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**An Exploration of Statistical Methods  
in Determining the Gaussianity of LIGO  
Detector Data**

A project in  
Data Science  
by

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# Abstract

The Advanced Laser Interferometer Gravitational-wave Observatory (LIGO) is one of the most sophisticated instruments ever built, capable of measuring motion 10,000 times smaller than a proton, and was the first device to detect a Gravitational Wave (GW) event. Due to its high sensitivity, a common issue is its susceptibility to glitches: transient, non-Gaussian noise bursts occurring at a high enough rate to contaminate the time series data obtained from the detector. The current methods to detect and study glitches, though highly effective for analyzing the strain data during the detection run, prove to be slow when working with a large throughput of detector data. Here we study a few possible statistical approaches to detecting these glitches in the time-amplitude domain. By sampling the strain data, conditioning it, and employing tests of normality, mainly the Shapiro-Wilk test, the Kolmogorov-Smirnov test, and the Anderson-Darling test, we gauge their effectiveness in determining the Gaussianity of a sample time-series strain data from the detector. The alternate hypothesis of these tests, i.e., the sample belonging to a non-Gaussian distribution, indicates the presence of a glitch or a signal. The results of this experiment explore in detail the viability of these tests as efficient alternatives to the current solutions used in detecting a glitch or astrophysical event in a time series signal.

## 1 Introduction

Nearly a century after Einstein’s prediction of the existence of Gravitational Waves (GWs) in 1916, the first direct gravitational wave detection was achieved by the Advanced Laser Interferometer Gravitational-Wave Observatory (aLIGO) and Virgo collaboration during the binary black hole merger event GW150914 on September 14, 2015. The LIGO Livingston (L1) interferometer underwent several upgrades following this run - effectively a massive redesign - enhancing its sensitivity by 15% to 25% [1]. This improvement was evident during the O2 observing run during which L1, in conjunction with its Hanford (H1) counterpart and Virgo (V1), detected eleven new gravitational wave signals [2]. Subsequently, during the O3 run, all three detectors operated at their best possible sensitivity, leading to the first single-detector GW detection, GW190425, achieved by LIGO Livingston [3]. There have been over 90 GW events recorded at a high level of confidence since the LIGO-Virgo collaboration’s inception to date.

A consequence of these detectors’ sensitivities is their susceptibility to noise. During observation runs, various noise sources, such as seismic noise, suspension thermal noise, and sensing noise, affect the data collected by the interferometers. All these sources collectively produce time series signals which can be treated as stochastic processes with their corresponding joint probability distributions and statistical properties [4]. In the absence of astronomical signals or glitches, the probability distribution of the noise follows a normal distribution, also known as *Gaussian* noise. In the event of a Gravitational wave or any other signal, the noise exhibits a high signal-to-noise ratio (SNR), making it *non-Gaussian*.

Among these noise sources, the most problematic are **glitches**: transient events caused by non-astrophysical phenomena such as anthropogenic noise, weather conditions, or instrument malfunctions [4, 5]. Glitches manifest as localized bursts of excess power in interferometer time series data and often do not have well-defined sources. They can occur at energy levels and frequencies that overlap with GW signals, thereby mimicking them and increasing the number of false positive detections. During the first half of the third observing run (O3a) LIGO Hanford and Livingston recorded glitches rates of  $0.29 \text{ min}^{-1}$  and  $1.10 \text{ min}^{-1}$  respectively, which rose to  $0.32 \text{ min}^{-1}$  and

1.17 min<sup>-1</sup> during the second half (O3b) [6]. Of the 90 candidate events detected in this run, 17 had a probability of astronomical origin ( $p_{\text{astro}}$ ) below 0.5, suggesting significant ambiguity about their origin. A notable example of glitches posing such an issue was during the binary neutron star merger event GW170817 [7], during which instrumental noise transients were detected before the event’s coalescence time, complicating its detection and subsequent analysis.

Detecting and mitigating the effects of glitches in interferometric strain data remains an active area of research within astrophysical data analysis, with several techniques proposed and implemented for the same [8–10]. However, many of these are computationally expensive and lack the efficiency required for near-real-time assessment of the signals for glitch activity. The more popular solutions incorporate the *q-transform* [11, 12], a modification of the standard Fourier transform where the analysis window scales inversely with frequency. This q-transform computes a p-value depicting the statistical significance of excess power in the data. Assuming the background data to be Gaussian, the excess power that does not follow a Gaussian distribution suggests the presence of a glitch. While this method is effective for post-detection run analysis, it is computationally intensive for real-time uses. Performing q-transforms on 10-second sample of interferometer data on a laptop requires between 20 and 45 seconds. When scaled up to multiple samples, the computational time would increase significantly.

This project explores statistical hypothesis testing on time-amplitude domain data as a faster alternative to the current glitch detection methods working in the frequency domain. Building on the idea presented in [4], which treats detector noise as stochastic processes with joint probability distributions, it would be reasonable to assume that parametric and non-parametric statistical tests could be effectively applied to such data. This study focuses on applying (1) the Shapiro-Wilk test, (2) the Kolmogorov-Smirnov test, and (3) the Anderson-Darling test on preprocessed samples of clean and glitched data from the LIGO Livingston interferometer. The objective is to determine the normality of these samples and assess how well these tests differentiate between Gaussian (clean) and non-Gaussian (glitched) samples. This experiment also includes studying the distributions, waveforms, and frequency ranges, with particular emphasis on failure points for each statistical test across various glitch types. Furthermore, considering the frequency bands at which each glitch type occurs, this study also examines how each statistical test performs under band-pass filtering at various frequency ranges.

This report is organized as follows: Section 2 discusses how interferometer data is obtained and describes the properties of the time series data used in this study. It also outlines the process of acquiring clean and glitched samples and the preprocessing applied. Section 3 describes in detail the statistical tests of Gaussianity used to assess the sample data. The experimental procedures and results are presented in Sections 4 and 5. Finally, Section 6 summarizes the findings of our experiments, discussing the strengths and limitations of the methods, followed by the future scope in Section 7.

## 2 Data Acquisition and Conditioning

The Advanced LIGO and Virgo interferometers are large-scale, heavily modified versions of the Michelson interferometer (Figure 1a), originally invented by American physicist Albert A. Michelson in 1887 [6, 13]. LIGO operates in a vacuum, using a laser beam of light split into two orthogonal parts with the help of a half-silvered mirror mounted on horizontal seismometer suspensions. The orthogonally split beams are then sent through two arms of the interferometer, known as Fabry–Pérot cavities. Each of these arms is 4 kilometers long, consisting of mirrors at each end. The first of the mirrors is fixed in place, while the second one is movable with the help of precise micrometer drives. The laser beams, when reflected by the mirrors on either end of the arms, are combined again at the beam splitter and sent to photoelectric detectors. The aLIGO interferometer is designed such that if the beams travel equal distances, the recombination would lead to a destructive interference pattern, resulting in no light coming out of the instrument [14]. When a disturbance of either astrophysical or terrestrial origin is detected, an infinitesimally small change occurs in lengths of the detector arms, in the order of  $10^{-8}m$  [15]. One of the arms is stretched, and the other arm is compressed in the perpendicular direction, altering the lengths of the reflected and combined beams, misaligning them and resulting in an interference pattern (Figure 1b). This interference pattern, coupled with results from several other sensors, provides detailed information on the *strain* of the GW or glitch event being observed.



Figure 1: Illustrations of a basic Michelson interferometer [16, 17] and what an interference pattern would look like.

The **GWpy** Python package is widely used in this project. It provides a suite of tools to access and condition detector strain data from the Gravitational-Wave Open Science Centre (GWOSC) database [18]. This data is in the time domain, as timestamps in the GPS time system at nanosecond precision, and records the amplitude of the noise event as a differential change in lengths of the interferometer arms. **GWpy** handles detector data using the **TimeSeries** object, which is built upon **numpy** arrays. This allows compatibility with most of the core **numpy** utilities along with custom functions for signal processing, tabular data filtering, and visualization.

We use the strain data from LIGO Livingston (L1) during the first part of the third observing run (O3a) for this project. Figure 3 shows the steps taken to acquire signal data from the detector and condition it for statistical testing.

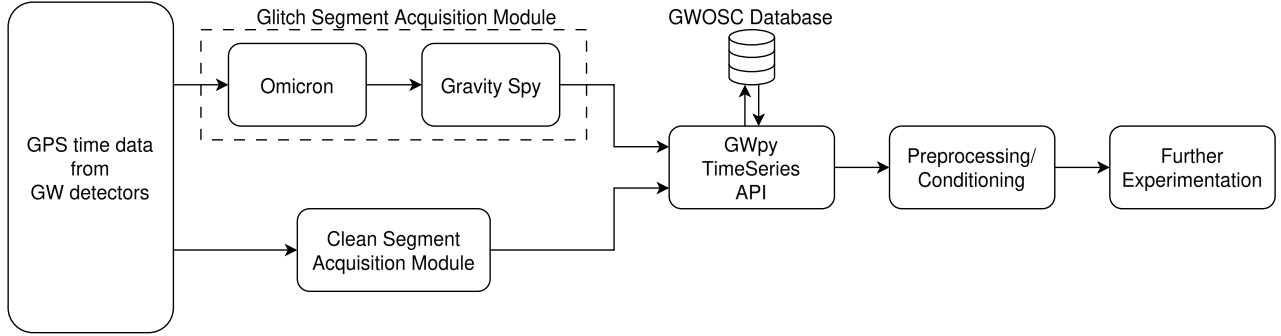


Figure 2: The Data Acquisition and Conditioning Pipeline

We use two separate modules to load the glitched time series and the clean time series sample data.

## 2.1 Glitch Samples

The GPS times of glitch occurrences are obtained using *Gravity Spy* [19], a large-scale citizen-science project that combines astrophysics, machine learning, and human efforts to classify glitches in GW interferometer data. The *Omicron* transient search algorithm is used by Gravity Spy to generate q-transform spectrograms and calculate SNR of the time series samples [8]. This algorithm is crucial in identifying the most useful samples for data classification and analysis. Based on the morphological characteristics from the spectrograms, a total of 22 glitch classes were identified with an SNR above 7.5 and peak frequencies between 10 Hz and 2048 Hz.

In the O3a data for L1, Fast\_Scattering and Tomte glitches are the most prevalent, while Chirp, 1080Lines and Wandering\_line glitches have fewer samples, as shown in Table 1. The No\_Glitch class represents glitch samples that lack significant traits or energy levels and do not fit in with the other classes morphologically. Hence, for our study, we do not consider this glitch class.

Glitch Class	Count	Glitch Class	Count
Fast_Scattering	21749	Whistle	896
Tomte	18708	Low_Frequency_Lines	788
Blip_Low_Frequency	7549	Scratchy	207
Scattered_Light	5398	Repeating_Blips	164
No_Glitch	5358	Violin_Mode	164
Extremely_Loud	4319	Paired_Doves	155
Koi_Fish	4268	Light_Modulation	72
1400Ripples	2363	Helix	21
Blip	1947	Wandering_Line	20
Power_Line	1189	1080Lines	9
Low_Frequency_Burst	1187	Chirp	6

Table 1: Glitch counts per class for LIGO Livingston (L1) during the O3a run.

Using the glitch GPS times, the time series information is obtained from the GWOSC database using the `TimeSeries.fetch_open_data()` API provided by GWpy. Here, a time window of 10 seconds is taken on either side of each of the GPS times with the glitch in the center, sampled at a rate of 4096 Hz. The TimeSeries objects obtained are then conditioned for statistical testing and cropped down to a 1-second sample for further use.

## 2.2 Clean Samples

The process of finding gaps of clean detector noise is done using `gwtrigfind`, a package developed to search for event triggers files from GW detectors, in conjunction with `EventTable`, provided by GWpy.

Taking the start and end GPS times of the O3a run, `gwtrigfind` is used to find the file path containing Omicron triggers from the *L1:GDS-CALIB-STRAIN* channel of the L1 detector. `EventTable` is then used to load all the trigger data, containing information on the start and end GPS times of the events. Taking the time frames between the end and start times of successive events, we obtain the gaps between glitches/GW triggers, which do not have a significant amount of noise activity. The sizes of the gaps are clamped between 7 and 30 seconds because too short of a gap could lead to the inclusion of glitches in the sample, as the time series data may not have enough time to stabilize after a glitch; and too long of a time gap could be indicative of detector malfunction or a period of time when it is not operational.

The GPS start and end times of the clean segments are then used to calculate their Q-transform and corresponding p-values. The GPS time intervals with a p-value greater than 0.95 are considered to be clean segments of data, and are used to obtain the corresponding TimeSeries data from GWpy. The TimeSeries data is then, similar to the glitch data conditioned for statistical testing and cropped down to 1-second samples for further use.

## 2.3 Data Conditioning

The TimeSeries data obtained from GWpy needs to be conditioned before use for statistical testing. The two main steps taken for this are **whitening** and **filtering**.

### 2.3.1 Whitening

The information obtained from GW detectors encompasses a wide range of frequencies. Due to this, low frequency noise often dominates the data, hence hiding the high frequency components which would be indicative of a signal's presence. Hence, some signal processing is required to counteract this.

Figure 3: Example of a Tomte glitch with a high SNR. Note that the unwhitened data is dominated by low frequency noise, hence making it difficult to detect the glitch. The whitened data, however, shows a clear peak at the glitch.

Consider the example of a Tomte glitch  
Whitening is the process of

### 2.3.2 Filtering

## 3 Methods

### 3.1 Motivation

### 3.2 Shapiro-Wilks Test

### 3.3 KS

### 3.4 AD

## 4 Experimentation with the complete frequency range

## 5 Experimentation with a band pass filter applied

## 6 Conclusions

## 7 Future Scope

## 8 Appendix

## References

- [1] Andrew Grant. “Advanced LIGO ramps up, with slight improvements”. en. In: *Physics Today* 2016.11 (Nov. 2016), p. 12128. ISSN: 19450699. DOI: [10.1063/pt.5.9074](https://pubs.aip.org/physicstoday/online/12128). URL: <https://pubs.aip.org/physicstoday/online/12128> (visited on 04/05/2025).
- [2] The LIGO Scientific Collaboration, the Virgo Collaboration, et al. “GWTC-1: A Gravitational-Wave Transient Catalog of Compact Binary Mergers Observed by LIGO and Virgo during the First and Second Observing Runs”. In: *Physical Review X* 9.3 (Sept. 2019). arXiv:1811.12907 [astro-ph], p. 031040. ISSN: 2160-3308. DOI: [10.1103/PhysRevX.9.031040](https://arxiv.org/abs/1811.12907). URL: <http://arxiv.org/abs/1811.12907> (visited on 04/05/2025).
- [3] R. Abbott et al. *GWTC-2: Compact Binary Coalescences Observed by LIGO and Virgo During the First Half of the Third Observing Run*. arXiv:2010.14527 [gr-qc]. Mar. 2021. DOI: [10.1103/PhysRevX.11.021053](https://arxiv.org/abs/2010.14527). URL: <http://arxiv.org/abs/2010.14527>.
- [4] The LIGO Scientific Collaboration, the Virgo Collaboration, et al. “A guide to LIGO-Virgo detector noise and extraction of transient gravitational-wave signals”. In: *Classical and Quantum Gravity* 37.5 (Mar. 2020). arXiv:1908.11170 [gr-qc], p. 055002. ISSN: 0264-9381, 1361-6382. DOI: [10.1088/1361-6382/ab685e](https://arxiv.org/abs/1908.11170). URL: <http://arxiv.org/abs/1908.11170> (visited on 04/12/2025).



- [5] The LIGO Scientific Collaboration and the Virgo Collaboration. “Characterization of transient noise in Advanced LIGO relevant to gravitational wave signal GW150914”. In: *Classical and Quantum Gravity* 33.13 (July 2016). arXiv:1602.03844 [gr-qc], p. 134001. ISSN: 0264-9381, 1361-6382. DOI: [10.1088/0264-9381/33/13/134001](https://doi.org/10.1088/0264-9381/33/13/134001). URL: <http://arxiv.org/abs/1602.03844> (visited on 04/11/2025).
- [6] The LIGO Scientific Collaboration, the Virgo Collaboration, et al. *GWTC-3: Compact Binary Coalescences Observed by LIGO and Virgo During the Second Part of the Third Observing Run*. arXiv:2111.03606 [gr-qc]. Oct. 2023. DOI: [10.1103/PhysRevX.13.041039](https://doi.org/10.1103/PhysRevX.13.041039). URL: <http://arxiv.org/abs/2111.03606>.
- [7] The LIGO Scientific Collaboration and The Virgo Collaboration. “GW170817: Observation of Gravitational Waves from a Binary Neutron Star Inspiral”. In: *Physical Review Letters* 119.16 (Oct. 2017). arXiv:1710.05832 [gr-qc], p. 161101. ISSN: 0031-9007, 1079-7114. DOI: [10.1103/PhysRevLett.119.161101](https://doi.org/10.1103/PhysRevLett.119.161101). URL: <http://arxiv.org/abs/1710.05832> (visited on 04/17/2025).
- [8] Florent Robinet et al. “Omicron: A tool to characterize transient noise in gravitational-wave detectors”. In: *SoftwareX* 12 (2020), p. 100620. ISSN: 2352-7110. DOI: <https://doi.org/10.1016/j.softx.2020.100620>. URL: <https://www.sciencedirect.com/science/article/pii/S2352711020303332>.
- [9] Duncan M. Macleod et al. “GWpy: A Python package for gravitational-wave astrophysics”. In: *SoftwareX* 13 (2021), p. 100657. ISSN: 2352-7110. DOI: <https://doi.org/10.1016/j.softx.2021.100657>. URL: <https://www.sciencedirect.com/science/article/pii/S2352711021000029>.
- [10] D. Davis et al. “Subtracting glitches from gravitational-wave detector data during the third observing run”. In: *Classical and Quantum Gravity* 39.24 (Dec. 2022). arXiv:2207.03429 [astro-ph], p. 245013. ISSN: 0264-9381, 1361-6382. DOI: [10.1088/1361-6382/aca238](https://doi.org/10.1088/1361-6382/aca238). URL: <http://arxiv.org/abs/2207.03429>.
- [11] S. Chatterji et al. “Multiresolution techniques for the detection of gravitational-wave bursts”. In: *Classical and Quantum Gravity* 21.20 (Oct. 2004). arXiv:gr-qc/0412119, S1809–S1818. ISSN: 0264-9381, 1361-6382. DOI: [10.1088/0264-9381/21/20/024](https://doi.org/10.1088/0264-9381/21/20/024). URL: <http://arxiv.org/abs/gr-qc/0412119> (visited on 04/15/2025).
- [12] Leah Vazsonyi and Derek Davis. “Identifying glitches near gravitational-wave signals from compact binary coalescences using the Q-transform”. In: *Classical and Quantum Gravity* 40.3 (Feb. 2023). arXiv:2208.12338 [astro-ph], p. 035008. ISSN: 0264-9381, 1361-6382. DOI: [10.1088/1361-6382/acaf2](https://doi.org/10.1088/1361-6382/acaf2). URL: <http://arxiv.org/abs/2208.12338> (visited on 04/14/2025).
- [13] R. Weiss et al. *Quarterly Progress Report No. 105*. Apr. 1972. URL: <https://dspace.mit.edu/handle/1721.1/56271>.
- [14] The LIGO Scientific Collaboration. *What is an Interferometer?* URL: <https://www.ligo.caltech.edu/page/what-is-interferometer> (visited on 04/07/2025).
- [15] Sudarshan Ghonge et al. *Assessing and Mitigating the Impact of Glitches on Gravitational-Wave Parameter Estimation: a Model Agnostic Approach*. arXiv:2311.09159 [gr-qc]. Oct. 2024. DOI: [10.48550/arXiv.2311.09159](https://doi.org/10.48550/arXiv.2311.09159). URL: <http://arxiv.org/abs/2311.09159>.

- [16] Stannered. *Simple Michelson interferometer diagram*. 2007. URL: <https://commons.wikimedia.org/wiki/File:Interferometer.svg>.
- [17] WiredSense. *The Michelson Interferometer - A Laser Lab Alignment Guide*. WiredSense Tutorials. URL: <https://www.wiredsense.com/tutorial/the-michelson-interferometer-a-laser-lab-alignment-guide>.
- [18] D. M. Macleod et al. “GWpy: A Python package for gravitational-wave astrophysics”. In: *SoftwareX* 13 (2021), p. 100657. ISSN: 2352-7110. DOI: [10.1016/j.softx.2021.100657](https://doi.org/10.1016/j.softx.2021.100657). URL: <https://www.sciencedirect.com/science/article/pii/S2352711021000029>.
- [19] M Zevin et al. “Gravity Spy: integrating advanced LIGO detector characterization, machine learning, and citizen science”. In: *Classical and Quantum Gravity* 34.6 (Feb. 2017), p. 064003. ISSN: 1361-6382. DOI: [10.1088/1361-6382/aa5cea](https://doi.org/10.1088/1361-6382/aa5cea). URL: <http://dx.doi.org/10.1088/1361-6382/aa5cea>.