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<tr><th>journal</th><td>Neural Information Processing Systems</td></tr>
<tr><th>volume</th><td>32</td></tr>
<tr><th>doi</th><td>None</td></tr>
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<tr><th>id</th><td>id-2087147303269411797</td></tr>
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<tr><th>id</th><td>id8430741386225735956</td></tr>
<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 $d - 1$. 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 $100\text{,}000$ 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, $\mathcal{O}( m )$ time and memory, with error scaling as $\mathcal{O}( d / \sqrt{m} )$. We discuss implementations of LMUs on analog and digital neuromorphic hardware.</td></tr>
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