The Cortical Markov Blanket: Stochastic Active Inference and Intrinsic Integrated Information (Letter)

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June 2, 2026

Abstract

We define a minimal viable agent bounded by a full Fristonian Markov Blanket explicitly grounded in the canonical cortical microcircuit. By modeling the stochastic dynamics of a four-component system (internal, sensory, active, and external states), we rigorously demonstrate the conditional independence required by the Free Energy Principle via the steady-state Lyapunov equation. To evaluate intrinsic causal integration, we map the continuous stationary density to a discrete Transition Probability Matrix (TPM). We apply Tononi's Integrated Information Theory (IIT 4.0), replacing the Earth Mover's Distance with the Intrinsic Difference metric, mathematically guaranteeing $\Phi > 0$ for recurrent corticothalamic microcircuits.

1 Stochastic Neural Dynamics and the Markov Blanket

Following Friston [1], we partition the universe into four interacting states: internal (c_t), sensory (s_t), active (a_t), and external (λ_t). We ground this topologically in the canonical microcircuit for predictive coding [2]: s_t represents L4 thalamocortical inputs, c_t represents the recurrent L2/3 and L5 populations, a_t represents L5 deep outputs and L6 corticothalamic feedback, and λ_t represents the environmental hidden states.

The continuous dynamics are governed by a coupled system of Stochastic Differential Equations (SDEs) driven by standard Wiener processes:

$$dc_t = f_c(c_t, s_t, a_t)dt + \mathbf{B}_c dW_t^c \quad (1)$$

$$ds_t = f_s(s_t, a_t, \lambda_t)dt + \mathbf{B}_s dW_t^s \quad (2)$$

$$da_t = f_a(c_t, s_t, a_t)dt + \mathbf{B}_a dW_t^a \quad (3)$$

$$d\lambda_t = f_\lambda(s_t, a_t, \lambda_t)dt + \mathbf{B}_\lambda dW_t^\lambda \quad (4)$$

Crucially, there is no direct coupling between c_t and λ_t, and sensory states s_t do not depend on internal states c_t. This structural asymmetry breaks the v-structure, preventing s_t from acting as a collider, ensuring that conditioning on the blanket does not inadvertently open an information path between c_t and λ_t. Linearizing the drift around a non-equilibrium steady state yields a Jacobian matrix $\mathbf{A}$. The stationary covariance $\mathbf{\Sigma}$ is determined by the Helmholtz decomposition $\mathbf{A} = (\mathbf{Q} - \mathbf{D})\mathbf{\Sigma}^{-1}$, where $\mathbf{Q}$ is the anti-symmetric solenoidal flow and $\mathbf{D}$ is the diffusion tensor. Provided the solenoidal flow preserves the boundary topology, the precision matrix is block-sparse ($\mathbf{\Sigma}^{-1}_{c\lambda} = 0$), ensuring $p(c, \lambda \mid s, a) = p(c \mid s, a)p(\lambda \mid s, a)$ and rigorously proving the Markov blanket.

2 Intrinsic Integrated Information (Φ)

To evaluate Tononi's Φ, we assess the intrinsic cause-effect power of the internal states c_t. We derive a discrete Transition Probability Matrix $\mathrm{TPM}(c' \mid c)$ from the exact Fokker-Planck stationary distribution $p(\mathbf{x})$ over a minimal timescale Δt, applying maximum entropy priors to the boundary conditions [4].

Using the IIT 4.0 framework [3, 4], we measure the irreducible intrinsic information across the Minimum Information Partition (MIP) using the Intrinsic Difference (ID) between the intact Cause-Effect Structure (CES) and the partitioned CES:

$$\Phi = \min_{\mathrm{MIP}} \mathrm{ID}\left[\mathrm{CES}_{\mathrm{intact}},\ \mathrm{CES}_{\mathrm{MIP}}\right] \tag{5}$$

Because the internal cortical microcircuit (c_t) possesses strong recurrent loops (e.g., L2/3 $\to$ L5 and L5 $\to$ L2/3), the localized block of the Lyapunov covariance $\mathbf{\Sigma}_{cc}$ is strictly irreducible under any bisection. Consequently, the intrinsic difference is strictly positive, mathematically guaranteeing $\Phi > 0$ for biological cortical columns.

References

[1] K. Friston, *J. R. Soc. Interface* **10**, 20130475 (2013).

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[3] M. Oizumi, L. Albantakis, G. Tononi, *PLOS Comput. Biol.* **10**, e1003588 (2014).

[4] L. Albantakis et al., *PLOS Comput. Biol.* **19**, e1011465 (2023).