Zoo of RNNs: A comprehensive analysis of recurrent neural networks trained on synthetic behavioral tasks

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Abstract

System neuroscientists regularly investigate cognitive functions by studying model animals through predefined behavioral tasks in controlled laboratory environments.To extend this study to neural mechanisms in silico, the advent of artificial intelligence research has enabled the exploration of neural computation strategies within artificially trained neural networks on similar synthetic behavioral tasks. However, these synthetic tasks lack systematic evaluation and are often non-standardized and fragmented across several prior works. To address this issue, we introduce a comprehensive benchmark of standardized behavioral tasks, on which we train recurrent neural network (RNN) models. To dissect the computational strategies employed by RNNs, we utilize the recently developed latent circuit theory, which effectively maps the computations of high-dimensional RNN units onto an interpretable low-dimensional dynamical system, i.e., the latent circuit. Building on this framework, we quantify the complexities of various tasks and establish a mechanistic equivalence between two widely used RNN models in systems neuroscience, further enhancing our understanding of their functional capabilities. To facilitate future extensions of the benchmark and support ongoing research in this field, we outline detailed methodologies for standardizing these tasks and offer a publicly accessible codebase. Our findings lay a standardized and principled foundation, paving the way for future comparative studies of neural computation in systems neuroscience.

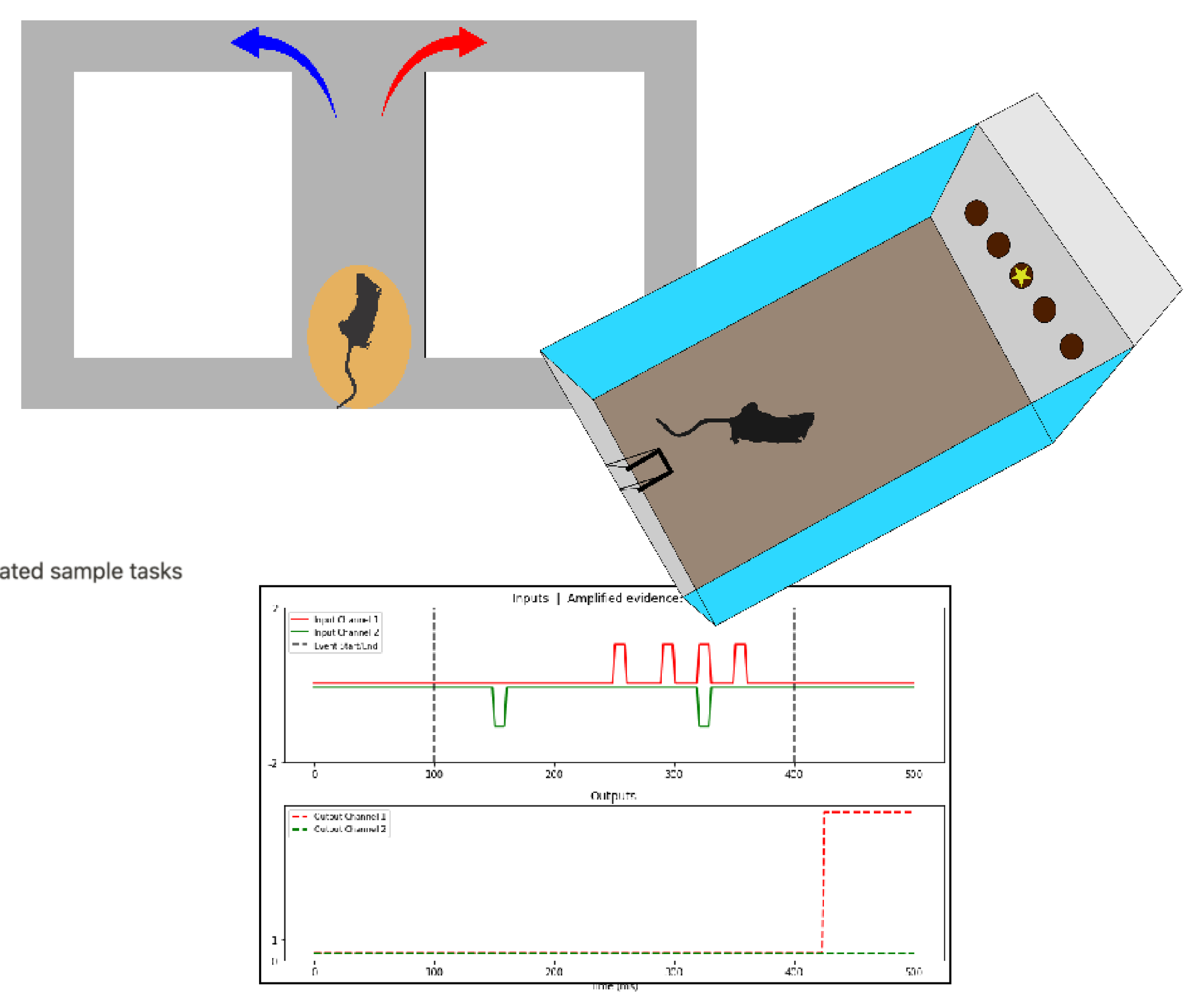
Module 1: A zoo of artificially designed behavioral tasks

Machine learning tasks

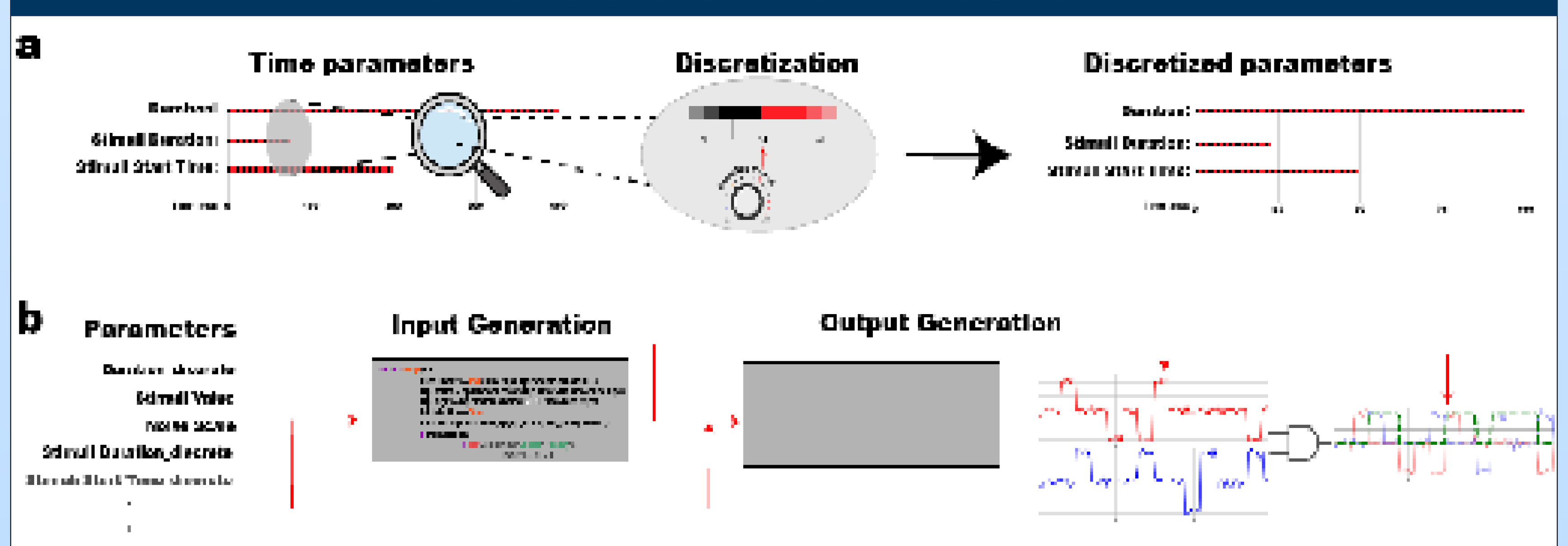
- Addition task
- Multiplication task
- K-back prediction task
- Addition or multiplication combined task
- 3-bit flip flop task
- Sin-wave generation task
- Two-point moving average task

Memory and decision tasks

- Delayed match to sample task
- Delayed match to rotated sample task
- Delayed cue task combining sample and rotated sample tasks
- ABBA and ABCA tasks
- Dual delayed match to sample task
- Multisensory decision making
- Contextual decision making
- Parametric working memory
- Perceptual decision making

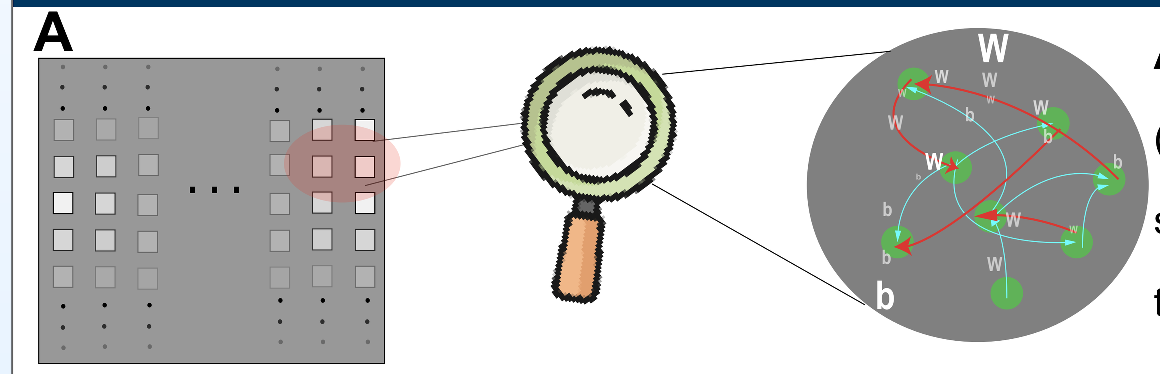


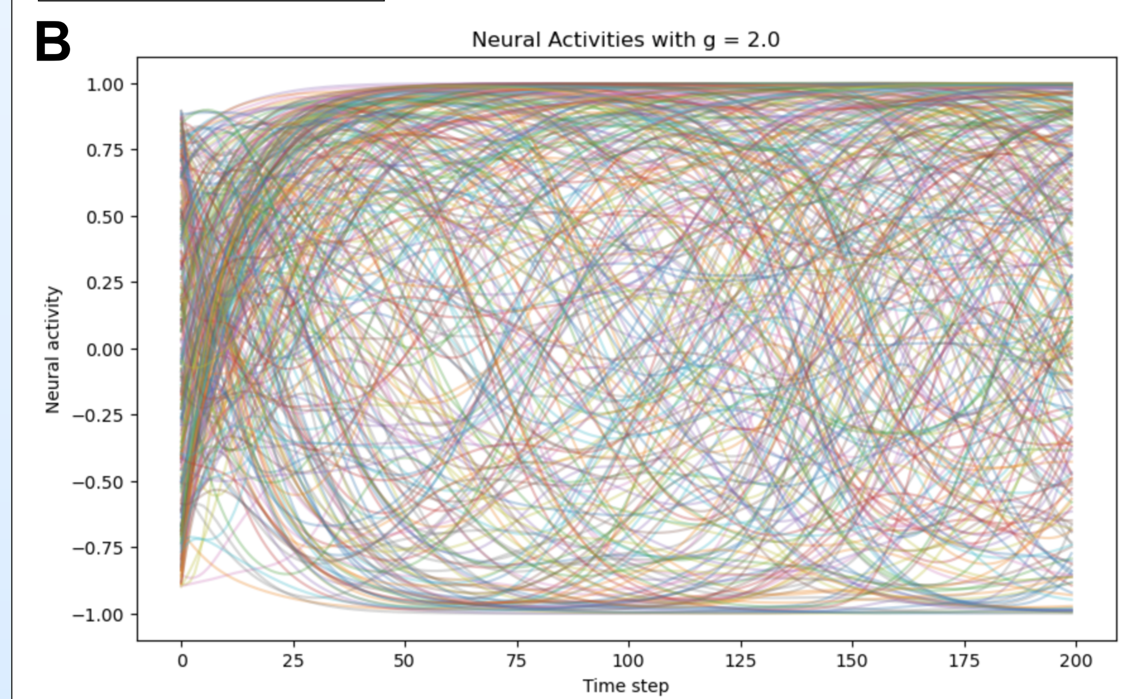
Towards standardized tasks



A) This part illustrates the discretization process. All time-related parameters are discretized based on a chosen sampling period. A smaller sampling period results in more frequent sampling, providing more detailed information. Conversely, a larger sampling period decreases the detail and makes the task less informative. **B)** The standardized task generation process is depicted. To ensure consistency and evaluability, unique parameters are incorporated into each task. These parameters are crucial for replicating real-life conditions within the task framework.

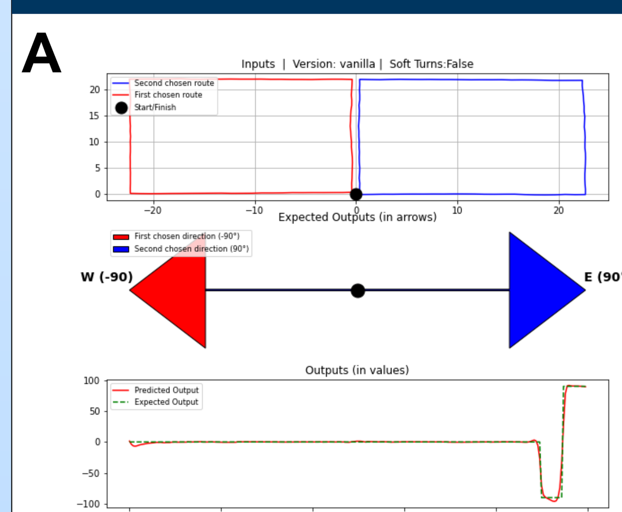
Module 2: A collection of network architectures

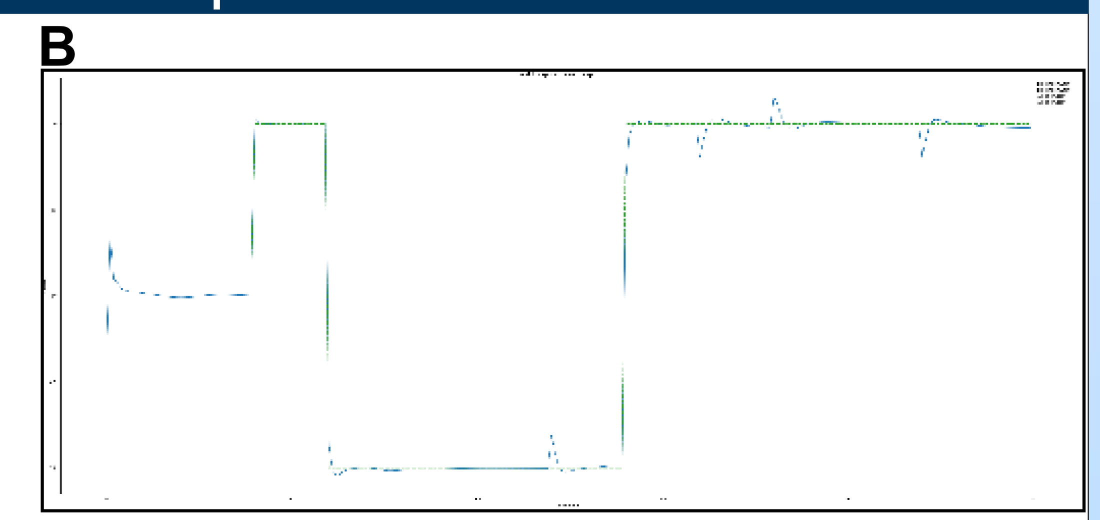




A) Recurrent neural networks (RNNs) are widely utilized for synthetic behavioral tasks due to their ease of use and convenient training process. Their inherent structure often leads to chaotic dynamics, making them particularly intriguing to analyze. RNNs come in various forms, such as leaky-firing, leaky-current, dendritic, and more, yet this chaotic nature is observed across all types. Additionally, employing different types of RNNs can uncover distinct aspects of the learning processes involved. **B)** In addition to the chaotic dynamics inherent to RNNs, chaos can also be induced between neurons by adjusting a gain factor. Introducing chaos into the model may help uncover different facets of its behavior. Although chaotic neural activity typically lacks a coherent pattern, it has been shown that such activity can still generate robust and coherent outcomes. Investigating how a model behaves under chaotic conditions can be explored through the latent circuit theorem (LCT).

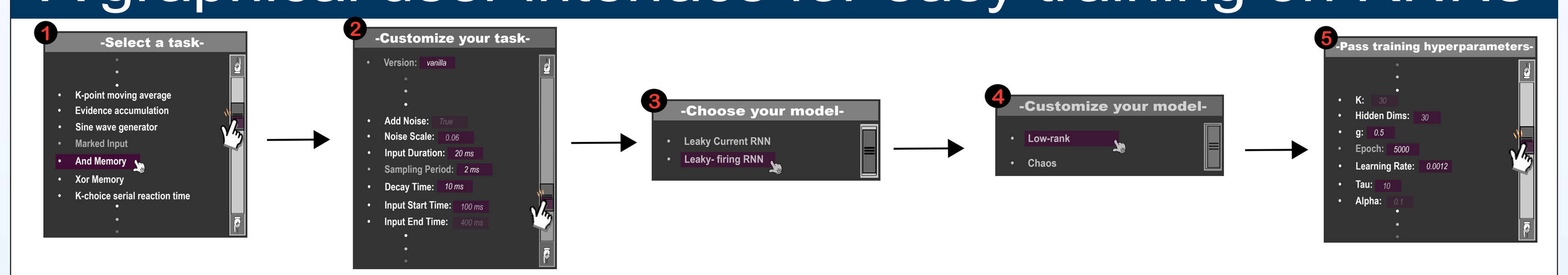
Module 3: Training RNNs on artificially created neuro-inspired tasks

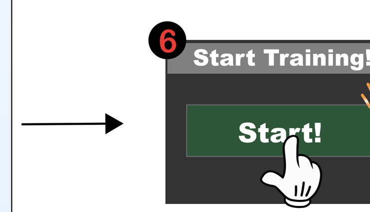




A) The training results of the T-Maze task are displayed. Task training can be configured with various options, such as setting a threshold to stop training once a specified accuracy or loss value is reached. **B)** Multiple tasks can be trained simultaneously with a desired number of quantity. This approach may offer new insights into the underlying structures of the tasks, thereby enhancing the application of the Latent Circuit Theorem (LCT).

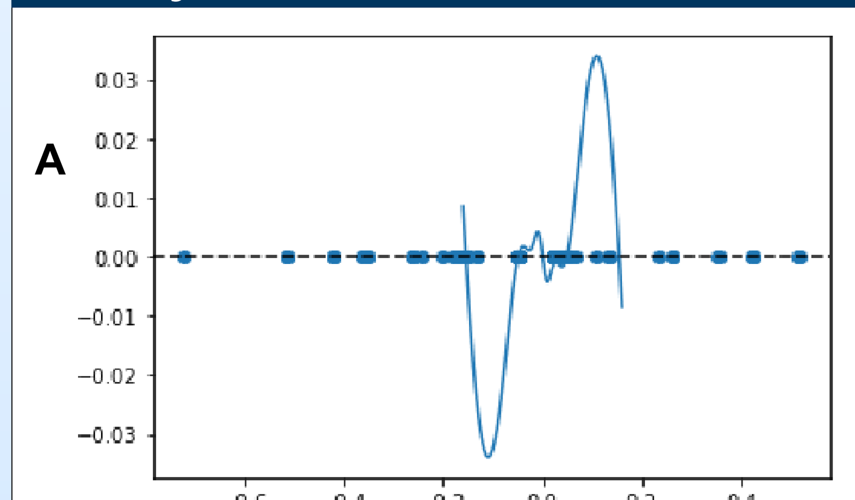
A graphical user interface for easy training on RNNs

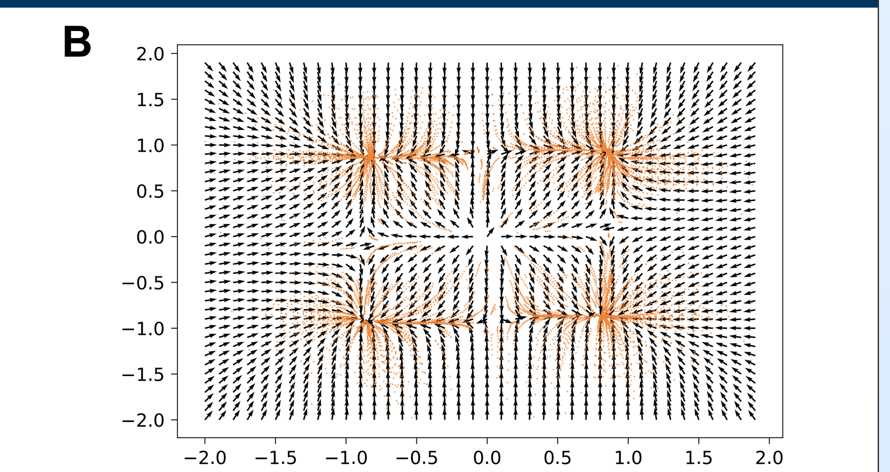




1-2) Task selection and customization: The desired task(s) are chosen, and values are assigned to uniquely defined parameters to configure the task. **3-4) Model selection:** The model is selected, and customization settings are applied. **5) Hyperparameters** are set for training. **6)** The **training** process begins!

Analysis of latent circuits in recurrent neural networks





A) Latent circuit of two combined 1-bit flip-flop tasks, where one task is silenced and the other operates normally. The model successfully captured underlying dynamics of the task. The outer fixed points represent the inputs of -1 and +1, while the inner fixed points correspond to the silenced task's fixed point at 0. The point at the center marks the unstable fixed point. **B)** The fixed points of a 2-bit flip-flop task are shown in orange. The underlying dynamics, as indicated by the arrows, can be reverse-engineered to reveal the logical behavior of the system.

Summary

1) Synthetic behavioral tasks have been updated with more realistic parameters and standardized, with three distinct versions developed for each task. **2)** Different types of RNN models are used to explore dynamic differences, with options for incorporating chaos and low-rank structures. **3)** Extensive training options are applied to expand the scope of LCT across a variety of settings. **4)** An intuitive GUI is designed to streamline comprehensive benchmarking, allowing for easy selection and assignment of tasks, models, and training options. **5)** Latent Circuit Theory (LCT) is used to uncover a model's underlying dynamics by projecting high-dimensional data onto a more interpretable, lower-dimensional space.