

Neuroscience-inspired deep learning algorithms for computational mechanics

Abstract

Deep learning has achieved remarkable accuracy in computational mechanics, but its dense communication incurs prohibitive computational and energy costs, limiting scalability and deployment on edge devices. Spiking Neural Networks (SNNs) emulate the efficiency of biological neural systems, yet conventional SNNs succeed mainly in classification and struggle with the continuous-valued regression central to scientific computing. This thesis bridges this gap by introducing the Variable Spiking Neuron (VSN), which combines event-driven communication with continuous-valued processing through graded spike responses. This enables accurate regression while maintaining sparse neural activity. The VSN is first validated in feed-forward and graph neural networks, the latter yielding the Variable Spiking Graph Neural Network (VS-GNN). It is then extended to operator learning through the Neuroscience-inspired Bayesian Operator Network (NBONet) and the Variable Spiking Wavelet Neural Operator (VS-WNO). To reduce reliance on costly solver-generated data, VSNs are also integrated into physics-informed learning. NeuroPINNs use stochastic projection for faithful residual evaluation, and SPINONet and NeuroPOL extend this to physics-informed operator learning. These models achieve accuracy comparable to dense baselines despite sparse communication. Because sparse computation introduces predictive variability, Split Conformal Prediction is incorporated as a post-processing layer. The resulting Conformalized NBONet (CoNBONet) and Conformalized Randomized Prior VS-WNO (CRP-VSWNO) provide distribution-free, finite-sample calibrated prediction intervals without altering the sparse architecture. Scalability is demonstrated on two large-scale applications. In the first, CoNBONet performs time-dependent reliability analysis of a 76-story benchmark structure under stochastic loading. In the second, the Neuroscience-inspired Spherical Wavelet-weighted Neural Operator (Ni-SWNO), trained on ERA5 data, performs centennial climate modelling. Collectively, this work establishes VSNs as a versatile, energy-efficient building block for scalable and deployable scientific machine learning.