

Quantum Anomaly Detection for Future Gravitational-Wave Observatories

Domenica Dibenedetto, Shi Qiu, Ibarrola Saz Alejandro

Department of Advanced Computing Sciences, Maastricht University, The Netherlands

`domenica.dibenedetto@maastrichtuniversity.nl`

Future gravitational-wave (GW) observatories such as LISA and third-generation ground-based detectors will produce long, high-sensitivity data streams with increased source overlap and weak-signal regimes. We investigate quantum machine-learning approaches for semi-supervised GW anomaly detection, focusing on Quantum Variational Rewinding (QVR) and Quantum Reservoir Computing (QRC). QVR is evaluated on real LIGO data, LISA Data Challenge 2a Sangria data, and synthetic LISA streams with massive-black-hole-binary injections, while QRC is explored as a reservoir-based extension on LISA open data. The results show that quantum anomaly-detection methods can support event flagging, weak-signal screening, anomaly-based ranking, and follow-up prioritization, providing a basis for scaling toward realistic LISA and Einstein Telescope scenarios.

1 Introduction

Next-generation observatories such as LISA [1] and the Einstein Telescope [2, 3] are opening new GW regimes, characterized by longer signals, higher event rates, and increased source overlap. Current ground-based detectors such as LIGO [4, 5] provide an essential real-data testbed for assessing whether new methods can operate reliably on interferometer noise and recover GW transients. This expanding observational landscape creates severe data-analysis challenges. Traditional matched filtering [6, 7, 8] relies on large template banks and becomes increasingly demanding for long-duration or high-dimensional searches. Third-generation detectors are expected to further increase data volumes and computational costs, pushing classical analysis pipelines toward their limits [9, 10]. These bottlenecks motivate complementary machine-learning (ML) approaches that can reduce reliance on exhaustive template searches. Classical ML methods, including convolutional and recurrent neural networks, autoencoders, and other representation-learning architectures, have already been explored for GW detection, glitch classification, parameter estimation, and anomaly detection [11, 12, 13, 14, 15, 16]. However, many of these approaches still require labelled examples, specialized architectures, large training sets, or subsequent statistical follow-up. Anomaly detection offers a semi-supervised alternative: learn the normal detector background and then flag departures from it as candidate deviations requiring future follow-up [15, 17, 18]. This formulation is particularly useful because, in real GW data, detector glitches are also anomalies; therefore, a flagged deviation should not be interpreted directly as a confirmed astrophysical signal. Since confirmed GW signals, simulated injections, and labelled glitch populations are limited or costly to obtain, training primarily on background-only data is appealing.

Quantum machine learning (QML) offers expressive feature-mapping tools for gravitational-wave time series [19, 20]. In particular, Quantum Variational Rewinding (QVR) [21, 22, 23] and Quantum Reservoir Computing (QRC) [24] can encode scalar strain signals into high-dimensional quantum representations, enabling temporal processing with shallow, hardware-native models. The central question is whether these approaches provide practical benefits for semi-supervised anomaly detection on realistic GW data, especially when compared with strong classical baselines. In this work we apply those two QML anomaly-detection approaches for GW detection. QVR is a hybrid algorithm that learns a “rewinding” map for background time-series dynamics. Each time-slice is encoded into a short quantum circuit, and a trained variational unitary aims to map non-anomalous inputs to a target state; anomalies yield large measured deviation. QRC uses a fixed dissipative quantum system (here a 6-qubit reservoir) as a feature generator for the time series, and only the classical readout is trained in a reconstructive task. Both methods need only background noise for training, and output an anomaly score per input window. The studies span real LIGO O3 strain data [5], the open LISA Data Challenge 2a Sangria dataset [25], and synthetic LISA streams with injected massive-black-hole-binary (MBHB) waveforms generated using the LISA Instrument package [26]. We report their performance (precision, recall, F1) and discuss strengths, limitations, and next steps toward LISA and third-generation ground-based detectors.

2 Quantum Anomaly detection

We consider two semi-supervised quantum anomaly-detection models, both trained on background data and evaluated through thresholded anomaly scores.

Quantum Variational Rewinding QVR frames each time series $x_i(t_j)$ as a sequence of scalar values and learns how non-anomalous dynamics should rewind to a reference measurement outcome. At each time t_j , the scalar value is encoded into a quantum state, for example through an X -rotation proportional to the input. A fixed-depth variational unitary $U_{\alpha,\theta}(t_j) = W(\alpha)D(\theta, t_j)W^\dagger(\alpha)$ is applied to $|x_i(t_j)\rangle$ where $W(\alpha)$ is trainable and $D(\theta, t_j)$ is a diagonal phase operation that depends on time, and the circuit depth is constant by design. The model is trained so that non-anomalous inputs map, after measurement, close to a fixed reference value, while anomalous inputs produce larger deviations. The anomaly score of a full window is the average measured deviation over all time steps.

This structure is well suited to GW anomaly detection. It can be trained using only background data, produces a direct thresholdable anomaly score, and remains compatible with near-term quantum devices because it uses a shallow circuit with few trainable parameters. In the LIGO setting, QVR is used to detect confirmed compact-binary signals as deviations from detector background [23]. In the LISA setting, the same rewinding principle is tested on simulated LISA-like time-delay-interferometry (TDI) data with injected MBHB waveforms.

Quantum Reservoir Computing QRC uses a fixed quantum dynamical system as a temporal feature generator. In the rotation-based reservoir considered here, a scalar input $u(t)$ is encoded by all-qubit rotations $R_x(\theta_t) = \exp(-i\theta_t\sigma_x/2)$, with $\theta_t = \pi u(t)$, followed by evolution under the fixed Hamiltonian $H = \sum_{i<j} J_{ij}Z_iZ_j + \sum_i h_i X_i$. Amplitude relaxation provides fading memory, and local Pauli expectation values form the readout feature vector $\phi(t) = [\langle X_i \rangle, \langle Y_i \rangle, \langle Z_i \rangle]_{i=1}^N \oplus 1$, giving 18 measured features plus a bias term for $N = 6$. A classical readout is trained on normal data to reconstruct $s(t - \tau)$, and the anomaly score is defined as $A(t) = |s(t - \tau) - \hat{s}(t - \tau)|$. The threshold is calibrated on normal validation errors, and large reconstruction errors are interpreted as deviations from learned normal dynamics.

3 Data and Results

LIGO data We used strain data from the LIGO Livingston interferometer collected during the third observing run. The data were represented as one-second time series sampled at 4096 Hz. Background-only segments, sampled away from confirmed GW events, were used as non-anomalous data for training and threshold calibration. GW candidates labeled by the LIGO–Virgo–KAGRA collaboration as auxiliary, marginal, or confident were used as anomalous examples.

LISA data We use two simulated LISA data sets. The open LISA Data Challenge 2a Sangria data comprise a one-year training and a one-year blind time-delay-interferometry dataset in the X , Y , and Z observables, sampled at a 5 s cadence [25]. These streams are transformed to the standard A , E , and T basis and a power-spectral-density-based whitening procedure is applied separately to both A and E channels before analysis. We additionally use controlled synthetic LISA TDI streams generated with the LISA Instrument package [26], with injected MBHB waveforms treated as anomalous signals with different scalings relative to the simulated background. The data are sampled at 4 Hz in the A and E channels, and each time series contains 4736 samples, corresponding to around 19.7 min. A similar whitening procedure is applied before analysis.

Results On real LIGO O3 strain data, QVR achieved a mean test accuracy of 0.919 across five noiseless circuit-simulation runs after band-pass and notch filtering, with four runs perfectly separating the selected LIGO GW-event windows from the noise-only test segments [23]. On the Sangria blind dataset, QVR produced above-threshold anomaly scores in windows containing each of the six MBHB signals identified in [27]. Owing to the page limit, this result is reported without an additional figure. The left panel of Fig. 1 shows the separation between the noise-only and signal-injected anomaly-score distributions for QVR applied to synthetic LISA TDI streams. The amplitude scale a multiplies the pure GW contribution before it is re-added to the same estimated noise background. Thus, $a = 1$ represents the original unscaled injection and corresponds to a mean whitened RMS contrast $C_{\text{rms}} = \langle \text{RMS}(h_{\text{GW}}) / \text{RMS}(n_{\text{noise}}) \rangle = 1.22$, meaning that the GW component has an RMS amplitude approximately 1.22 times that of the background noise. The separation is quantified using $d' = (\mu_{\text{GW}} - \mu_{\text{noise}}) / \sqrt{(\sigma_{\text{GW}}^2 + \sigma_{\text{noise}}^2) / 2}$, where μ_{GW} and μ_{noise} are the mean anomaly scores of the signal-injected and noise-only samples, respectively, and σ_{GW} and σ_{noise} are their standard deviations. Thus, $d' = 0$ indicates no separation between the distribution means, while larger positive values indicate stronger mean-score separation.

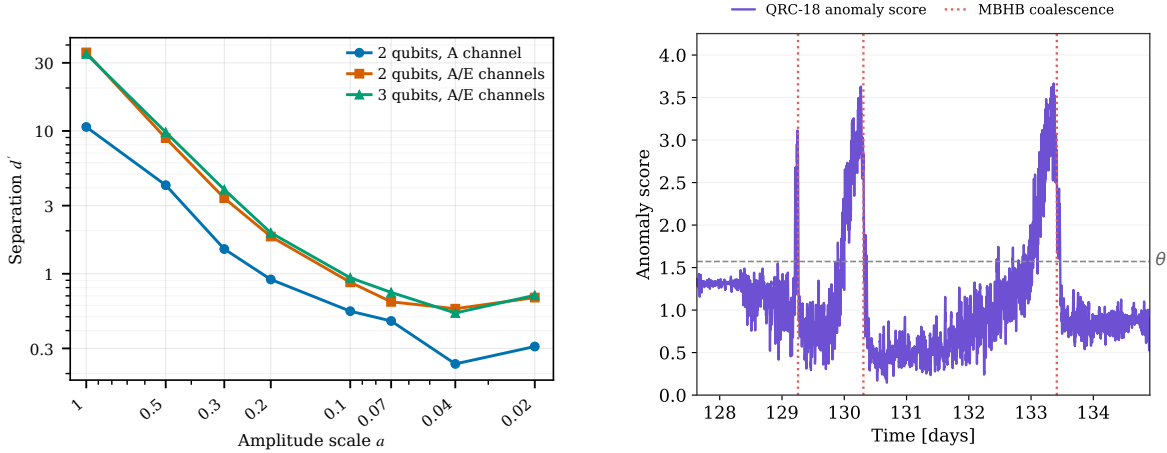


Figure 1: **Left:** Separation d' between the noise-only and signal-injected anomaly-score distributions for QVR evaluated on synthetic LISA TDI streams generated using the LISA Instrument package. Results are shown as a function of the injected signal-amplitude scale a for three QVR configurations. **Right:** QRC-18 reconstruction-error anomaly score $A(t)$ on the whitened E channel of the LISA Sangria dataset, with the detection threshold θ and the three MBHB coalescences.

Table 1 reports the corresponding precision, recall, and F_1 score at each amplitude. Both bivariate QVR configurations achieve perfect recall down to $a = 0.3$ and retain higher recall and F_1 scores than the univariate configuration as the signal becomes weaker. However, augmenting the bivariate QVR circuit with an additional unencoded auxiliary qubit does not produce a substantial or consistent improvement. This suggests that the performance gain arises primarily from including the second TDI stream rather than from enlarging the quantum register with the auxiliary qubit.

Amplitude scaling a	2 qubits, A channel (univariate)			2 qubits, A/E channels (bivariate)			3 qubits, A/E channels (bivariate)		
	Precision	Recall	F_1	Precision	Recall	F_1	Precision	Recall	F_1
1.00	0.9524	1.0000	0.9756	0.9091	1.0000	0.9524	0.9091	1.0000	0.9524
0.50	0.9524	1.0000	0.9756	0.9091	1.0000	0.9524	0.9091	1.0000	0.9524
0.30	0.9167	0.5500	0.6875	0.9091	1.0000	0.9524	0.9091	1.0000	0.9524
0.20	0.9231	0.6000	0.7273	0.8947	0.8500	0.8718	0.8889	0.8000	0.8421
0.10	0.8750	0.3500	0.5000	0.8182	0.4500	0.5806	0.8571	0.6000	0.7059
0.07	0.5000	0.0500	0.0909	0.7778	0.3500	0.4828	0.8333	0.5000	0.6250
0.04	0.8000	0.2000	0.3200	0.7500	0.3000	0.4286	0.8182	0.4500	0.5806
0.02	0.7500	0.1500	0.2500	0.8182	0.4500	0.5806	0.8182	0.4500	0.5806

Table 1: Detection performance on synthetic LISA TDI streams generated using the LISA Instrument package. Metrics are reported at each injected signal-amplitude scale using one fixed, globally tuned threshold for each QVR configuration.

The right panel of Fig. 1 shows the QRC reconstruction error $A(t)$ at reconstruction lag $\tau = 5$ on the whitened E channel of the LISA Sangria training dataset, for a representative reservoir seed. The test window contains three MBHB catalogue coalescences (days 129.26, 130.31, and 133.41). The six-qubit reservoir is trained only on event-free background, and the detection threshold θ is the 99.5th percentile of the validation reconstruction error. Away from events the smoothed error stays near the background level; it rises into each labelled coalescence window as the inspiral signal grows, with the strongest peak reaching $3.22 \times \theta$ near day 130.3. Averaged over seven reservoir seeds, the QRC attains precision 0.528 ± 0.213 , recall 0.416 ± 0.129 , and $F_1 = 0.420 \pm 0.070$ over the labelled test window. Trained on background alone, the reservoir therefore produces reconstruction-error peaks that coincide with the MBHB coalescences, showing that a small dissipative quantum reservoir can flag GW events in simulated LISA data. The moderate precision reflects the broad evaluation window placed around each catalogue coalescence time, within which the error remains elevated, rather than a failure to localise the events.

4 Conclusion

We presented QVR and QRC as quantum machine-learning approaches for semi-supervised GW anomaly detection. QVR shows strong performance on real LIGO data and detects MBHB injections in simulated LISA-like streams, while QRC shows that small dissipative reservoirs can generate useful temporal features for reconstructive anomaly detection. These feasibility results motivate longer LISA-like tests, multi-channel Sangria benchmarks, hardware-aware noise studies, and event-level metrics for LISA and Einstein Telescope scenarios.

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