

Multivariate quantum reservoir computing with discrete and continuous variable systems

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Abstract

Quantum reservoir computing (QRC) is an appealing quantum machine learning model: the quantum system acts as a fixed dynamical feature map and only a linear readout is trained, so learning reduces to a convex problem that avoids the barren plateaus and costly variational loops of quantum neural networks, while remaining well suited to near-term hardware. Yet QRC has been studied almost exclusively on *univariate* time series, and whether genuinely quantum resources help when processing *multivariate* data is unknown. We establish a systematic framework for multivariate QRC: we propose three multivariate encoding schemes, introduce the *mixing capacity* to quantify how effectively a reservoir combines independent data streams, and benchmark two physically distinct quantum reservoirs, a discrete-variable (DV) transverse-field Ising system and a continuous-variable (CV) network of coupled harmonic oscillators. We find that the optimal encoding is strongly system- and task-dependent and, crucially, that peak performance coincides with regimes exhibiting non-classical resources, namely entanglement (DV) and squeezing (CV), linking quantum resources to multivariate processing power.

Motivation

Quantum reservoir computing (QRC) is a quantum machine learning (QML) model for temporal data in which a quantum system serves as a fixed, high-dimensional dynamical feature map and only a linear readout is trained on the measured observables [1, 2]. Several of its properties are particularly attractive for near-term QML. Training reduces to linear regression, a convex problem solved in a single step, sidestepping the barren plateaus and costly gradient-based circuit optimization that hinder variational quantum neural networks [3]. Because the dynamics are fixed rather than parameterized, no deep controlled-gate circuits are needed and dissipation acts as a computational resource [4], making QRC well suited to noisy near-term hardware. Its intrinsic dynamics also provide a built-in fading memory for native temporal processing, without data re-uploading or explicit recurrence. These features have motivated a range of quantum platforms, from spin systems [1] to continuous-variable Gaussian-state systems [5, 6].

Despite these advantages, QRC has been developed almost entirely for *univariate* time series, whereas the most relevant real-world data are multivariate. How to encode several input streams into a quantum reservoir, and how this interacts with the choice of platform, is not systematically understood [7–9]. A second, more fundamental question concerns the role of quantum resources: for univariate tasks, coherence [10], entanglement [11], and squeezing [12] correlate with performance without being strictly necessary. The multivariate setting, in which information from different streams must be distributed and mixed across the system, poses a distinct challenge that has barely been studied [9].

We address both questions with a systematic framework [13]. Our contributions are: (i) three multivariate encoding schemes evaluated across two physically distinct quantum platforms; (ii) the *mixing capacity*, a new metric quantifying how well a reservoir combines independent input streams; and (iii) evidence linking multivariate performance to genuinely quantum resources.

Reservoir platforms and multivariate encodings

We study two complementary reservoirs (Fig. 1a). The DV reservoir is a dissipative transverse-field Ising model of n spins with random couplings: the input enters through time-dependent local fields, dissipation supplies the fading memory required for reservoir computing [1, 4], and we read out local

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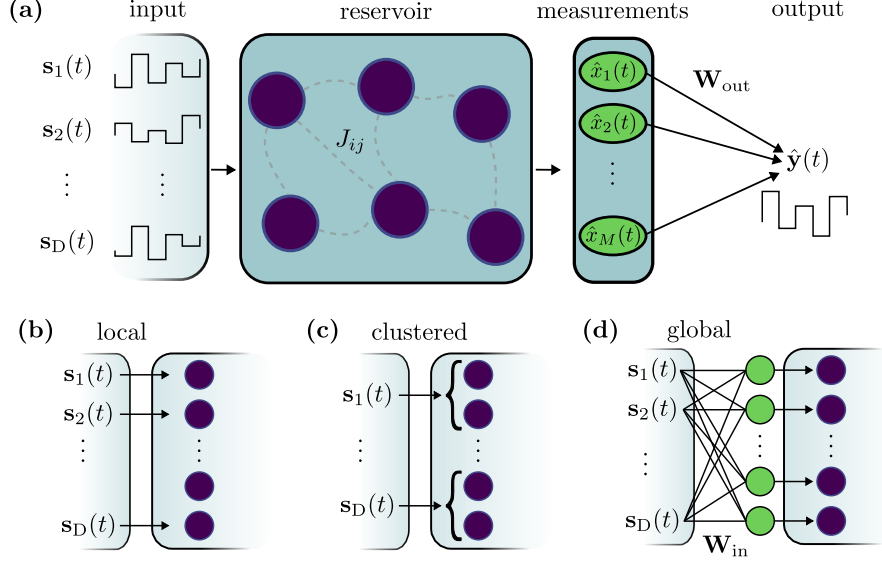


Figure 1: (a) QRC setup: input streams $s_i(t)$ are encoded into a fixed reservoir; only the linear readout $\mathbf{W}_{\text{out}}$ acting on measurements $\hat{x}_i(t)$ is trained. (b–d) The three multivariate encoding schemes: (b) *local* maps each input dimension to one node, (c) *clustered* assigns each dimension to a block of nodes with random masking, and (d) *global* multiplexes the full input across all nodes via a random input matrix.

Pauli expectation values. The CV reservoir is a network of n coupled quantum harmonic oscillators with Gaussian dynamics [5]: the input modulates the oscillator frequencies, which corresponds to a squeezing operation, and we read out position covariances.

To map a D -dimensional input onto n nodes we compare three encodings (Fig. 1b–d): **local**, mapping each input dimension to a single distinct node; **clustered**, assigning each dimension to a block of nodes scaled by random masking weights; and **global**, multiplexing the entire input across all nodes through a random, L_1 -normalized input matrix. Local and clustered encodings saturate at $D \leq n$ input streams, whereas global encoding accommodates arbitrarily many dimensions.

Mixing capacity

Standard reservoir computing metrics do not isolate the ability to *combine* distinct inputs. We therefore define the mixing capacity C_{mix} as the summed, significance-thresholded reconstruction quality of target signals built from products of two different input streams at independent time delays, $y(t) = s_i(t - \tau_1) s_j(t - \tau_2)$ with $i \neq j$, which directly measures cross-stream mixing.

We find that C_{mix} grows with system size and, in general, with the number of input streams. The optimal encoding, however, *diverges between platforms*: global encoding is best for the DV reservoir, whereas local encoding is best for the CV reservoir, underscoring the need for task- and platform-specific input design. Notably, despite its far larger state space, the DV reservoir does not outperform the CV reservoir at comparable size, suggesting that it cannot fully exploit that space for mixing. Phase diagrams over coupling and encoding strength further show that global encoding sustains a high C_{mix} across a wide parameter range, as mixing the inputs at injection relieves the internal dynamics of scrambling.

Chaotic Lorenz-63 prediction

To test the processing of correlated streams on a realistic task, we forecast the chaotic Lorenz-63 system [14]. Supplying additional state components as inputs improves single-component prediction, confirming that the reservoir extracts relevant cross-component information. Local encoding underperforms clustered and global encoding: accurate forecasting requires robust memory of each individual input,

which the distributed encodings preserve. As in the mixing-capacity results, the CV reservoir attains a lower error than the DV reservoir.

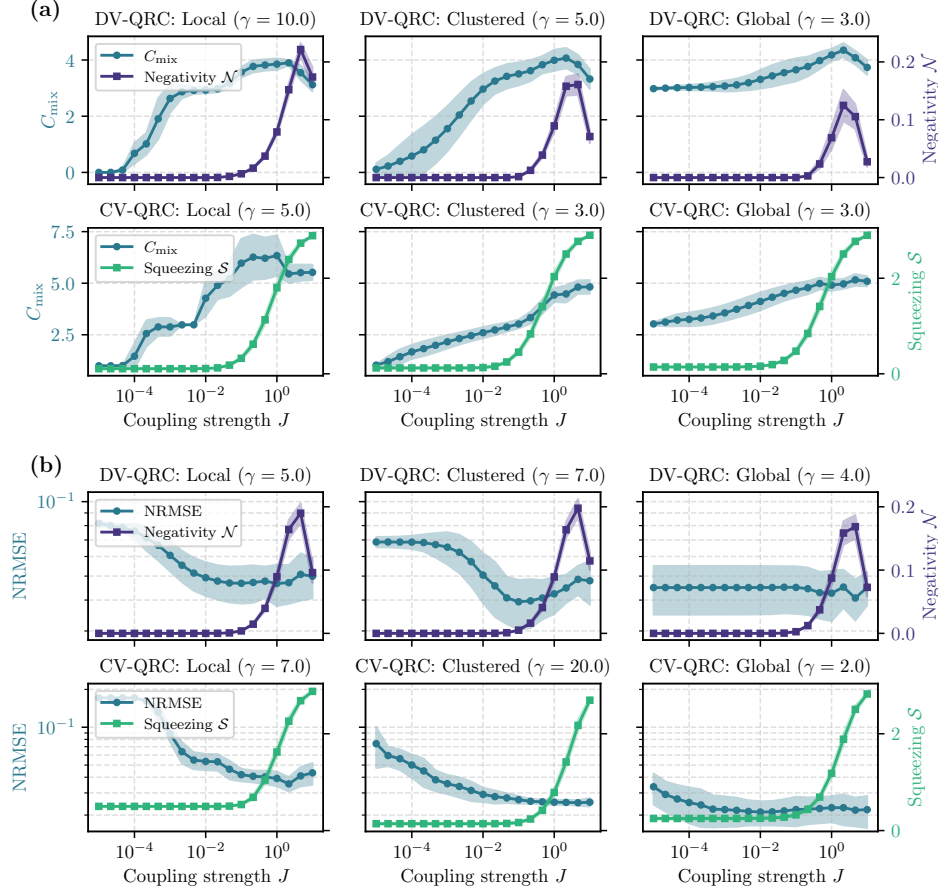


Figure 2: Mixing capacity for two input streams (a) and Lorenz-63 prediction error (b), together with the underlying quantum resources (negativity for the DV reservoir, squeezing for the CV reservoir), as a function of coupling strength J for the three encodings at $n = 6$. Peak performance coincides with regimes that exhibit entanglement or squeezing.

Quantum resources and multivariate performance

Do quantum resources help? We quantify entanglement via the bipartition-averaged negativity [15] for the DV reservoir and the maximum squeezing for the CV reservoir, and track them against task performance as a function of the coupling strength J (Fig. 2). Both are negligible at weak coupling, rise as stronger coupling correlates and delocalizes the network, and saturate or decline at large coupling. Strikingly, peak mixing capacity and peak Lorenz-63 accuracy both fall within the regimes where entanglement or squeezing is present. Substantial performance also persists where these resources effectively vanish, so they are not strictly necessary; nonetheless, the consistent alignment of peak performance with distinctly non-classical regimes, observed across two physically different platforms and all encoding schemes, indicates that quantum resources play a constructive role in multivariate QRC.

Outlook

Building on this framework, promising directions include inputs with varying correlation structure, robustness to data and hardware noise for near-term implementations, and the processing of intrinsically multivariate *quantum* data.

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