AI for Gravitational Waves Workshop @ CERN

GravCloud: A stacked LSTM-Pointcloud Framework for LIGO Glitch Classification

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1 Introduction

LIGO Scientific Collaboration gravitational-wave analysis relies on detecting displacements as small as 10^{-4} times the width of a proton, making noise mitigation a major challenge. Alongside instrumentation improvements, noise modeling provides another approach by **identifying** and **separating** detector noise from true astrophysical signals.

Current LIGO Scientific Collaboration pipelines use **Bayesian** and **statistical methods** to separate noisy and pristine data, using SNR thresholds that discard valuable information and struggle with transient noise bursts (**TNBs**). Most approaches analyze data in **1D or 2D spectrograms**, limiting capturing complex glitches.

GravCloud uses a *higher-dimensional representation* of detector data, combining **SNR**, **frequency**, **amplitude** and **q-values** to better visualize and characterize transient noise features.

2 Objective

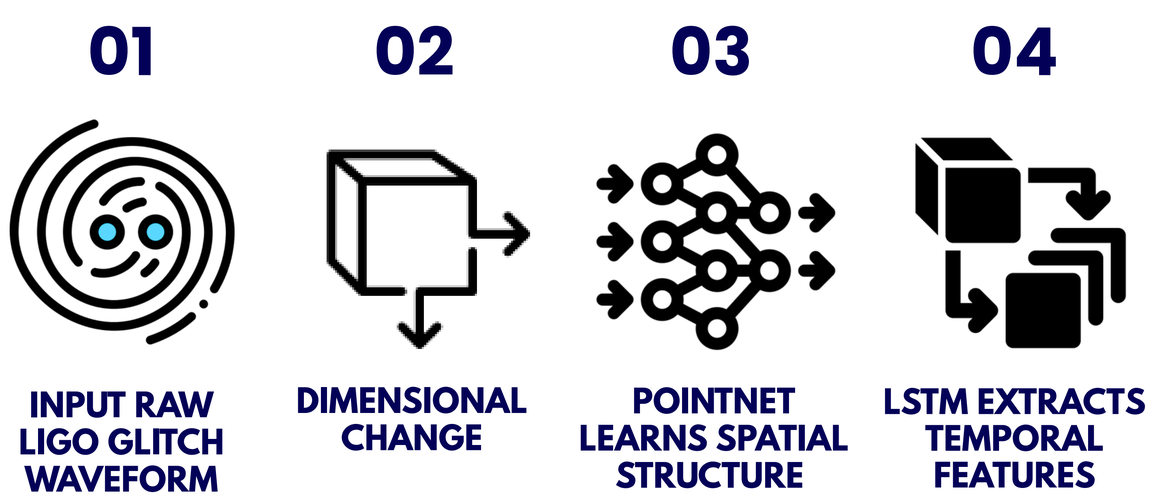
GravCloud aims to **identify** and **localize** *transient noise bursts* within the LIGO Scientific Collaboration interferometer in **real time** using higher-dimensional data representations and deep learning. The project focuses on:

- Characterizing noise **beyond traditional** (1D, 2D) analyses
- Detector data in a **4D feature space** for improved detection
- Tracking **transient** bursts over time rather than **static** frames
- Performing **multi-class classification** to predict noise origins
- Flagging **noisy observation periods** without discarding data

3 Methodology

We use the **O3b observation** run from LIGO Scientific Collaboration public data available through **Gravitational Wave Open Science Center (GWOSC)**. Triggers are generated using the Omicron pipeline, which isolates noisy segments of detector data based on key parameters.

These extracted **“Omicron triggers”** are then processed by our custom model. This combines a **PointNet model**, which classifies trigger frames at individual time steps, with an LSTM network that learns the temporal behavior of transient noise bursts (**TNBs**). PointNet identifies the **class** of each signal snapshot, as the LSTM captures **temporal patterns** in successive frames, improving noise-source classification.



Related literature

Hochreiter, S. & Schmidhuber, J. (1997). Long Short-Term Memory.
Wang, Y. et al. (2019). Dynamic Graph CNN for Learning on Point Clouds.
Cavaglia, M. et al. (2019) Finding the origin of noise transients in LIGO data with machine learning.

4 Progress

Preliminary results show that **point clouds** and **dynamic graphs** improve glitch separation *beyond traditional 1D methods*.

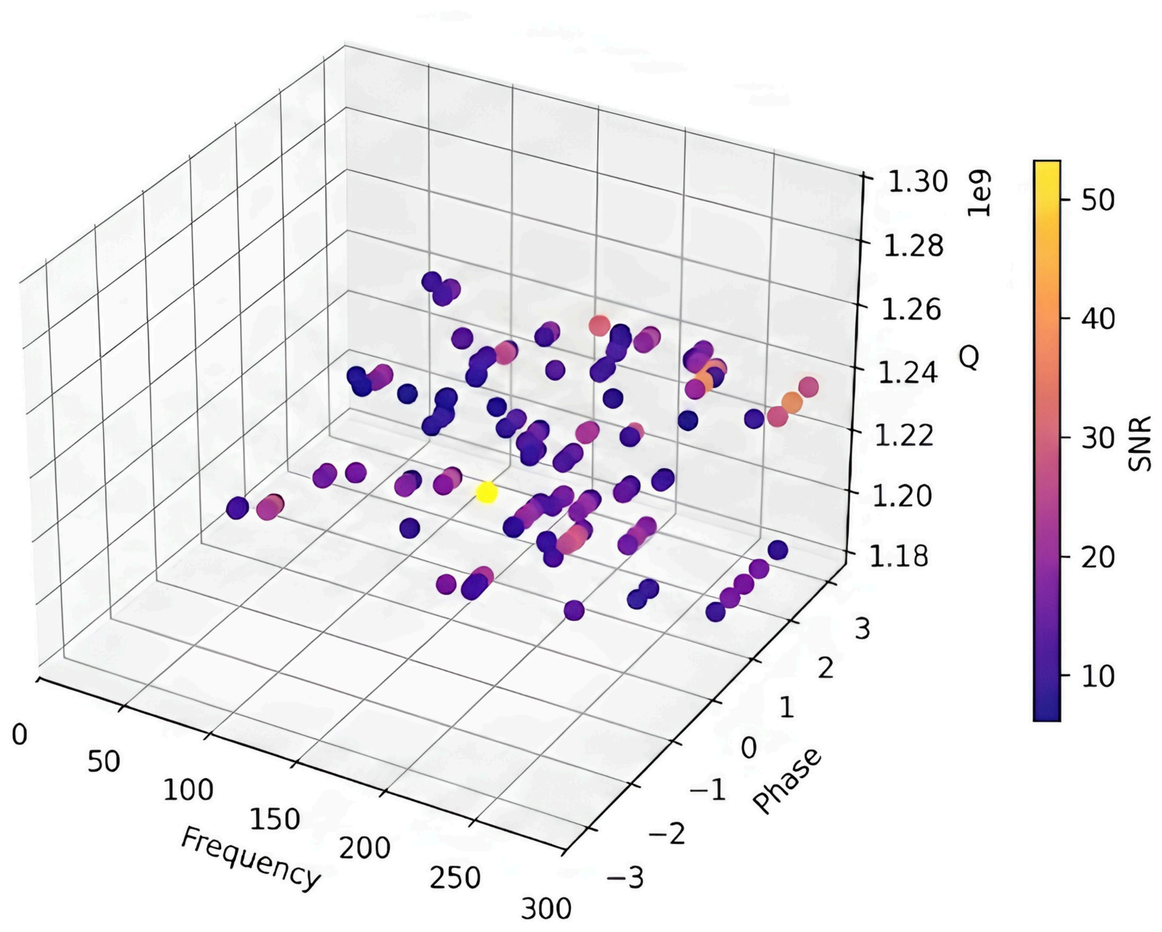


Figure 1. Point cloud representation of LIGO glitches

By capturing **structural correlations** in a higher-dimensional space, this framework provides an efficient solution for *automated noise characterization* in gravitational-wave detectors.

5 Future Scope

As this research project is ongoing, future work includes **developing more robust data representations**, particularly by investigating latent-space approaches. Instead of constraining to a fixed-dimensional feature space, we aim to explore transforming the data into a latent space using techniques such as **t-SNE** and by training a **custom CNN** to classify the origins of the noise.