hebbRNN: A Reward-Modulated Hebbian Learning Rule for Recurrent Neural Networks

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DOI: 10.21105/joss.00060

Software

- Review
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Summary

How does our brain learn to produce the large, impressive, and flexible array of motor behaviors we possess? In recent years, there has been renewed interest in modeling complex human behaviors such as memory and motor skills using neural networks (Sussillo et al. 2015; Rajan, Harvey, and Tank 2016; Hennequin, Vogels, and Gerstner 2014; Carnevale et al. 2015; Laje, Buonomano, and Buonomano 2013). However, training these networks to produce meaningful behavior has proven difficult. Furthermore, the most common methods are generally not biologically-plausible and rely on information not local to the synapses of individual neurons as well as instantaneous reward signals (Martens and Sutskever 2011; Sussillo and Abbott 2009; Song, Yang, and Wang 2016).

The current package is a Matlab implementation of a biologically-plausible training rule for recurrent neural networks using a delayed and sparse reward signal (Miconi 2016). On individual trials, input is perturbed randomly at the synapses of individual neurons and these potential weight changes are accumulated in a Hebbian manner (multiplying pre- and post-synaptic weights) in an eligibility trace. At the end of each trial, a reward signal is determined based on the overall performance of the network in achieving the desired goal, and this reward is compared to the expected reward. The difference between the observed and expected reward is used in combination with the eligibility trace to strengthen or weaken corresponding synapses within the network, leading to proper network performance over time.

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