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<tr><th>authors</th><td>Aaron Voelker
Ivana Kajic
Chris Eliasmith</td></tr>
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<tr><th>abstract</th><td>We propose a novel memory cell for recurrent neural networks that dynamically maintains information across long windows of time using relatively few resources. The Legendre Memory Unit (LMU) is mathematically derived to orthogonalize its continuous-time history -doing so by solving d coupled ordinary differential equations (ODEs), whose phase space linearly maps onto sliding windows of time via the Legendre polynomials up to degree d âˆ’ 1. Backpropagation across LMUs outperforms equivalently-sized LSTMs on a chaotic time-series prediction task, improves memory capacity by two orders of magnitude, and significantly reduces training and inference times. LMUs can efficiently handle temporal dependencies spanning 100,000 time-steps, converge rapidly, and use few internal state-variables to learn complex functions spanning long windows of time -exceeding state-of-the-art performance among RNNs on permuted sequential MNIST. These results are due to the network's disposition to learn scale-invariant features independently of step size. Backpropagation through the ODE solver allows each layer to adapt its internal time-step, enabling the network to learn task-relevant time-scales. We demonstrate that LMU memory cells can be implemented using m recurrently-connected Poisson spiking neurons, O(m) time and memory, with error scaling as O(d/ âˆš m). We discuss implementations of LMUs on analog and digital neuromorphic hardware.</td></tr>
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https://github.com/abr/neurips2019</td></tr>
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