摘要

理解大脑如何实现高效学习，是计算神经科学与类脑智能领域长期关注的重大科学问题。尽管反向传播算法在深度学习中已取得巨大成功，但生物大脑中是否存在类似的基于梯度的高效学习机制，以及神经元树突计算是否能够支撑这样一种机制，仍是未解之谜。传统神经科学研究主要集中于以赫布学习规则为代表的无监督学习，而对于树突尺度上生物可行的有监督学习机制，迄今尚未形成清晰的理论。同时，现有类脑智能领域虽然广泛采用梯度优化算法，但其神经网络受限于简化的神经元模型，无法体现真实神经元依靠树突结构所展现的强大计算能力。

为破解上述难题，本文以树突计算（dendritic computation）的生物学机制为出发点，基于生物物理细节丰富的精细多舱室神经元模型（biophysically detailed multi-compartment model），提出了一系列树突计算驱动、基于梯度的精细神经元高效学习方法。这些方法根据树突计算复杂度的递进，系统地解决了从**被动树突**（仅通过膜电位扩散整合输入）到**主动树突**（具备门控电流通道，可主动调控输入信号）环境下的梯度优化难题，首次建立了树突尺度上高效有监督学习的完整理论框架。本文工作的主要创新点如下：

第一，针对树突计算研究中应用最广泛的被动树突模型，提出基于被动树突稳态计算和暂态计算的稳态替代模型和暂态替代模型，以及对应的精细神经元学习方法。稳态替代模型在 DeepDendrite 平台上实现了具有复杂（被动）树突结构的深度精细神经网络在数据驱动任务上的高效训练。暂态替代模型则突破稳态假设限制，实现了主动树突在暂态条件下的显式梯度计算和高效训练，并首次应用于 BAAIWorm 线虫精细神经网络模型的训练，可以准确重构线虫生理实验观测到的钙信号特征，并驱动线虫接近生物真实的运动行为，通过消融实验揭示了神经网络结构对线虫行为模式的关键调控作用。

第二，进一步突破性地发现并严格证明了精细神经元梯度计算与神经元数值仿真过程之间的数学等价性，提出了一种名为“前向回放梯度仿真”的创新学习方法。该方法通过精细神经元前向回放特定电流的数值仿真过程，可以高效准确地求解主动树突突触权重梯度，为生物神经元如何利用自身生理机制实现梯度计算提供了理论依据。

第三，基于前述梯度仿真方法，通过深入分析梯度成分，进一步提出更加高效的“反向回放学习方法”，极大降低了精细神经元突触权重梯度的计算成本，实验表明结合该方法可以在大幅减少计算开销的同时仍能达到与精确梯度方法相媲美的学习性能。此外，本文创新性地设计了顶树突调控的条件选择实验，成功展示了精细神经元模型

可以通过树突计算高效解决传统点神经元模型难以完成的复杂学习任务，进一步凸显了树突计算带来的显著计算优势。

综上所述，本文首次系统解决了树突计算驱动下精细神经元尺度上的高效有监督学习问题，不仅验证了树突尺度学习方法的高效性与生物真实性，还明确揭示了树突计算对神经网络系统级功能的重要贡献。本文的工作为理解大脑高效学习机制提供了全新理论基础和方法论支撑，推动类脑智能与计算神经科学领域迈向更加智能、高效且生物可行的新型智能体系。

关键词：计算神经科学，类脑智能，神经动力学，脉冲神经网络，树突计算

Dendritic Computation-driven Learning Methods for Biophysically Detailed Neuron Models

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ABSTRACT

Understanding how the brain achieves efficient learning remains a fundamental and longstanding scientific question in computational neuroscience and brain-inspired intelligence research. Although the backpropagation algorithm has achieved remarkable success in deep learning, it remains unclear whether the biological brain employs a similar gradient-based efficient learning mechanism, and whether neuronal dendritic computation could support such a mechanism. Traditional neuroscience studies primarily focus on unsupervised learning mechanisms, exemplified by Hebbian plasticity. However, a clear theoretical framework for biologically plausible supervised learning at the dendritic scale is yet to be established. Meanwhile, existing studies in brain-inspired intelligence predominantly utilize simplified point-neuron models optimized by gradient-based algorithms, neglecting the powerful computational potential inherent to real neurons with complex dendritic structures.

To address these gaps, this dissertation takes dendritic computation mechanisms as a biological basis, and employs biophysically detailed multi-compartment neuron models to propose a series of dendrite-driven, gradient-based efficient learning methods for detailed neuron models. These methods systematically tackle the gradient optimization challenge, progressively from passive dendrites (integrating inputs through passive voltage diffusion) to active dendrites (actively regulating inputs via voltage-gated ion channels), establishing for the first time a comprehensive theoretical framework for efficient supervised learning at the dendritic level. The main innovations include:

First, focusing on passive dendrite models—the most widely adopted in dendritic computation research—this dissertation proposes steady-state and transient surrogate models based on passive dendritic steady-state and transient computations, respectively. The steady-state surrogate model enables efficient training of deep, detailed neural networks with complex dendritic structures on data-driven tasks using the DeepDendrite platform. The transient surrogate model breaks through the steady-state assumption, achieves explicit gradient

computation and efficient training for active dendrites under transient conditions, and is applied for the first time to train the BAAIWorm detailed C. elegans neural network model. This approach accurately reconstructs experimentally observed calcium signals from biological recordings, and successfully generates worm locomotion closely resembling biological behaviors. Ablation experiments further revealed the critical role of network structure in regulating the worm's behavioral patterns.

Second, this dissertation further discovers and rigorously proves the mathematical equivalence between gradient computation and numerical simulation in detailed neuron models, leading to a novel learning method named “forward replay gradient simulation”. Through forward replay of specific gradient currents during numerical simulation, this method achieves accurate and efficient computation of synaptic weight gradients, providing a theoretical basis for how biological neurons might leverage their physiological mechanisms to compute gradients.

Third, based on the above gradient simulation method, this dissertation proposes an even more computationally efficient “backward replay learning method” by analyzing gradient components in-depth. This new approach significantly reduces the computational cost of calculating synaptic weight gradients for detailed neuron models, while maintaining learning performance comparable to exact gradient methods. Moreover, this dissertation innovatively designs dendrite-mediated contextual selection experiments, successfully demonstrating that detailed neuron models can efficiently solve complex learning tasks that are challenging for traditional point-neuron models, thus highlighting the substantial computational advantage of dendritic computation.

In summary, this dissertation systematically addresses the challenge of efficient supervised learning at the dendritic scale driven by dendritic computation, verifying the efficiency and biological plausibility of the proposed dendrite-level learning methods and explicitly elucidating the significant contribution of dendritic computation to system-level neural network functions. This dissertation provides a novel theoretical foundation and methodological framework for understanding efficient learning mechanisms in the brain, significantly advancing the fields of brain-inspired intelligence and computational neuroscience toward intelligent, efficient, and biologically plausible computational paradigms.

KEY WORDS: Computational Neuroscience, Brain-inspired Intelligence, Neuronal Dynamics, Spiking Neural Networks, Dendritic Computation