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DeepExtractor: Time-domain reconstruction of signals and glitches in gravitational wave data with deep learning

Gravitational wave (GW) interferometers, such as LIGO, Virgo, and KAGRA, detect faint signals from distant astrophysical events. However, their high sensitivity also makes them susceptible to background noise, which can obscure these signals. This noise often includes transient artifacts called “glitches”, that can mimic genuine astrophysical signals or mask their true characteristics. Fast and accurate reconstruction of both signals and glitches is crucial for reliable scientific inference. In this study, we present \textit{DeepExtractor}, a deep learning framework that is designed to reconstruct signals and glitches with power exceeding interferometer noise, regardless of their source. We design DeepExtractor to model the inherent noise distribution of GW interferometers, following conventional assumptions that the noise is Gaussian and stationary over short time scales. It operates by predicting and subtracting the noise component of the data, retaining only the clean reconstruction of signal or glitch. Our innovative approach achieves superior generalization capabilities for arbitrary signals and glitches compared to methods that directly map inputs to the clean training waveforms. We focus on applications related to glitches and validate DeepExtractor's effectiveness through three experiments: (1) reconstructing simulated glitches injected into simulated detector noise, (2) comparing its performance with the state-of-the-art BayesWave algorithm, and (3) analyzing real data from the Gravity Spy dataset to demonstrate effective glitch subtraction from LIGO strain data. Our proposed model achieves a median mismatch of only 0.9 for simulated glitches, outperforming several deep learning baselines. Additionally, DeepExtractor surpasses BayesWave in glitch recovery, offering a dramatic computational speedup by reconstructing one glitch sample in approximately 0.1 seconds on a CPU, compared to BayesWave's processing time of approximately one hour per glitch.

AI keywords

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Primary author: DOONEY, Tom

Presenter: DOONEY, Tom

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