

CANNs: Continuous Attractor Neural Networks Toolkit with ASA for Attractor Structure Analysis

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Summary

CANNs (Continuous Attractor Neural Networks toolkit) is a Python library built on BrainPy, a powerful framework for brain dynamics programming. It streamlines experimentation with continuous attractor neural networks and related brain-inspired models. The library delivers ready-to-use models, task generators, analysis tools, and pipelines—enabling neuroscience and AI researchers to move quickly from ideas to reproducible simulations.

Statement of need

Continuous Attractor Neural Networks (CANNs) provide a theoretical framework for understanding how the brain encodes continuous variables through stable neural activity patterns. Despite their importance in computational neuroscience, CANN research suffers from fragmentation: researchers implement models from scratch using incompatible codebases, creating reproducibility barriers and steep learning curves.

CANNs addresses this gap by providing a unified Python toolkit built on BrainPy (Wang et al. 2023). It delivers standardized CANN implementations, integrated task generation and analysis pipelines, and high-performance computation via JAX JIT compilation with optional Rust acceleration.

Software design

The CANNs library follows a modular architecture ([Figure 1](#)) with five independent modules: Models, Tasks, Analyzers, Trainers, and Pipeline. This separation ensures maintainability and extensibility through abstract base classes that define standard interfaces.

The library supports CANN modeling and simulation, experimental data analysis, brain-inspired learning, and automated parameter sweeps. All models inherit from BrainPy's `DynamicalSystem` base class (Wang et al. 2023), leveraging JAX JIT compilation for GPU/TPU acceleration. A companion Rust library provides optional accelerated backends for performance-critical operations.

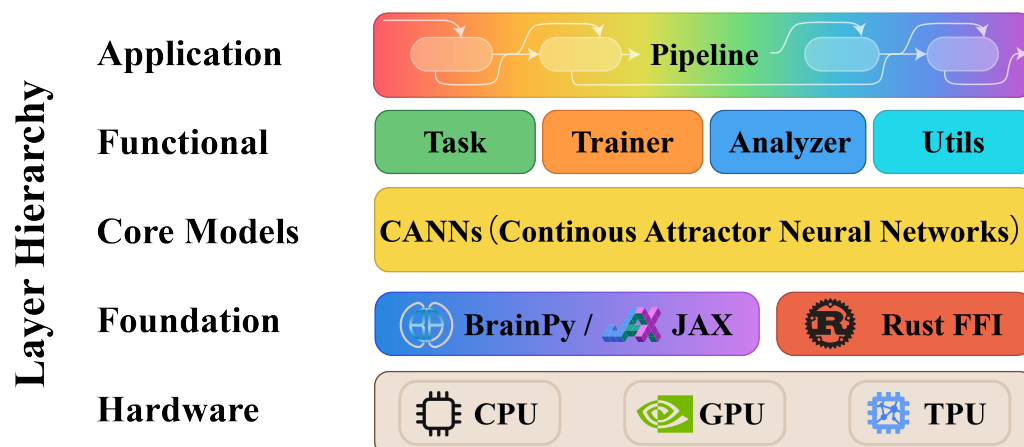


Figure 1: Layer hierarchy of the CANNs library showing five levels: Application (Pipeline orchestration), Functional (Task, Trainer, Analyzer, Utils modules), Core Models (CANN implementations), Foundation (BrainPy/JAX and Rust FFI backends), and Hardware (CPU/GPU/TPU support).

Related Works

While general-purpose neural network simulators like NEST (Gewaltig and Diesmann 2007), Brian 2 (Stimberg, Brette, and Goodman 2019), and NEURON (Hines and Carnevale 1997) exist, they lack specialized support for continuous attractor dynamics. Existing CANN implementations remain fragmented, lab-specific codebases without standardized APIs or comprehensive tooling.

CANNs builds upon BrainPy (Wang et al. 2023), a modern brain dynamics framework leveraging JAX (Bradbury et al. 2018) for JIT compilation and GPU/TPU acceleration. CANNs extends BrainPy with CANN-specific abstractions: standardized model implementations, task-generation APIs, analysis pipelines, and optional Rust-accelerated backends for performance-critical operations.

AI usage disclosure

AI-assisted tools were used for code quality reviews and documentation writing. All core library code was written by human developers, and AI-generated content was reviewed and validated by the authors.

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