PROCEEDINGS OF SCIENCE

Data Quality and Event Validation in LIGO-Virgo-KAGRA Fourth Joint Observational Campaign

Francesco Di Renzo, on behalf of the Virgo Collaboration

Université Lyon, Université Claude Bernard Lyon 1, CNRS, IP2I Lyon / IN2P3, UMR 5822, F-69622 Villeurbanne, France

E-mail: f.di-renzo@ip2i.in2p3.fr

The success of gravitational wave astronomy hinges on precise data quality assessment and the meticulous validation of detected events. This contribution highlights the critical role of these processes within the ongoing O4 observational campaign by the LIGO, Virgo, and KAGRA collaborations. We begin by introducing detector data and the concept of data quality. Next, we examine how common data-quality issues impact the detection of astrophysical signals, affecting both their significance and the reliability of astrophysical parameter estimates. We then describe the statistical methods used to identify and mitigate these issues, followed by an overview of the event validation framework employed in O4 to confirm the astrophysical origins of candidate signals.

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1. Interferometric Gravitational-Wave Detector Data

Gravitational waves (GWs) are ripples in spacetime caused by the acceleration of massive astrophysical objects, such as merging black holes or neutron stars. The LIGO [1], Virgo [2], and KAGRA [3] (LVK) detectors use highly sensitive interferometers to detect these waves from the strain produced on the detector arms. Many phenomena of no astrophysical origin, either environmental or instrumental, can produce effects on the detector similar to a strain, hence constituting a source of *noise* for the identification of the astrophysical signal. The detector output can then be expressed as the time series: $x(t) = n(t) + s(t)$, where $n(t)$ represents the noise and $s(t)$ is the astrophysical signal we aim to detect. This noise is typically treated as a *stochastic process*. Our ability to extract the information on the astrophysical signal depends critically on how well we know the statistical properties of this noise [4].

The fourth joint observational campaign (O4) of the LVK, which began in May 2023, continuously records data and sends out alerts for transient GW event candidates. Ensuring the quality of this data and the thorough characterization of the various noise sources is essential for accurately identifying and interpreting GW signals, as discussed in the following sections.

2. Data Quality Issues and Their Effects

Common GW data analysis techniques assume that the detector noise can be modeled as a *stationary* and *Gaussian* process [4]. We briefly discuss here the case of model-based searches. In these searches, the signal is modeled using a bank of theoretical waveforms $h(t;\boldsymbol{\theta})$, with $\boldsymbol{\theta}$ a set of astrophysical parameters, such as masses and spins. The (unknown) astrophysical signal can then be approximated as $s(t) \approx \varrho\, h(t;\boldsymbol{\theta})$, with ϱ a proportionality factor for the signal strength.

Under the assumption of stationary and Gaussian noise, the optimal detection statistic is the *matched filter*, defined by the inner product:

$$(x|y) = 4\Re \int_0^\infty \frac{\tilde{x}(f)\, \tilde{h}^*(f)}{S(f)} df \tag{1}$$

where tilded quantities indicate Fourier transforms and $S(f)$ is the noise power spectral density (PSD). The PSD fully represents the statistical properties of a Gaussian process, and can be estimated from the data if the process is stationary (ergodic theorem). If these assumptions hold and the waveform models are normalized, according to the inner product in (1), such that $(h|h) = 1$, the expected value of the detection statistic becomes $E[(x|h)] = \varrho$, and its variance, in the absence of a signal, is $Var[(n|h)] = 1$ [5]. Thus, ϱ can be interpreted as the signal-to-noise ratio (SNR) of the template $h(t;\boldsymbol{\theta})$.

A *data quality* (DQ) issue refers to any deviation from the assumptions of stationarity and Gaussianity. These deviations can significantly affect GW searches [6]. For example, transient noise can mislead the estimation of the noise PSD, rendering the matched filter statistic (1) no longer optimal. If the PSD is incorrectly estimated as $S_w(f) = S(f)(1 + \epsilon(f))$, with $\epsilon(f)$ representing the error, the recovered SNR will be reduced as $\varrho/(1+O(\epsilon^2))$. This reduction in SNR decreases the search sensitivity and can result in missed detections [5].

Transient noise bursts, or "glitches," which can arise from instrumental malfunctions, transient seismic events, or electromagnetic disturbances, may also mimic true GW signals by producing spurious spikes in the detection statistic (1). These can lead to false detections or, if they overlap with real astrophysical signals, obscure their presence. For instance, the binary neutron star event GW170817 was partially obscured by a glitch, complicating the signal analysis [7].

DQ issues also impact the precision and reliability of parameter estimation. Noise transients in the vicinity or superimposing a true signal can introduce biases and uncertainties in the measurements of source properties, such as the masses and spins of binary objects, or the distance of the source [8]. Glitches can also distort the sky localization of the source, affecting how well the LVK collaboration can inform astronomers about the position of the detected candidate events in the sky [9]. This has significant consequences for follow-up observations by astronomical partners.

Additionally, non-stationary noise affects various other analyses, including the measurement of the Hubble constant H_0 using the standard-siren method [10], and introduces biases in tests of General Relativity [11].

3. Identifying Data-Quality Issues: Statistical Tests and Methods

As discussed in the previous section, identifying and mitigating DQ issues is crucial for ensuring the reliability of the data and robustness of the scientific results that are published by the LVK. To address these challenges, the collaboration employs a variety of methods to flag problematic data segments that may affect GW searches and parameter estimation [12, 13].

One key approach involves statistical tests aimed at verifying the properties of stationarity and Gaussiantity of the noise [14]. These tests are necessary for ensuring that the noise behaves as expected by the search pipelines over time. Another important set of tests focuses on monitoring variations in the PSD, which is critical for the accuracy of matched-filtering detection statistic (1) [15]. These PSD-based tests are especially useful for identifying DQ issues near candidate transient GW events. Additionally, if glitch subtraction procedures are applied to clean up noisy events (more details in the next section), these tests assess the success of that process [16].

Another category of tests specifically targets DQ issues by identifying excess energy in the detector data. A prominent example is the *omicron* algorithm [17]. Based on the *Omega pipeline* [18] and originally developed for detecting unmodeled burst signals, this algorithm is also highly effective at identifying excess noise in the data. It decomposes the detector data using a wavelet-based multi-resolution approach. Then, it flags statistically significant excesses in the values of the wavelet coefficients, helping to pinpoint glitches.

A growing number of statistical tests use machine learning and artificial intelligence (AI) techniques to differentiate between noise-induced excess energy and true astrophysical signals [19]. Many of these AI-driven tests rely on classifications of glitches performed in citizen science projects, such as Gravity Spy [20].

In addition to analyzing the main GW strain data, a wealth of information comes from the auxiliary channels that monitor the detectors environment and subsystems. These channels record seismic, acoustic, and magnetic disturbances, among others, and offer valuable insights into potential noise sources. Tests that correlate excess energy in the strain with signals in auxiliary channels are particularly powerful for identifying noise sources [14, 21]; if the excess energy in the strain data coincides with a signal in an auxiliary channel, especially one not expected to carry astrophysical information, it may suggest that the excess is noise-related, thereby ruling out the event as a GW signal. AI-based statistical correlation tests also play a role in this process. Trained on thousands of realization of glitches, these tests improve the ability to predict whether an observed excess of energy in the strain is of astrophysical or instrumental origin [22]. These methods are now integrated into search pipelines, allowing the significance of candidate events to be automatically reweighted based on the data quality information [23].

4. Validation of Candidate Events

The data collected by LVK detectors is continuously scanned in real-time for transient GW signals by search algorithms such as PyCBC Live, GstLAL, and MBTA [24]. These pipelines flag candidate events and assign them an SNR and a significance based on how closely they resemble modeled GW signals. Unmodeled search pipelines, like cWB, similarly evaluate the significance of coherent excess energy detected across multiple instruments When a significant candidate GW event is identified, an automatic alert is produced. This initiates a rigorous validation process to ensure the event is a genuine astrophysical signal and not contaminated by DQ issues.

The process of validation of a GW candidate event has greatly improved and automatized since O3 [25]. It still consists of two main phases: a prompt validation and an offline validation.

The prompt validation is carried out by the Rapid Response Team (RRT), a joint LVK team whose role is to provide human vetting of alerts generated after a significant event candidate is detected. They conduct a series of prescribed DQ checks, informed by the Data Quality Report (DQR) framework, which incorporates the statistical tests described in Sec. 3. The RRT assesses the DQR output for any signs of DQ issues and decides whether to retract the alert (if there is evidence of severe noise contamination) or validate it. If modest DQ issues are present but not severe enough to question the astrophysical origin of the candidate, a DQ statement is often added to the alerts sent out to the astronomical community.

The offline validation is performed on all candidate events identified by both online and offline search pipelines. This phase involves a more meticulous evaluation of the DQR output, including additional tests executed with higher latency. The preliminary evaluation by the RRT is either confirmed or revised. If DQ issues are detected, their impact on the data is assessed, and noise mitigation procedures may be initiated, as described in [16]. The results of the noise mitigation process are iteratively reassessed to ensure any residual DQ issues are identified and their impact on the analysis results is evaluated.

The final recommendation regarding which data to use or what noise mitigation procedure to apply is forwarded to all downstream LVK analyses.

This comprehensive validation process ensures the credibility of all alerts and the scientific results published by the LVK collaboration.

5. Conclusions

Data quality is a critical factor in the success of GW astronomy and is an integral part of the searches conducted by the LVK collaboration. By identifying and mitigating noise, and validating candidate events with rigorous statistical methods, the LVK ensures the robustness of its published scientific results and provides reliable data for the broader scientific community. As the detector

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sensitivity improves, continued efforts to refine DQ evaluation processes will play a key role in advancing our understanding of the universe through GW astronomy.

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