ePC: Fast and Deep Predictive Coding in Digital Simulation

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Predictive Coding (PC) offers a brain-inspired alternative to backpropagation for neural network training, described as a physical system minimizing its internal energy (Bogacz 2017; Whittington and Bogacz 2017, 2019; Millidge et al. 2022). While ideally suited for analog implementation, such hardware does not exist yet, and thus, in practice, PC is predominantly *digitally simulated*, requiring excessive amounts of compute while struggling to scale to deeper architectures (Pinchetti et al. 2025).

Our work reformulates PC to overcome this hardware-algorithm mismatch. First, we uncover how the canonical state-based formulation of PC (sPC) is, by design, deeply inefficient in digital simulation, inevitably resulting in exponential signal decay that stalls the entire numerical process. Then, to overcome this fundamental limitation, we introduce error-based PC (ePC), a novel reparameterization of PC which does not suffer from signal decay. Though no longer directly implementable in analog, ePC numerically computes *exact* PC weights gradients and runs orders of magnitude faster than sPC.

Experiments across multiple architectures and datasets demonstrate that (e)PC matches backpropagation's performance even for deeper models where sPC struggles. Besides practical improvements, our work provides theoretical insight into PC dynamics and establishes a foundation for scaling PC-based learning to deeper architectures in digital simulation while opening the path towards analog.

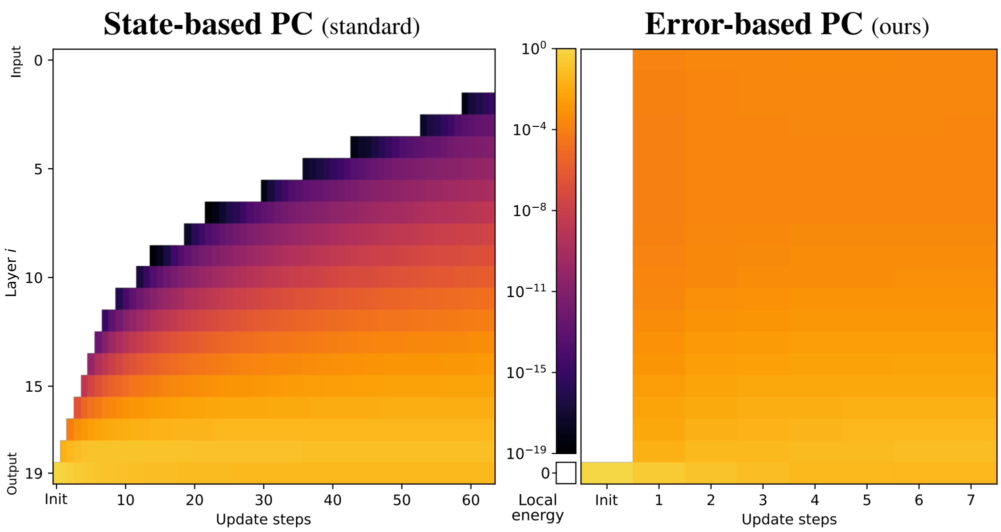

Figure 1: **Simulated dynamics of layerwise energies in Predictive Coding, demonstrating our main findings.** Standard state-based PC struggles to propagate signals through the network (from output to input), with progressively longer delays at deeper layers. By contrast, error-based PC converges to equilibrium in just a few update steps, thanks to its global signal propagation. Results for an untrained 20-layer MLP on a random MNIST input.

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