractor dynamics, which stabilize the network, and self-organization, which allows the system to adapt to new information. The model is implemented algorithmically as follows: 1. Initialize neural activity y_i and predictions \hat{y}_i . 2. Compute prediction error E using the equation above. 3. Update neural activity to minimize E using gradient descent. 4. Update predictions \hat{y}_i based on the new activity. 5. Repeat steps 2-4 until convergence. The model is novel in its integration of predictive coding with attractor dynamics and energy efficiency, addressing limitations of previous models that focus on only one of these aspects. For example, traditional predictive coding models often neglect the role of attractor dynamics in stabilizing neural activity, while models of attractor dynamics typically do not incorporate predictive coding. Our model bridges this gap, providing a more comprehensive explanation of cortical function. At the low level, the STDP-Based Energy Minimization mechanism implements the Predictive Energy Minimization model using biologically plausible neural mechanisms. This mechanism leverages spike-timing-dependent plasticity (STDP), a well-documented form of synaptic plasticity in which the strength of a synapse is modified based on the relative timing of pre- and post-synaptic spikes. STDP is used to minimize prediction errors by strengthening synapses that predict neural activity and weakening those that do not. Mathematically, the change in synaptic weight Δw is given by:

$$\Delta w = \eta \cdot (t_{\text{post}} - t_{\text{pre}}) \quad (2)$$

η is the learning rate, and t_{post} and t_{pre} are the times of post- and pre-synaptic spikes, respectively. Balanced inhibitory-excitatory interactions stabilize network dynamics, preventing runaway excitation or inhibition. Homeostatic plasticity mechanisms, such as synaptic scaling, ensure long-term stability by maintaining synaptic weights within a functional range. These mechanisms are supported by extensive experimental evidence, including studies on STDP (Bi & Poo, 1998) and homeostatic plasticity (Turrigiano, 1999). The STDP-Based Energy Minimization mechanism is novel in its application of STDP to minimize prediction errors, a departure from traditional uses of STDP in unsupervised learning. This approach is supported by recent experimental findings that suggest STDP plays a role in predictive coding (Brea et al., 2016). By integrating STDP with balanced inhibition and homeostatic plasticity, our mechanism provides a biologically plausible basis for real-time, energy-efficient learning in the cortex. This distinguishes our work from previous attempts, such as the Bayesian

Confidence Propagation Neural Network (BCPNN) (Lansner Ekeberg, 1989), which focuses on Bayesian inference but does not incorporate energy efficiency or predictive coding. Our framework thus offers a more comprehensive and biologically grounded explanation of cortical function.

3 Discussion

The Energy-Minimizing Neocortex framework offers a novel and unifying perspective on cortical function, integrating predictive coding, attractor dynamics, and information theory into a cohesive model. This framework has significant implications for neuroscience, as it provides a principled explanation for how the neocortex balances stability and adaptability while minimizing energy expenditure. By framing cortical computation as a predictive coding process that dynamically adjusts neural activity to reduce prediction errors, the framework bridges the gap between high-level theoretical models and low-level neural mechanisms. This has the potential to advance our understanding of brain function, particularly in areas such as perception, learning, and memory, where the balance between stability and adaptability is crucial.

One of the key implications of this framework is its ability to explain the efficiency of cortical information processing. By minimizing energy expenditure while maximizing information efficiency, the framework provides a mechanistic basis for the brain’s ability to process vast amounts of information with limited resources. This has important implications for both neuroscience and artificial intelligence, as it suggests new principles for designing energy-efficient computational systems. For example, the framework could inspire the development of new algorithms for machine learning that incorporate predictive coding and energy minimization, potentially leading to more efficient and robust AI systems.

Future directions for this research include experimental validation of the proposed mechanisms and further development of the computational model. Experimental studies could test the predictions of the STDP-Based Energy Minimization mechanism, particularly its role in minimizing prediction errors and balancing stability with adaptability. Additionally, the computational model could be extended to include more detailed representations of cortical circuits, such as the role of specific types of inhibitory interneurons or the impact of neuromodulators on plasticity. These extensions would provide a more comprehensive understanding of cortical function and could lead to new insights into neurological disorders, such as epilepsy or schizophrenia, where the balance between excitation and inhibition is disrupted.

Despite its strengths, the Energy-Minimizing Neocortex framework has several limitations that need to be addressed. One limitation is the complexity of the model, which integrates multiple theoretical components and mechanisms. This complexity makes it challenging to fully test the framework experimentally, as it requires precise measurements of neural activity and plasticity in vivo. Another limitation is the reliance on STDP as the primary mechanism for minimizing prediction errors, which may not fully capture the diversity of synap-

tic plasticity mechanisms in the cortex. Future research could explore the role of other forms of plasticity, such as long-term potentiation (LTP) and long-term depression (LTD), in the context of predictive coding and energy minimization.

In comparison to existing theories, the Energy-Minimizing Neocortex framework offers a more comprehensive and integrative approach to understanding cortical function. Traditional predictive coding models, such as those proposed by Rao and Ballard (1999), focus primarily on the role of prediction errors in perception but do not incorporate attractor dynamics or energy efficiency. Similarly, models of attractor dynamics, such as the Hopfield network (Hopfield, 1982), provide a framework for stable information representation but do not account for predictive coding or energy minimization. By integrating these components, our framework provides a more holistic explanation of cortical function, addressing limitations of previous models and offering new insights into the principles of brain computation.

In conclusion, the Energy-Minimizing Neocortex framework represents a significant step forward in our understanding of cortical function. Its implications for neuroscience and artificial intelligence are far-reaching, and its integration of predictive coding, attractor dynamics, and energy efficiency provides a novel and comprehensive model of brain computation. While there are limitations to the framework, future research has the potential to address these challenges and further refine our understanding of the neocortex. This work opens new avenues for exploring the principles of brain function and designing energy-efficient computational systems, with potential applications in both basic science and technology.

4 Conclusion

This paper presents the Energy-Minimizing Neocortex framework, a unified model of cortical function that integrates predictive coding, attractor dynamics, and information theory. By framing the neocortex as a self-organizing, energy-minimizing system, the framework explains how the brain balances stability and adaptability while optimizing information processing. The Predictive Energy Minimization model operationalizes this framework, demonstrating how the cortex minimizes energy expenditure by reducing prediction errors and dynamically adjusting neural activity. At the mechanistic level, the STDP-Based Energy Minimization mechanism provides a biologically plausible basis for this process, leveraging STDP, balanced inhibition, and homeostatic plasticity to enable energy-efficient, real-time learning. Together, these contributions offer a comprehensive and integrative explanation of cortical function, bridging theoretical models with empirical neuroscience. The framework has significant implications for understanding brain computation and designing energy-efficient artificial systems. Future research should focus on experimental validation of the proposed mechanisms, extensions of the computational model, and exploration of its applications in neuroscience and AI. This work advances our understanding of the neocortex and opens new avenues for interdisciplinary research in

brain-inspired computation.