Role of scrambling, noise, and symmetry in temporal learning with quantum systems

Weijie Xiong[2,3], Zoe Holmes[2,3], Armando Angrisani[2,3], Yudai Suzuki[2,3], Thiparat Chotibut[1], and Supanut Thanasilp[1,2,3]

[1]*Chula Intelligent and Complex Systems Center of Excellence, Faculty of Science, Chulalongkorn University, Bangkok, Thailand*
[2]*Institute of Physics, Ecole Polytechnique Federale de Lausanne (EPFL), Lausanne, Switzerland*
[3]*Centre for Quantum Sciences and Engineering, Ecole Polytechnique Federale de Lausanne (EPFL), Lausanne, Switzerland*

Scrambling quantum systems have been demonstrated as effective substrates for temporal information processing. While their potential and limitations for learning static data has been studied in our previous work [1], a theoretical understanding of their performance in temporal tasks, where quantum systems work as both computational substrate and memory, is still lacking. Going beyond our previous setting of a single step iteration and static data, here we consider a general quantum reservoir processing framework that captures a broad range of temporal learning models using quantum systems. We examine the scalability and memory retention of the model with scrambling reservoirs modelled by high-order unitary designs in both noiseless and noisy settings. In the former regime, we show that measurement readouts become exponentially concentrated with increasing reservoir size, yet strikingly do not worsen with the reservoir iterations. Thus, while repeatedly reusing a small scrambling reservoir with quantum data might be viable, scaling up the problem size deteriorates generalization unless one can afford an exponential shot overhead. In contrast, the memory of early inputs and initial states decays exponentially in both reservoir size and reservoir iterations. In the noisy regime, we also prove exponential memory decays with iterations for local noisy channels. We further prove that the scalability limitations also hold for model variants that incorporate mid-circuit measurements and feed-forward, which have been demonstrated as a source that improves performance of learning models. To sidestep these scalability barriers, we show that by employing less scrambling or symmetrized reservoirs, the exponential concentration of outputs can be avoided. Proving these results required us to introduce new proof techniques for bounding concentration in temporal quantum learning models. Our results lay the ground work for understanding the potential of a quantum advantage for temporal learning tasks using quantum reservoir processing.

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[1] W. Xiong, G. Facelli, M. Sahebi, O. Agnel, T. Chotibut, S. Thanasilp, and Z. Holmes, Quantum Machine Intelligence, 7(1) (2025) 20.