LMU

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- (selected) CSE 425
- EEE 474

What authors stated about memory cell dynamics?

The authors proposed 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. The memory cell dynamics are derived from the linear transfer function for a continuous-time delay, F(s) = e−θs, which is best-approximated by d coupled ordinary differential equations (ODEs). The key property of this dynamical system is that m represents sliding windows of u via the Legendre polynomials up to degree d − 1. This gives a unique and optimal decomposition, wherein functions of m correspond to computations across windows of length θ, projected onto d orthogonal basis functions. The authors also discussed how to discretize these equations for a recurrent neural network, and how to measure the approximation error.

What are state-art-of the approaches author compared with their model

The authors compare their proposed Legendre Memory Unit (LMU) model with two other models: Long Short-Term Memory (LSTM) and a hybrid model that alternates between LSTM and LMU layers. They then compare the performance of these models on a chaotic time-series prediction task called the Mackey-Glass series. The current state-of-the-art results on this task for RNNs include Zoneout with 95.9% test accuracy, indRNN with 96.0%, and the Dilated RNN with 96.1%. However, the authors note that it is difficult to compare across studies due to differences in permutation seeds and computational resources utilized by the models.

What datasets authors used in their experiment to established their model?

The authors did not introduce a new dataset for their experiments. Instead, they evaluated the performance of the Legendre Memory Unit (LMU) on several standard benchmarks for recurrent neural networks (RNNs), including the Sequential MNIST (seqMNIST) dataset, the Permuted Sequential MNIST (psMNIST) dataset, and the Copy Memory task. These benchmarks are designed to test the ability of RNNs to learn temporal relationships spanning long intervals of time. The authors also compared the performance of the LMU with several state-of-the-art approaches for RNNs on these benchmarks.

The authors used two datasets in their experiments to establish their model:

> Permuted sequential MNIST: a digit classification task that requires learning complex temporal relationships. Each 28 × 28 image is flattened into a one-dimensional pixel array and permuted by a fixed permutation matrix. Elements of the array are then provided to the network one pixel at a time.
> Mackey-Glass: a time-series prediction task that tests the ability of a network to model chaotic dynamical systems. A sequence of one-dimensional observations, generated by solving the Mackey-Glass differential equations, are streamed as input, and the network is tasked with predicting the next value in the sequence.

What is Linear-Nonlinear Processing in the LMU part explained by the author

Linear-Nonlinear Processing is a characteristic of the LMU that separates the functional role of the linear memory cell from that of the nonlinear hidden state. The authors argue that linear units maximize the information capacity of dynamical systems, while nonlinearities are required to compute useful functions across this information. The LMU formalizes this trade-off by decoupling the memory cell, which projects continuous-time signals onto orthogonal dimensions, from the hidden state, which learns to interact with the memory cell and compute nonlinear functions across time.

What is Neural Precision? how LMU understand and performed it

Neural Precision is a property of the spiking implementation of the LMU, which allows it to trade precision for energy-efficiency on neuromorphic hardware. The authors show that the dynamical system for the memory cell can be implemented by mapping each state-variable onto the postsynaptic currents of Poisson spiking neurons with fixed heterogeneous tuning curves. They prove that the error between the ideal input to the original rate neuron and the weighted summation of spike events has a variance of O(1/p), where p is the number of neurons per population. By repeating this for d independent populations, they obtain an overall RMSE of O(d/√m), where m is the total number of neurons. This means that the LMU can scale to the original network in the limit of large m, while reducing the amount of communication and computation required by spiking neurons.

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