Hybrid Quantum Reservoir Computing: Memory and Entanglement for Classification and Forecasting

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Abstract: We develop hybrid quantum reservoir computing architectures with memory enhancement and entanglement-driven feature maps for time-series forecasting and image classification, achieving improved accuracy, extended prediction horizons, and robust performance while remaining compatible with efficient classical simulation.

We develop hybrid quantum-classical learning architectures based on quantum reservoir computing (QRC) and quantum extreme learning machines (QELMs), addressing both chaotic time-series forecasting and image classification. By exploiting the high-dimensional structure of Hilbert space, these approaches generate expressive nonlinear feature maps while maintaining a simple training scheme restricted to a linear output layer.

We introduce memory-augmented designs in which classical post-processing enhances temporal correlations, eliminating the need for repeated coherent input injections and enabling efficient modeling of multivariate dynamical systems. Applied to benchmark tasks—including Mackey–Glass, Lorenz-63, and reduced Navier–Stokes dynamics—our framework achieves extended prediction horizons and robust performance.

For image classification, we combine dimensionality reduction, quantum encoding, and evolution under simple spin Hamiltonians, showing that quantum reservoirs systematically improve accuracy. We further identify a transition to high-performance regimes associated with the onset of entanglement. Notably, moderate and short-range entanglement is sufficient to enhance data embedding and separability, without requiring global complexity. These regimes remain compatible with efficient classical simulation.

Our results establish hybrid quantum reservoir computing as a practical and scalable framework for enhancing learning performance beyond classical feature maps in near-term quantum settings.

References

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