Modelling, Detection, and Classification: Applying Machine Learning to Gravitational Wave Astronomy

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Gravitational Wave Astronomy

Gravitational wave (GW) astronomy is an emerging field of astrophysics research that studies the ripples in spacetime caused by the movement of massive objects. Current GW research is centred at the Laser Interferometer Gravitational-wave Observatory (LIGO), which first detected gravitational waves in 2015 using the Advanced LIGO detectors.

As the volume and complexity of collected GW data increases, researchers are exploring the potential of implementing machine learning (ML) algorithms for three main purposes in the GW detection pipeline:

1. Improving the quality of data through the detection and classification of noise transients;
2. Modeling GW signals and detecting GW signals in real time; and
3. Implementing ML in related astrophysics research that use collected GW data.

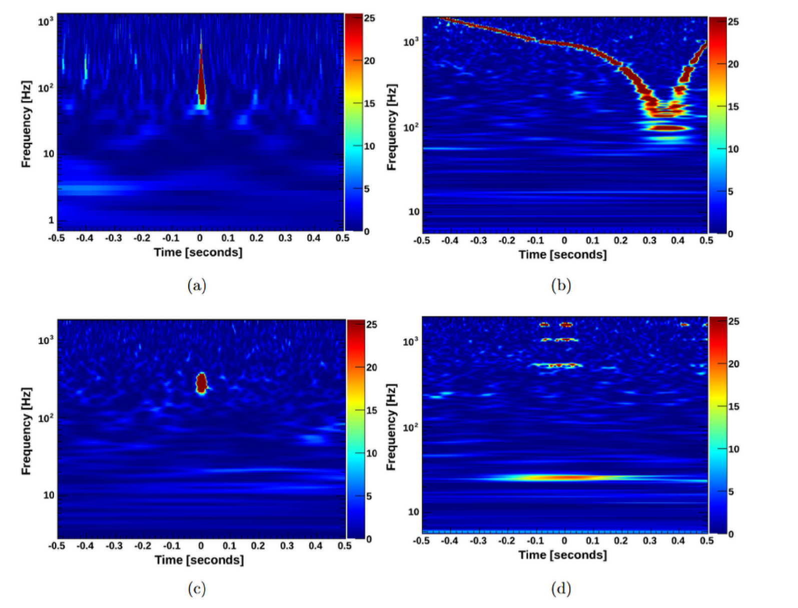


Figure 1: Examples of typical noise transient types in spectrograms from Advanced LIGO Livingston ER7 data [1].

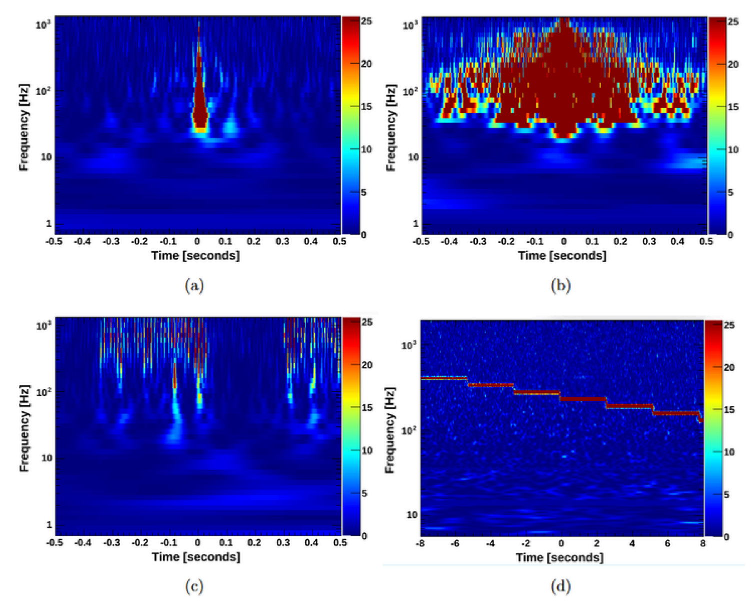
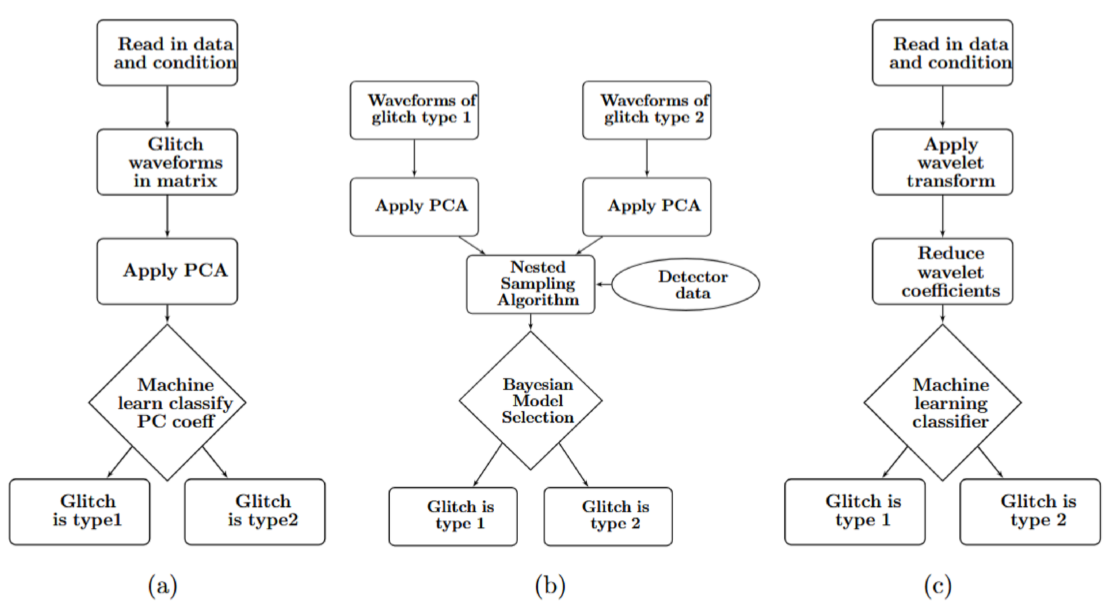


Figure 2: Examples of typical noise transient types in spectrograms from Advanced LIGO Hanford ER7 data [1].

Improving the Quality of Gravitational Wave Data With Machine Learning

Detecting and Classifying Noise Transients

Multiple sources of noise (both due to astrophysical bodies and instrumental limitations) can lead to the false detection of GW signals. Non-linear, non-Gaussian noise transients that are non-astrophysical in origin, called "glitches", commonly occur and must be removed from the data.



Principal Component Analysis for Transients (PCAT)

LALInference Burst (PC-LIB)

Wavelet Detection Filter and Machine Learning (WDF-ML)

Figure 3: Workflows for proposed transient ML classification algorithms [1].

Gravity Spy: Crowdsourcing Training Data

The lack of pre-classified, high-quality data can be a limitation in training effective ML algorithms for noise classification. The proposed Gravity Spy project [2] leverages human volunteers on the Zooniverse platform to classify glitches, providing an accurate training set for their ML model.

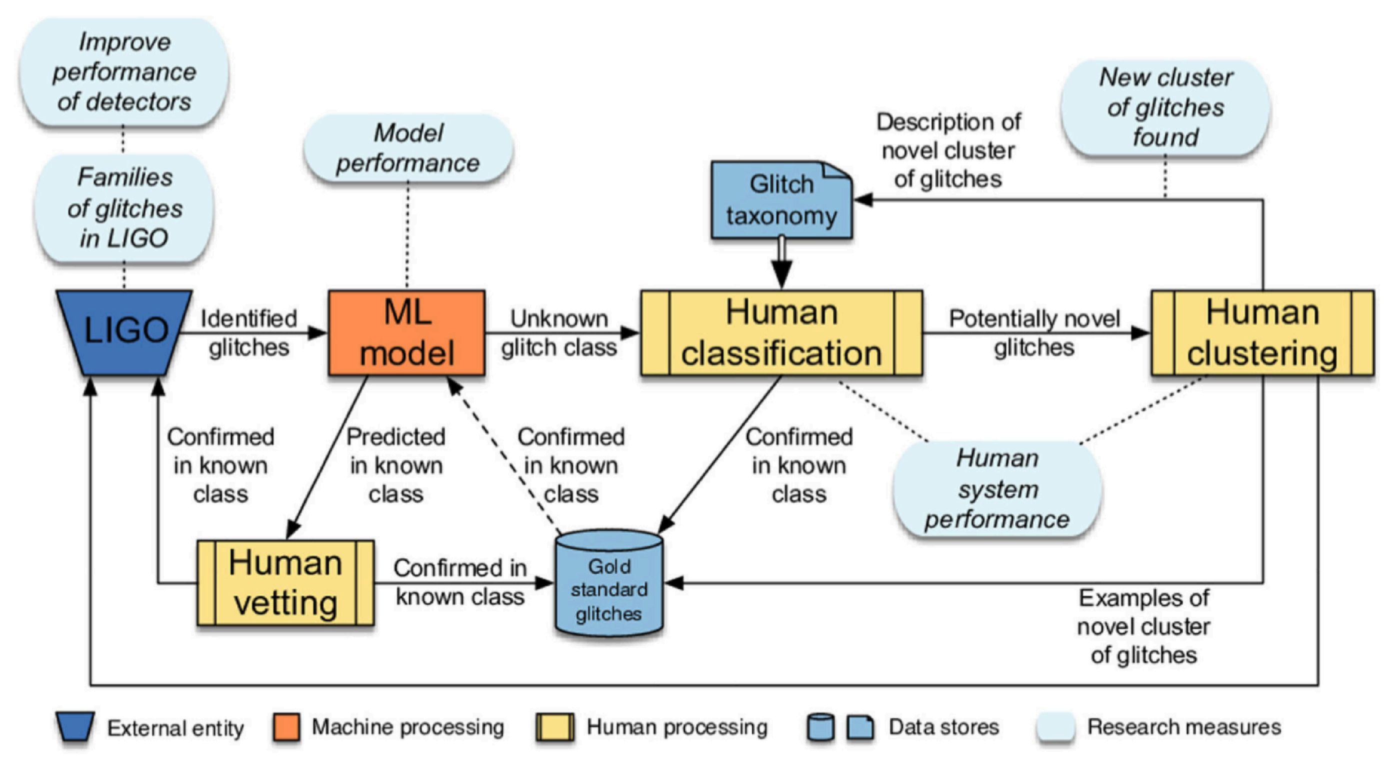


Figure 4: Gravity Spy system architecture [2].

Real-Time Gravitational Wave Detection

Developing accurate theoretical models of waveforms is crucial in order to accurately estimate the parameters of GW sources. These models can be developed with ML techniques such as Gaussian process regression and artificial neural networks [3].

Additionally, deep neural networks have been proposed to replace the current matched-filtering algorithms to complete glitch classification, signal detection, parameter estimation, and clustering in real time [4].

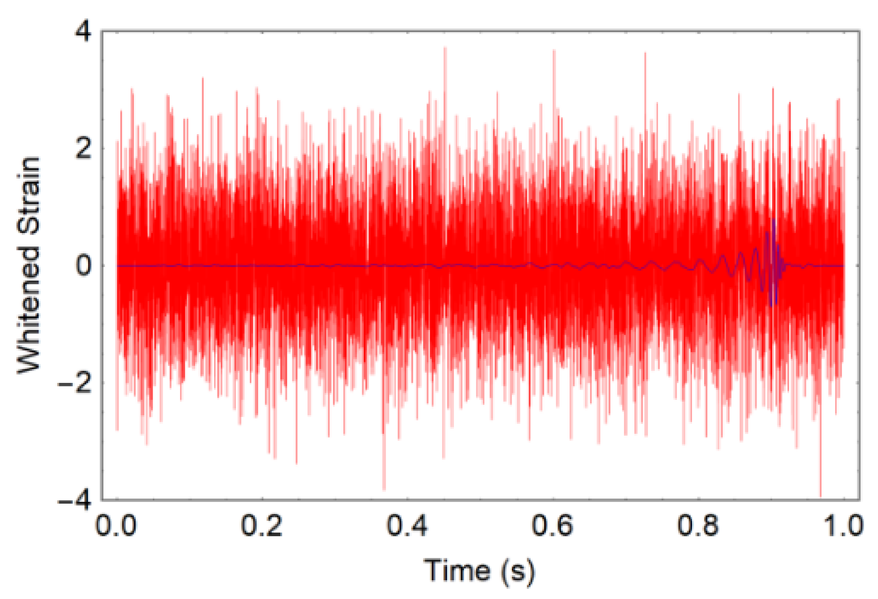


Figure 5: A sample GW signal (blue) injected into real LIGO noise. The signal was detected with over 99% sensitivity by the Deep Filtering algorithm [4].

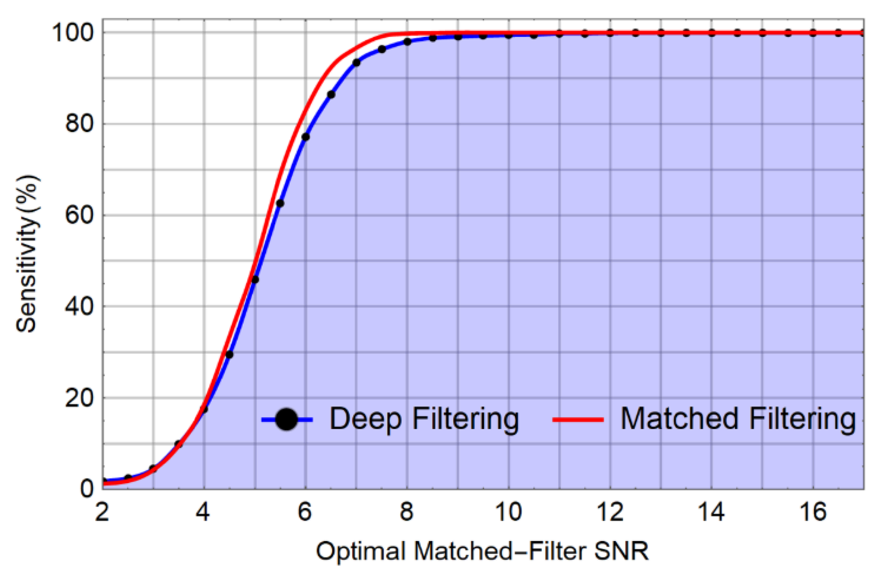


Figure 6: A comparison of the proposed Deep Filtering algorithm and the currently used Matched Filtering algorithm in sensitivity of GW signal detection [4].

Machine Learning in Applications of Gravitational Wave Astronomy

Machine learning techniques are also used in related fields of astrophysics research. For example, the Baryon Acoustic Oscillation (BAO) scale is an important cosmological constant that can be computed using GW data. Employing ML with photometric redshift estimates from Dark Energy Survey data, researchers obtained BAO values similar to the currently accepted values [5].

Future Work

Researchers plan to unify the proposed ML algorithms into a single pipeline that can detect GW signals, classify and eliminate noise, and perform data analysis in real time. This pipeline could be implemented in the Advanced LIGO detectors to improve data quality for further astrophysics research.

References

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5. Timothy M. C. Abbott et al. 2019. *Monthly Notices of the Royal Astronomical Society* 483, 4 (2019), 4866–4883. doi:10.1093/mnras/sty3351 (The Dark Energy Survey Collaboration).