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DeepExtractor

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

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EuCAIFCon · 19 June 2025

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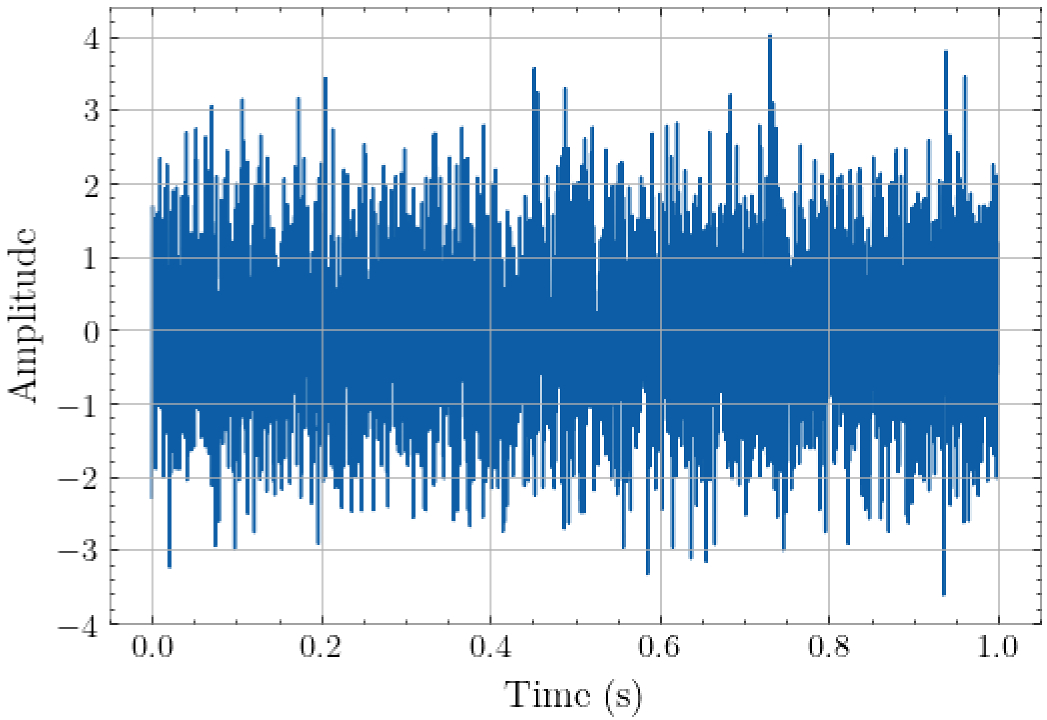
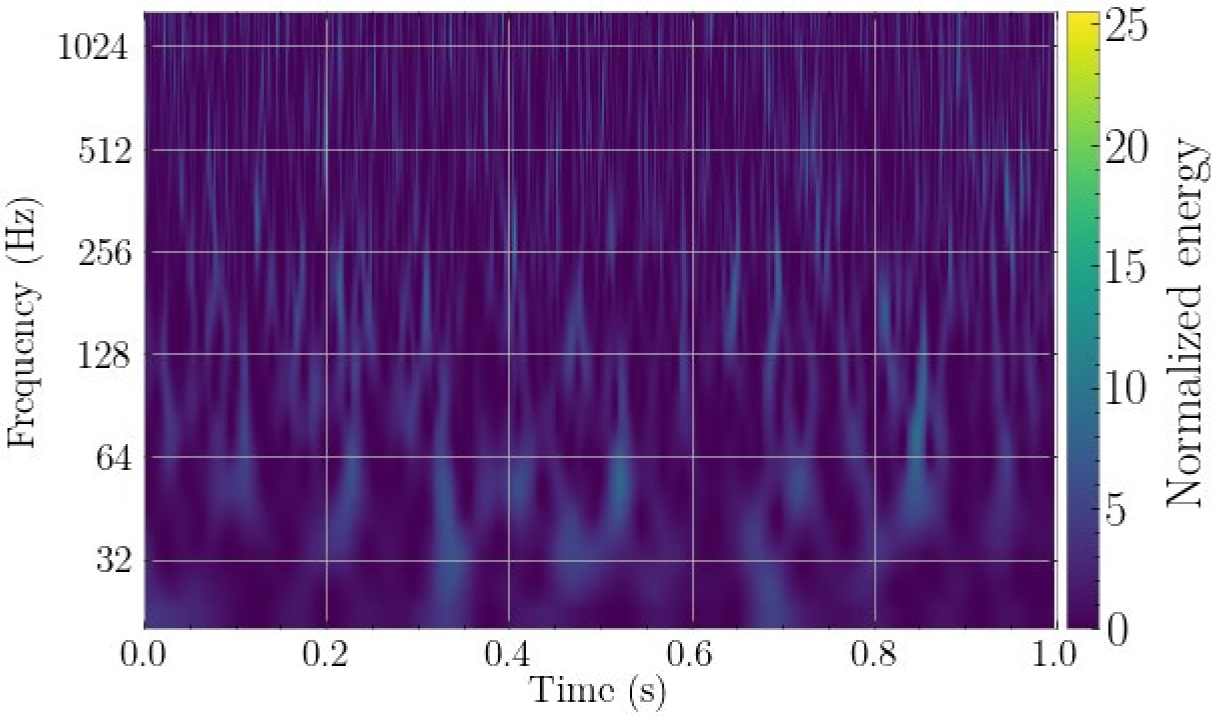
GW data





GW detector data
(Noise only)

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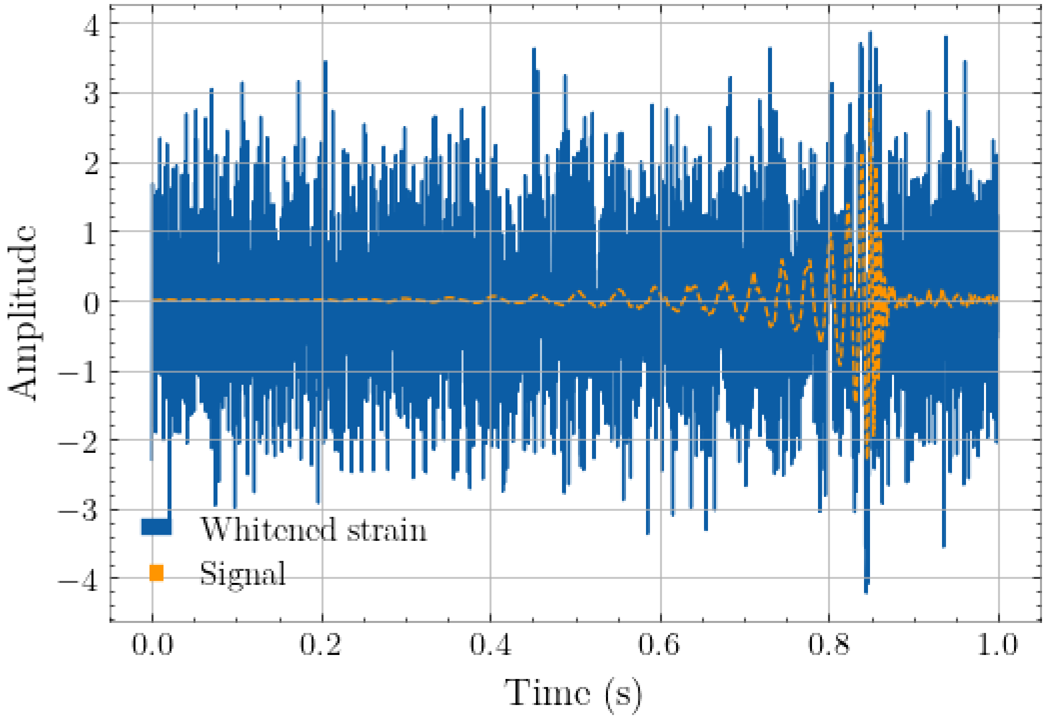
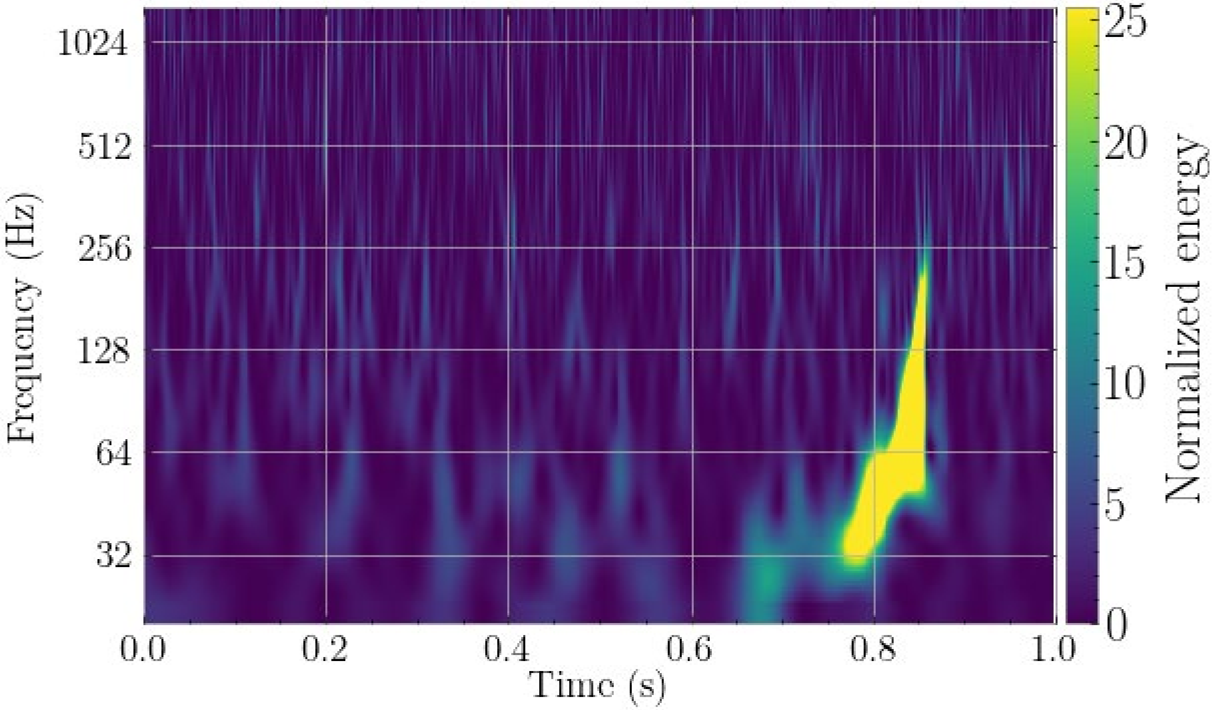
GW data





GW detector data
(Noise+Signal)

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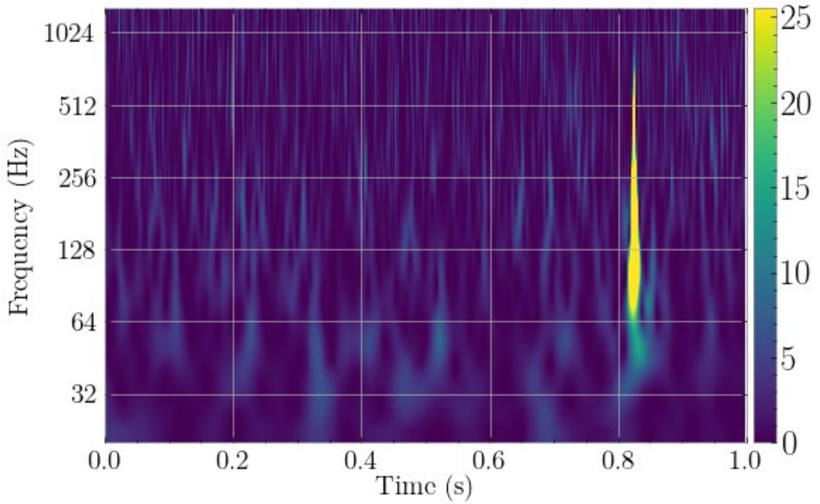
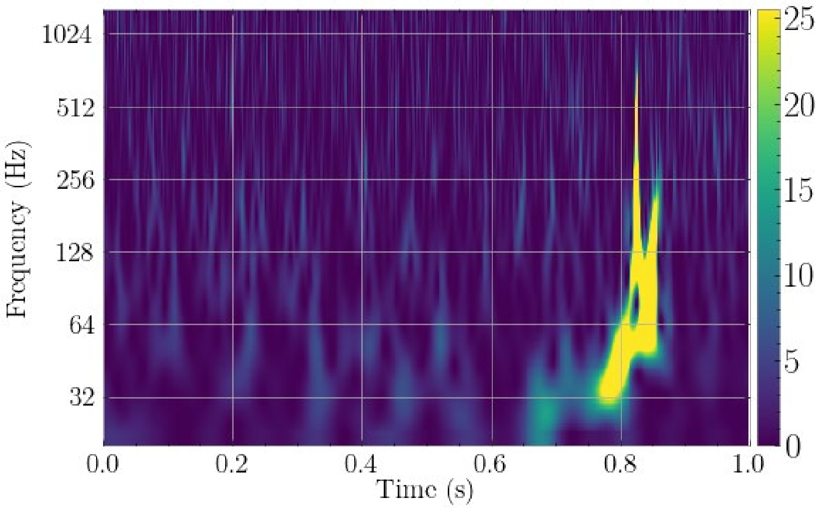
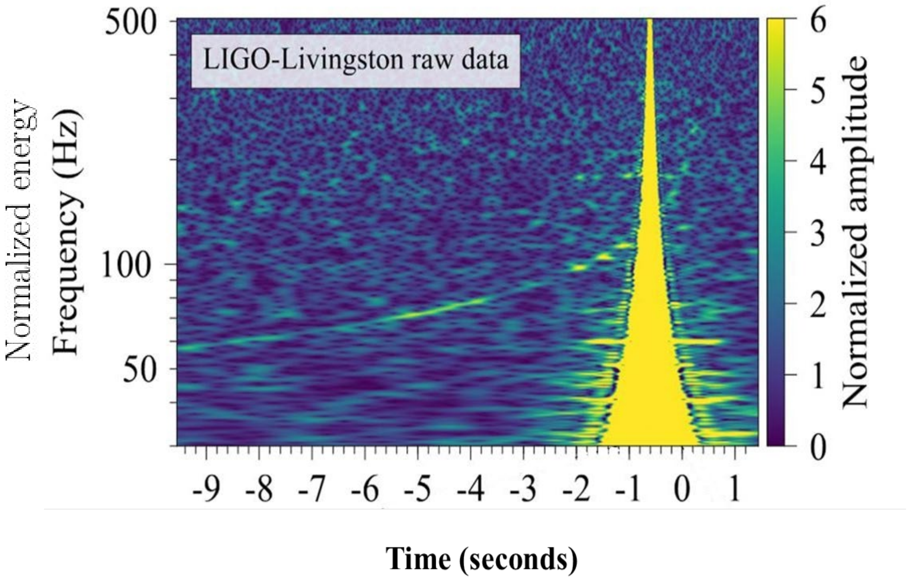
GW data



Noise + Glitch

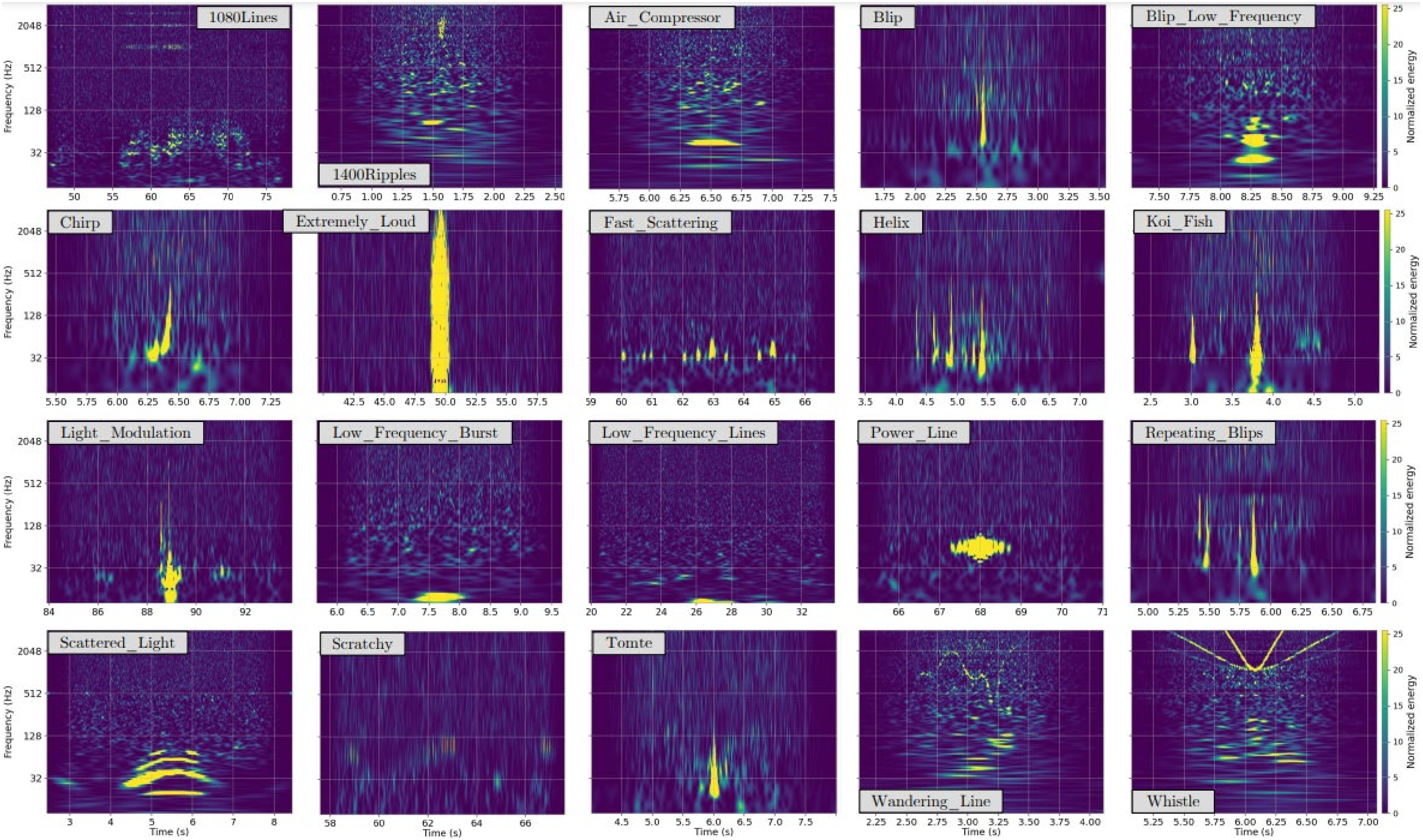


Noise + Signal+ Glitch



GW170817

LIGO Glitches (Gravity Spy)



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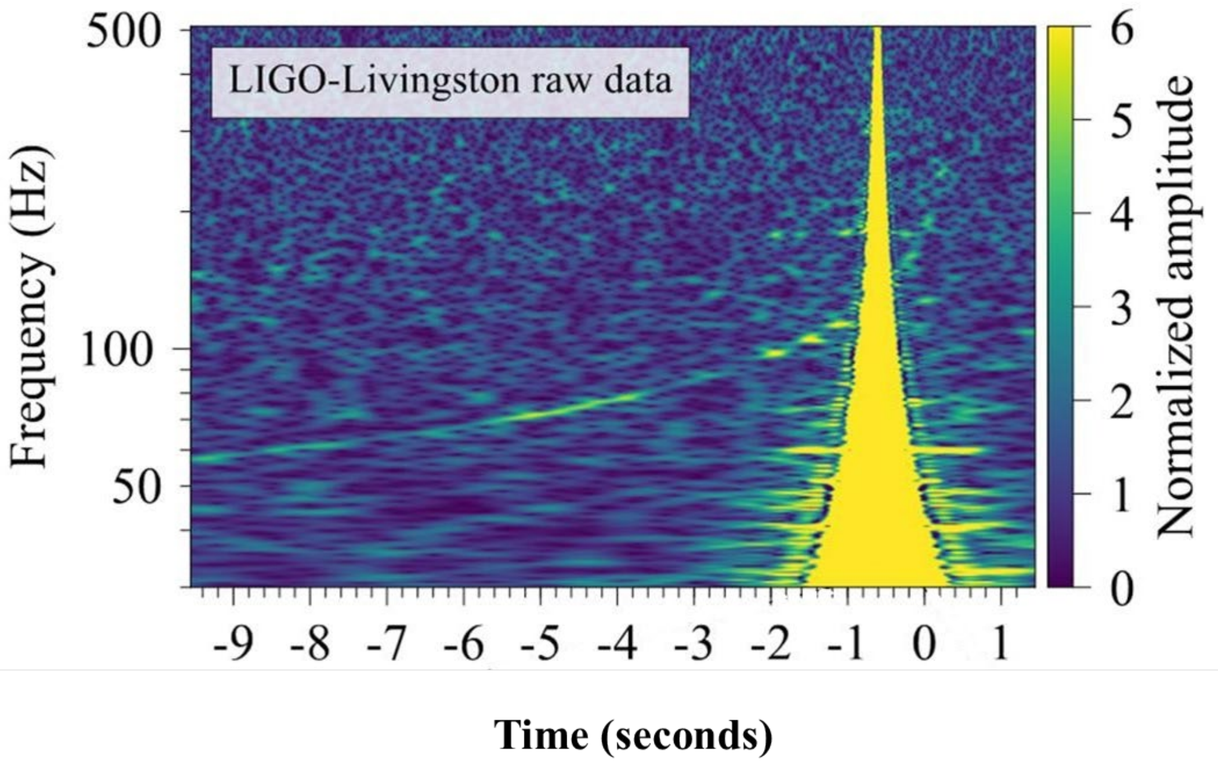
Motivation

- Glitches hinder GW data analysis
  - Increase false positives
  - Bias PE
  - Exacerbated in ET due to increased detections
- BayesWave can mitigate them
  - Effective but costly
  - O(1) CPU hour to model one glitch
- We aim to build a fast glitch reconstruction framework
  - MDCs
  - Glitch mitigation



Glitch overlapping with GW170817 (Image: ligo.caltech.edu).

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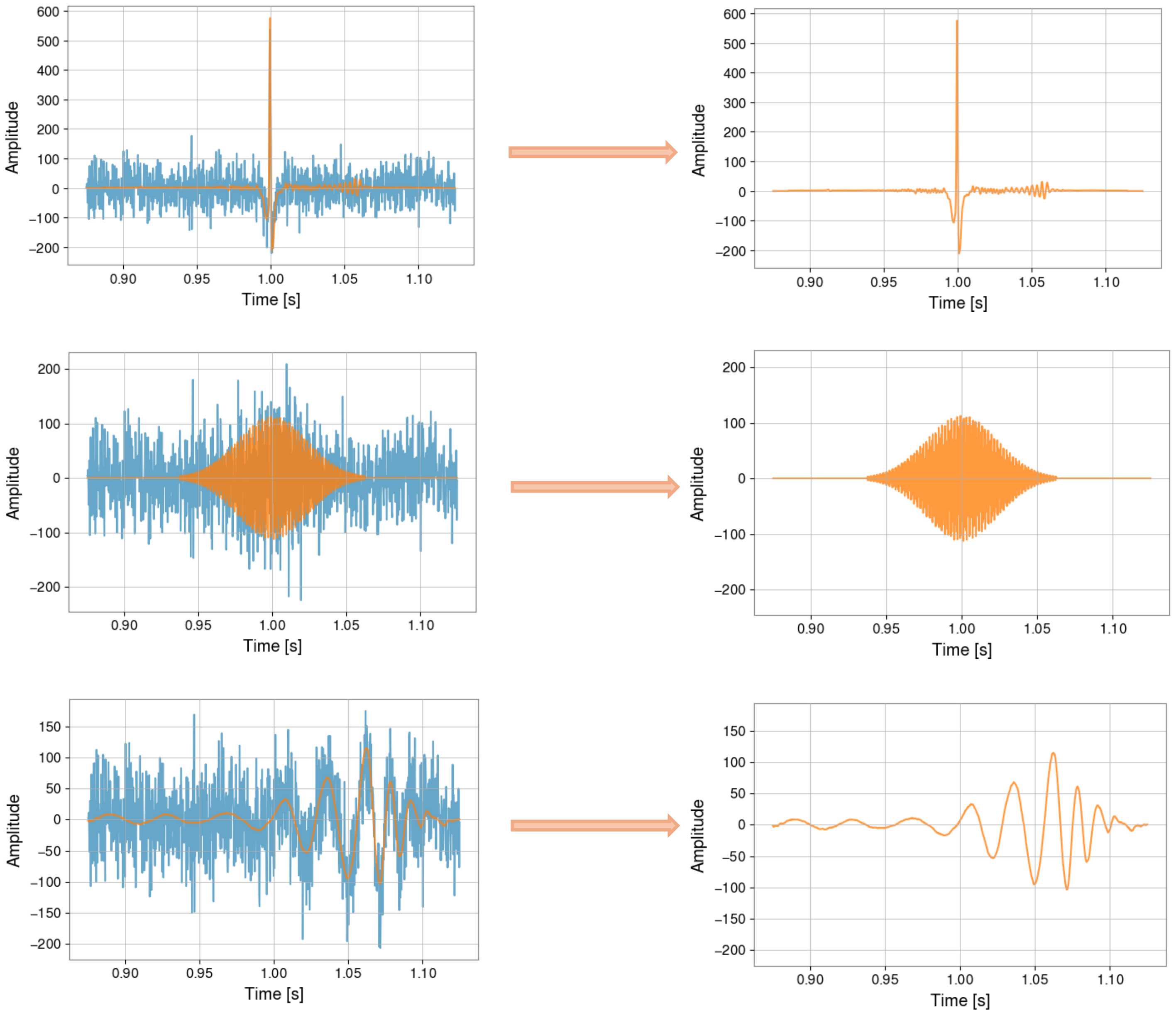
Goal

- Fast and accurate approach for time-domain reconstruction
- Reconstruct any power excess above Gaussian background
- Agnostic of source and morphology
- Compete with BayesWave accuracy and reduce inference time
- Deep learning is a good candidate



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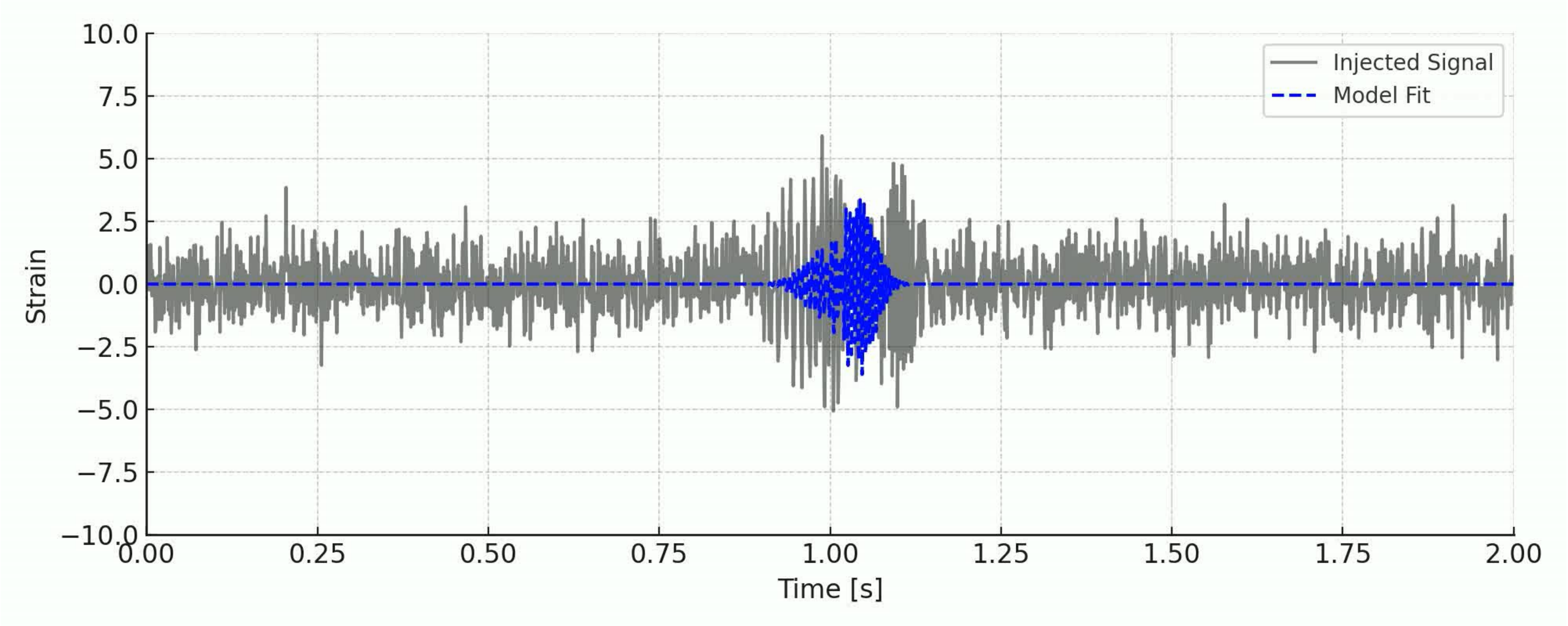
Toy example of BayesWave



BayesWave uses **RJMCMC** to:

1. find the **number** of these **wavelets**
2. their **parameters**

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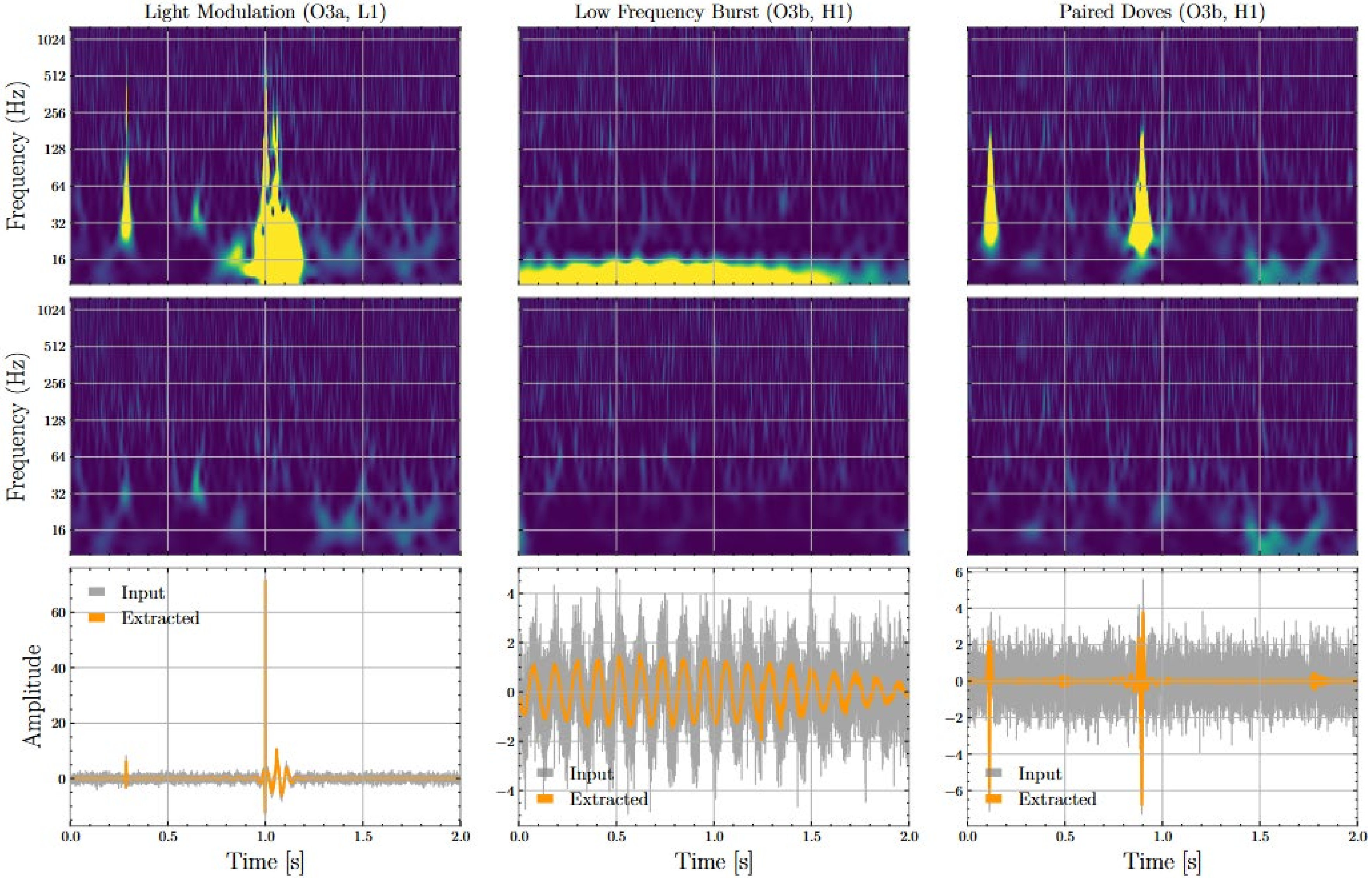
Gravity Spy Reconstructions via DeepExtractor

Input

Subtracted

Reconstruction



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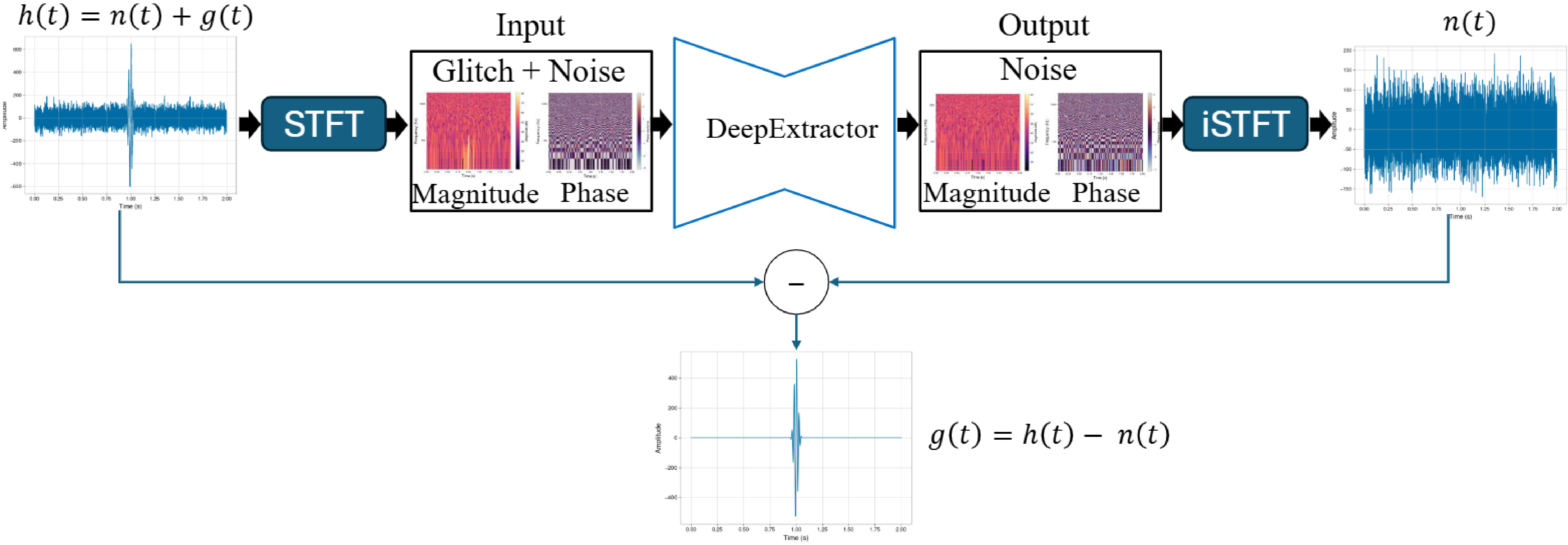
Framework Overview



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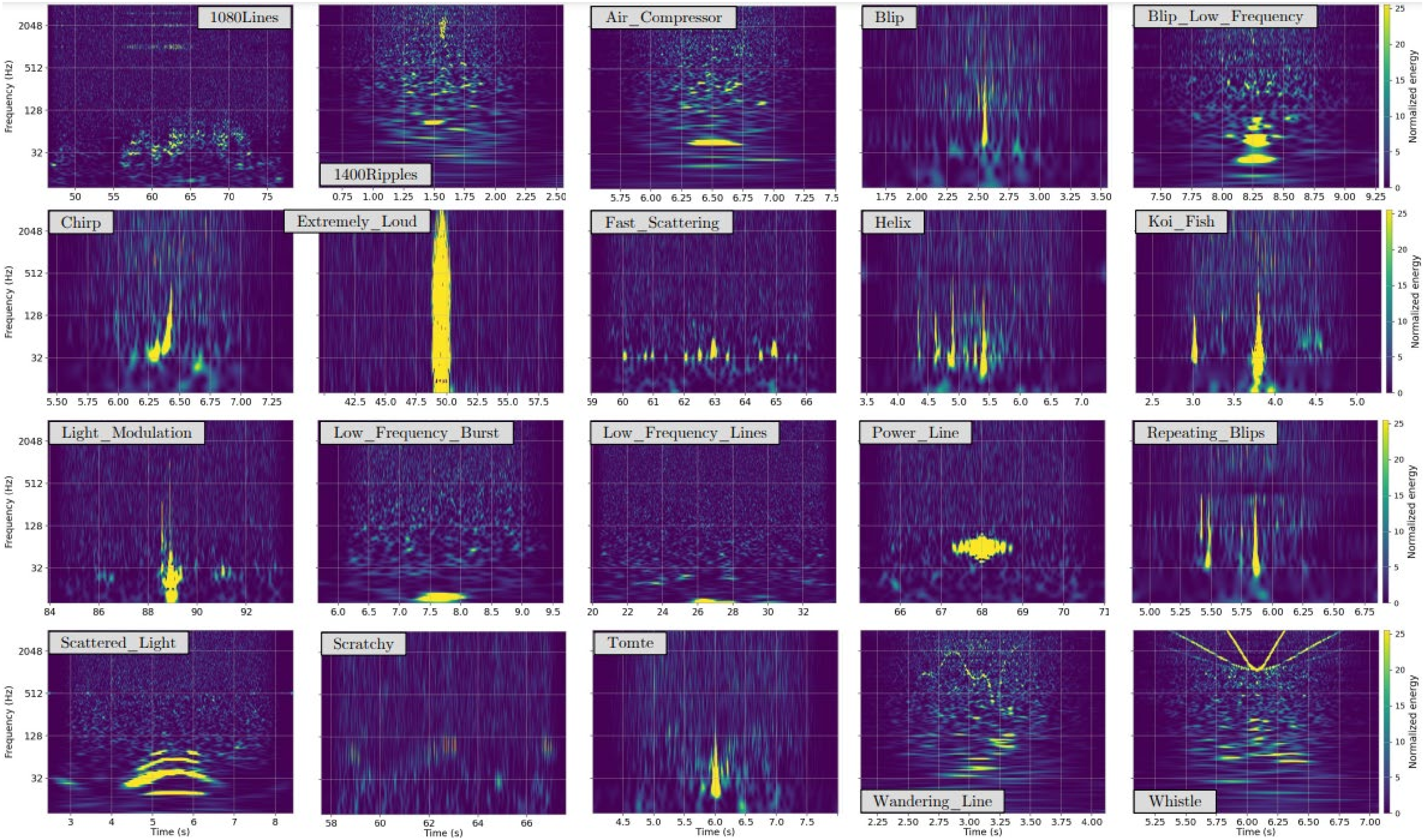
Model Gravity Spy glitches...



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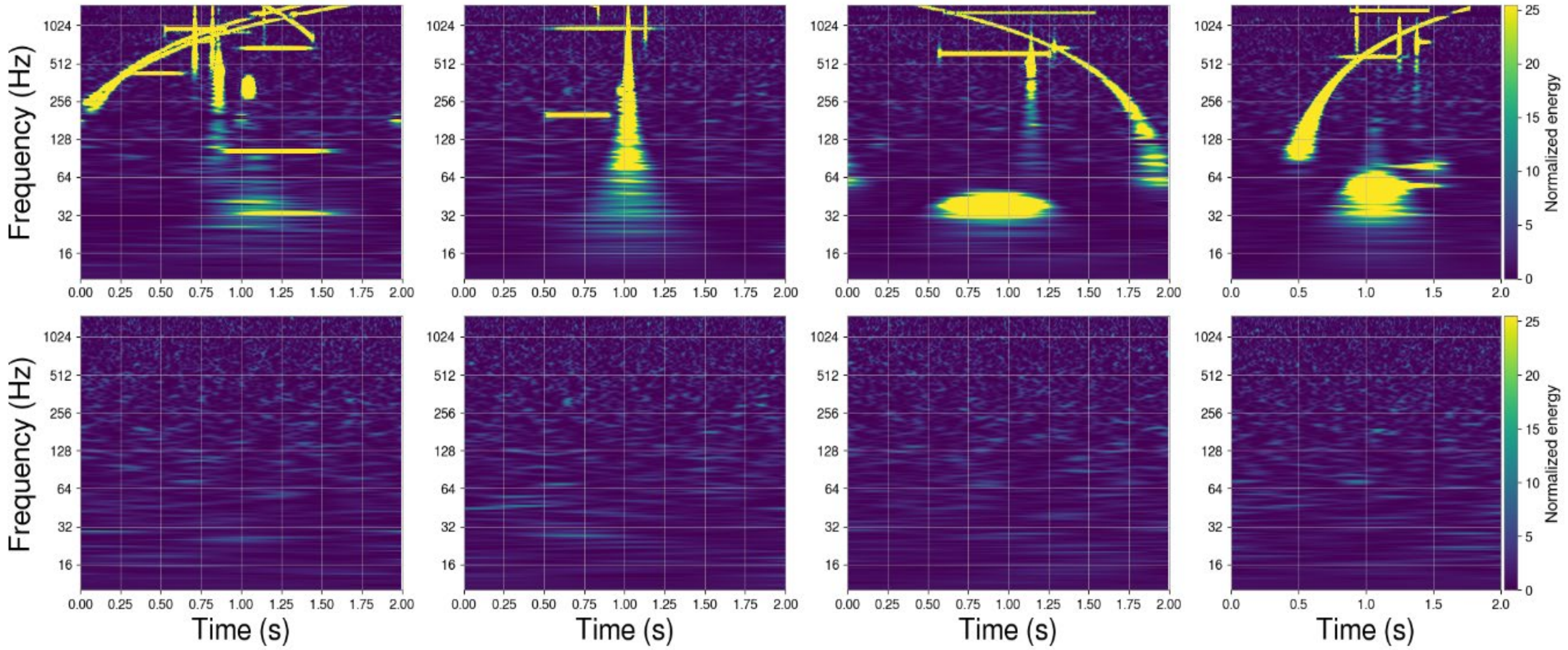
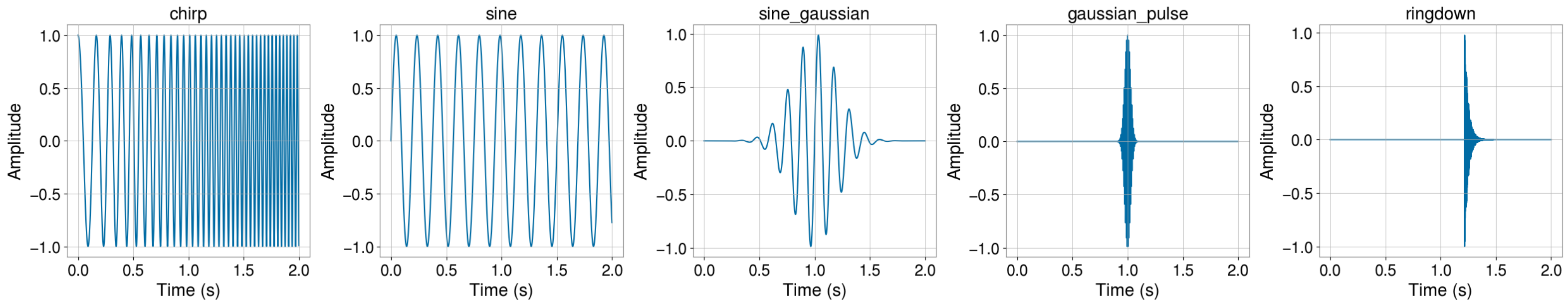
… using proxy glitches



Synthetic Training Data Generation



1. Start with 250,000 samples of simulated Gaussian background
    1. Sr=4096 Hz, 2s duration

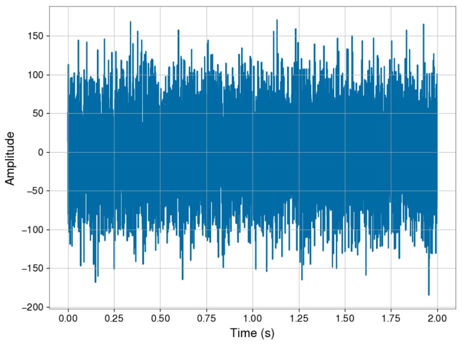
2. Generate between 1 and 30 signals randomly, with random parameters
    1. fmin= 1, fmax = Nyquist.
    2. Scale each signal to random SNR in [0, 250].

3. Inject set of signals into background, random time lag

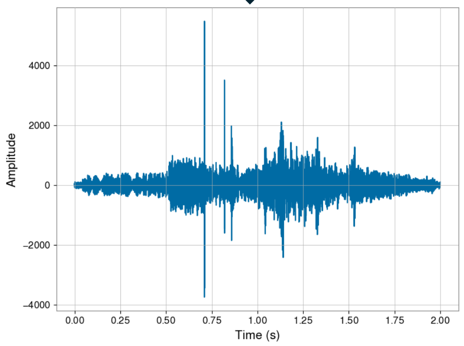
Assumptions:

1. Additive interactions
2. Approximate signal and glitch space by interpolating between these signals

Target



Input



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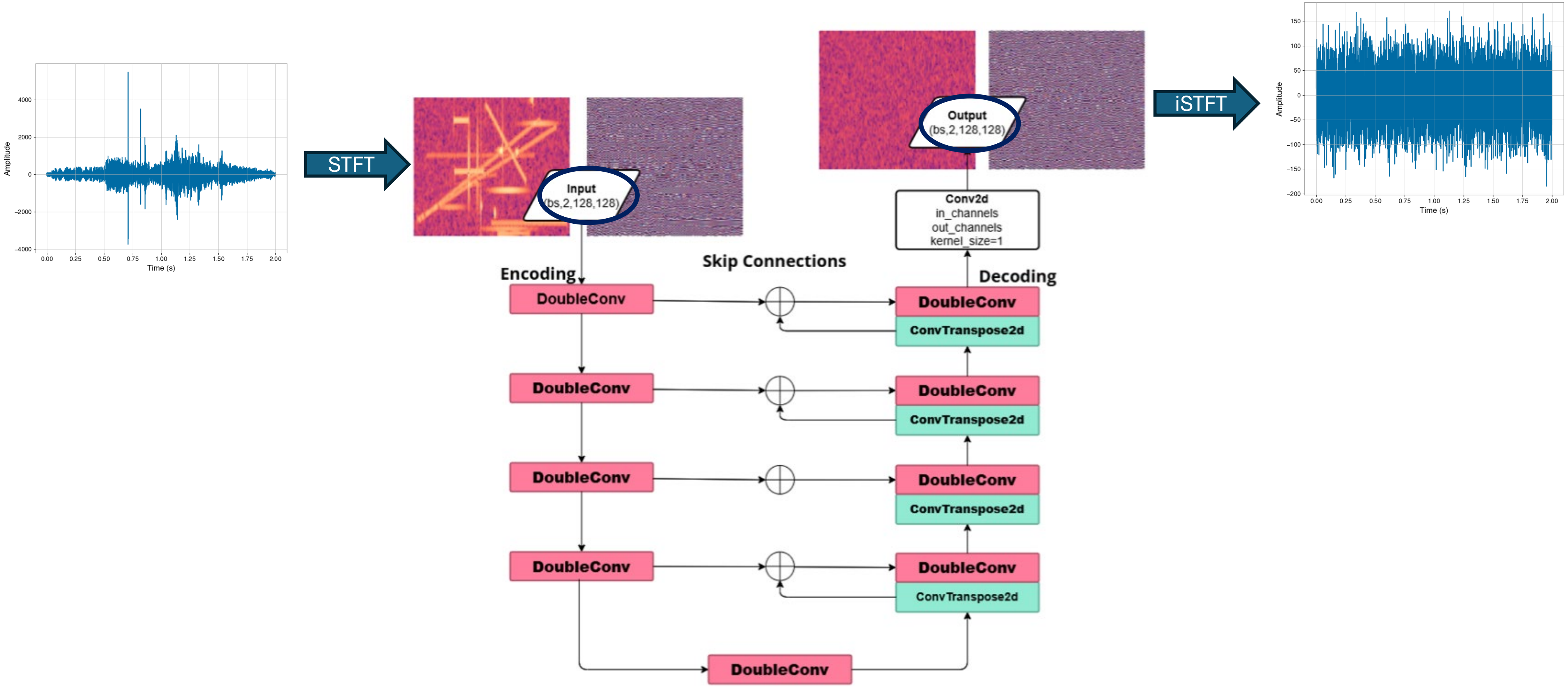
U-Net Architecture



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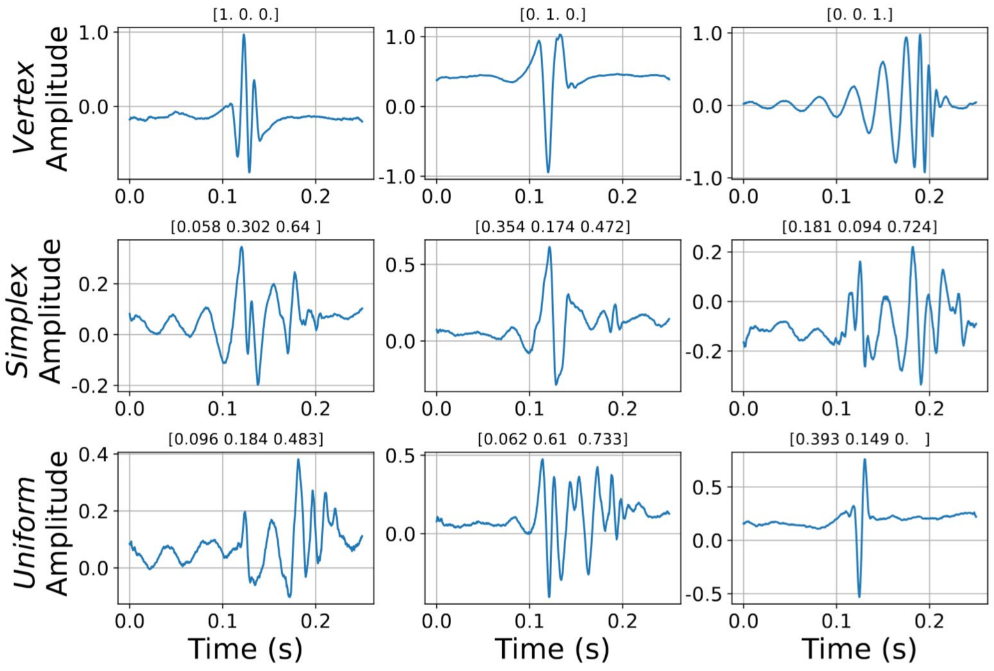
Experiments

1. **Simulated Experiments:**
   - Reconstruction accuracy (time-domain mismatch) with simulated glitch injections into simulated white noise
   - Comparison of various deep learning architectures
   - Unseen glitch/signal classes from glitch generators:
     - *gengli* (Lopez et al. arXiv:2203.06494) *and cDVGAN* (Dooney et al. arXiv:2401.16356)

2. **BayesWave Comparison:**
   - Apply BayesWave and DeepExtractor to the same data
   - time-domain mismatch

3. **Gravity Spy glitches:**
   - Analysis of real data from the Gravity Spy dataset.
   - Gravity Spy classification of reconstructions

4. **Reconstruct real GWs from LIGO O3**



Unseen test classes. In-class (vertex) and hybrid samples (simplex, uniform) from cDVGAN.

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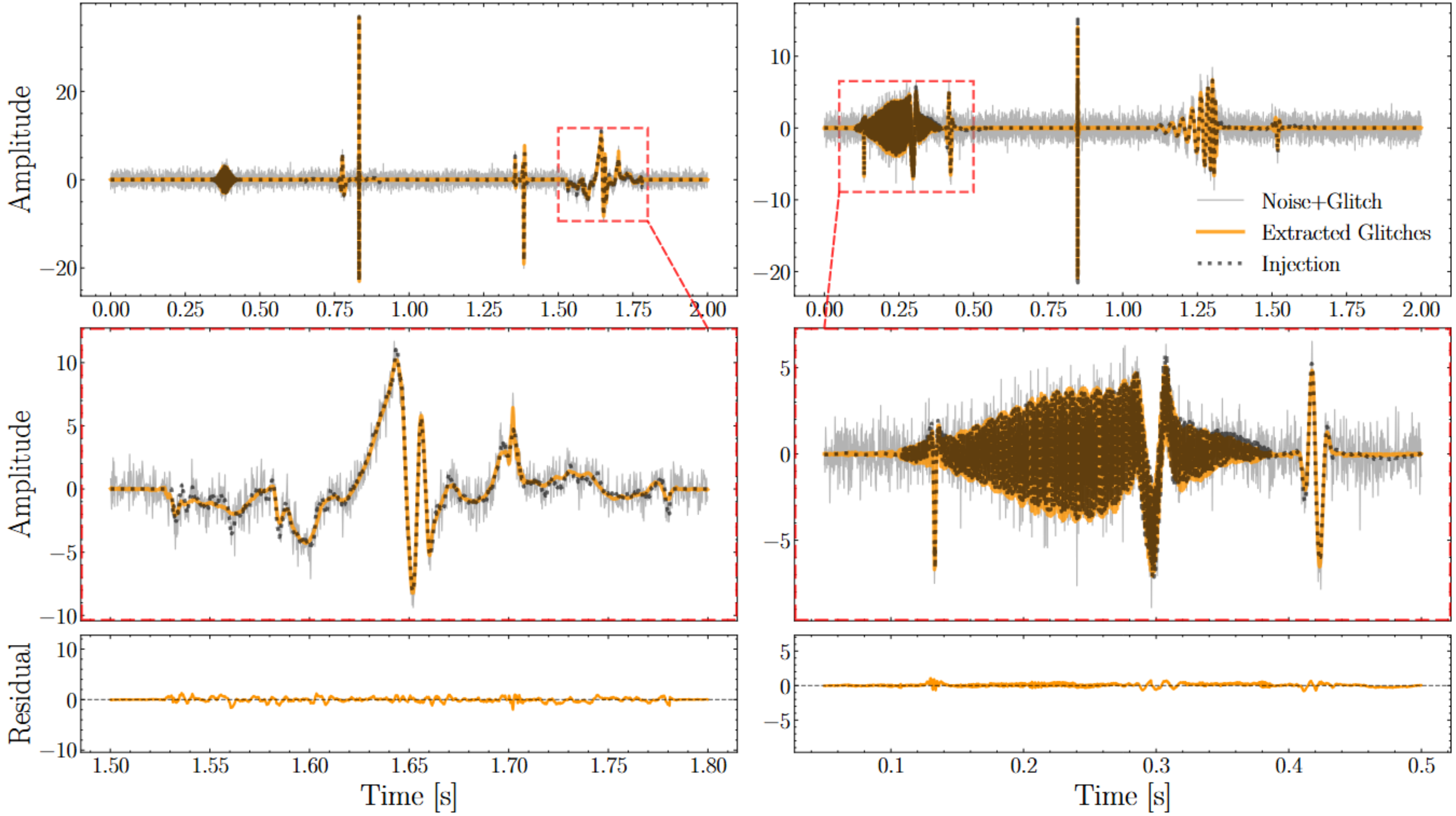
Unseen test classes

Full samples

Zoomed in



DeepExtractor reconstructs a 2s sample in 0.1s (CPU)

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BayesWave Comparison

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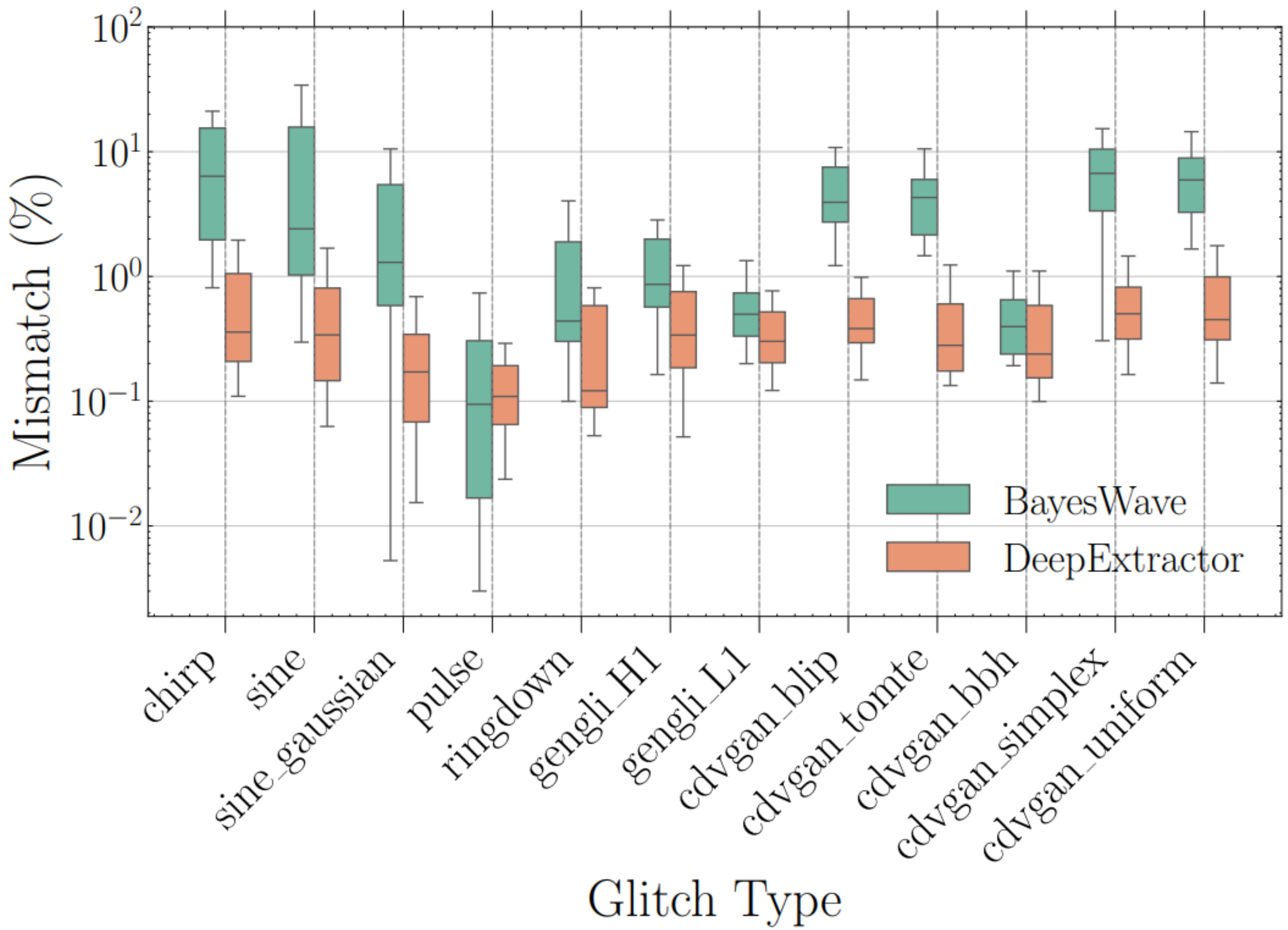
Results - BayesWave Comparison



Mismatch between injected and reconstructed samples with 30 samples per class (360 total).

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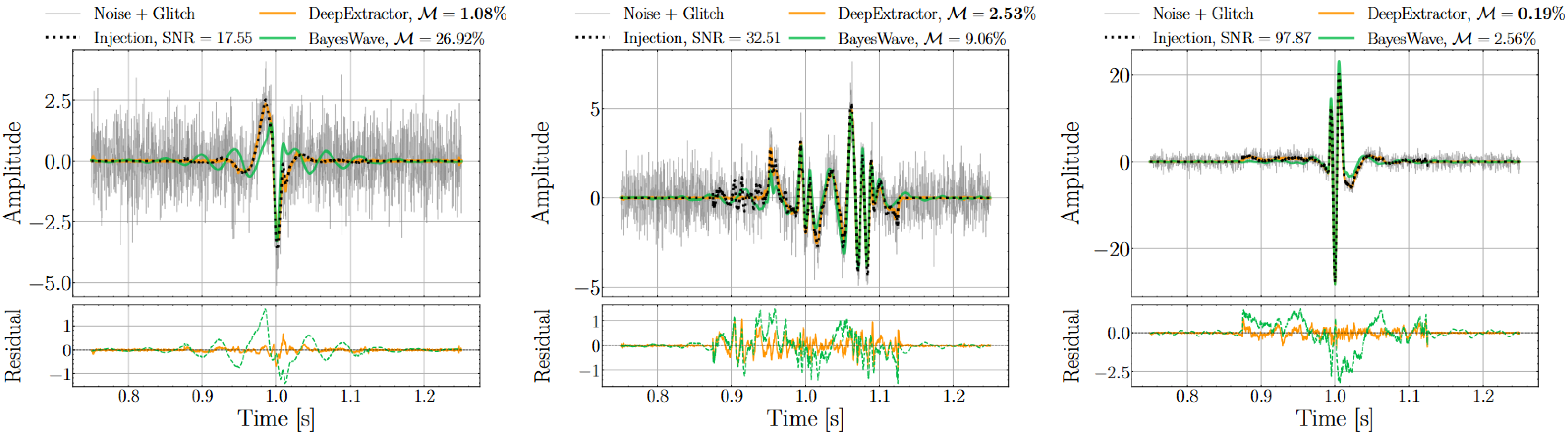
Results - BayesWave Comparison Examples



Example reconstructions from DeepExtractor and BayesWave

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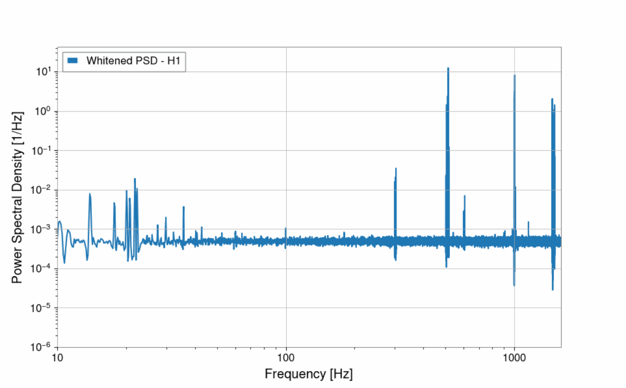
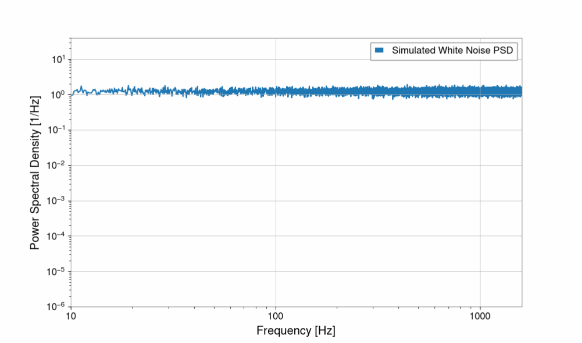
GravitySpy Analysis
(real LIGO data)

Transfer learning with real backgrounds

- We accumulate real LIGO backgrounds (H1, L1, O3a, O3b)
  - At least 2s outside of Omicron/signal triggers
  - 45,000 samples of 2s
- Analytical glitch injections (as before)
- Transfer learn our pretrained (simulated) model
  - Further training phase with real backgrounds
  - Additional knowledge about real background





Additional Knowledge (PSD)

Pre-Trained DeepExtractor

Transfer learning

Fine-tuned DeepExtractor

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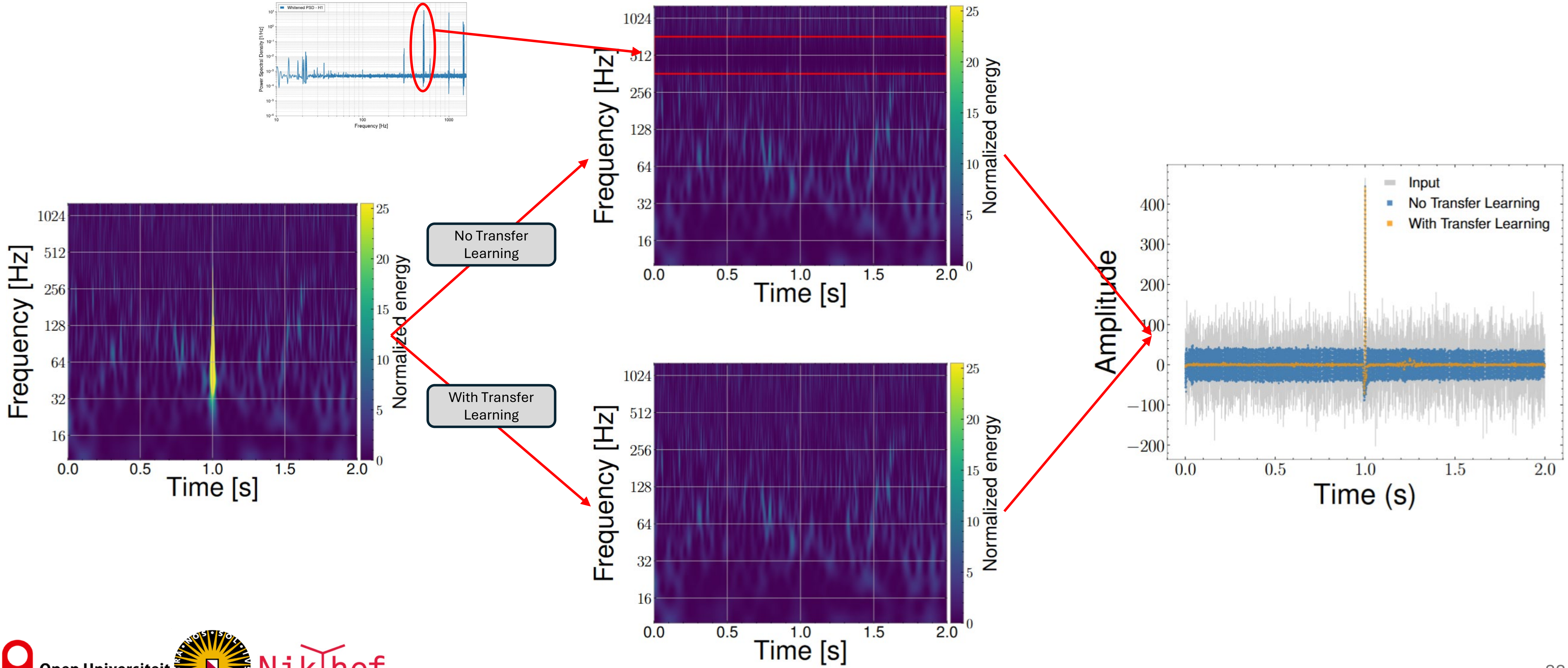
Improvements from Transfer Learning



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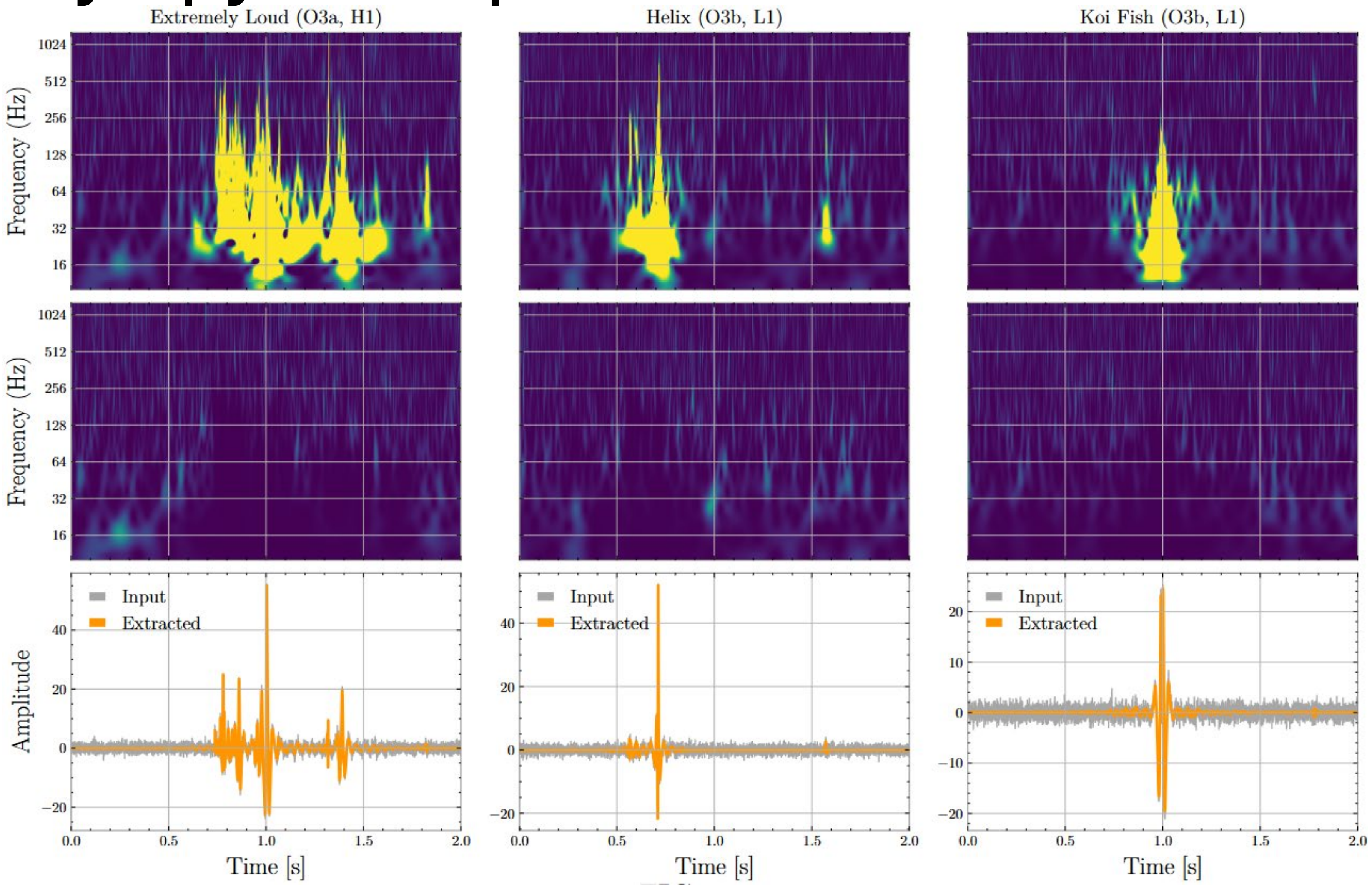
More Gravity Spy Examples

Input

Output

Reconstruction



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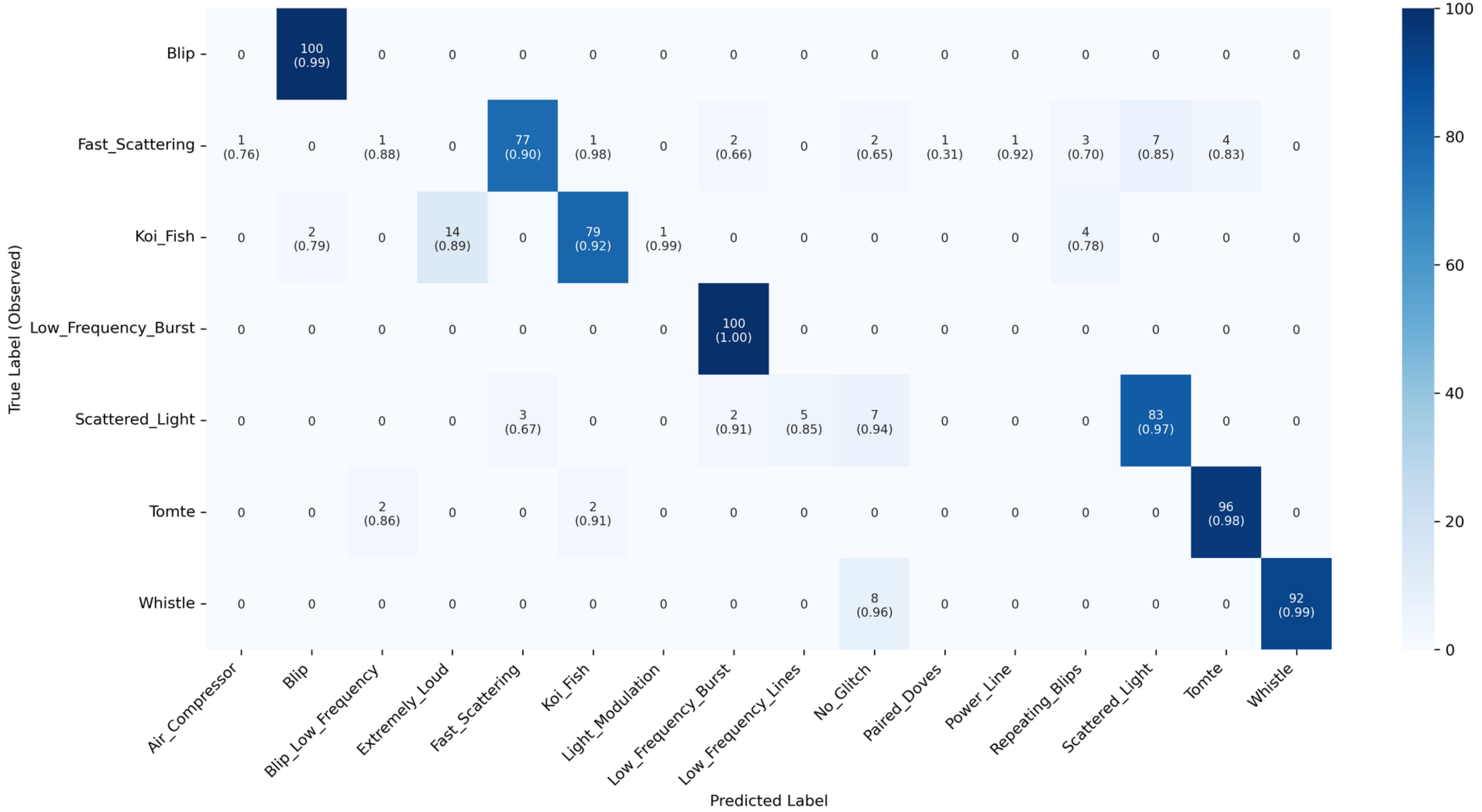
Validating reconstructions with Gravity Spy

100 samples/class (700 total)

90% of reconstructions are classified with correct label!



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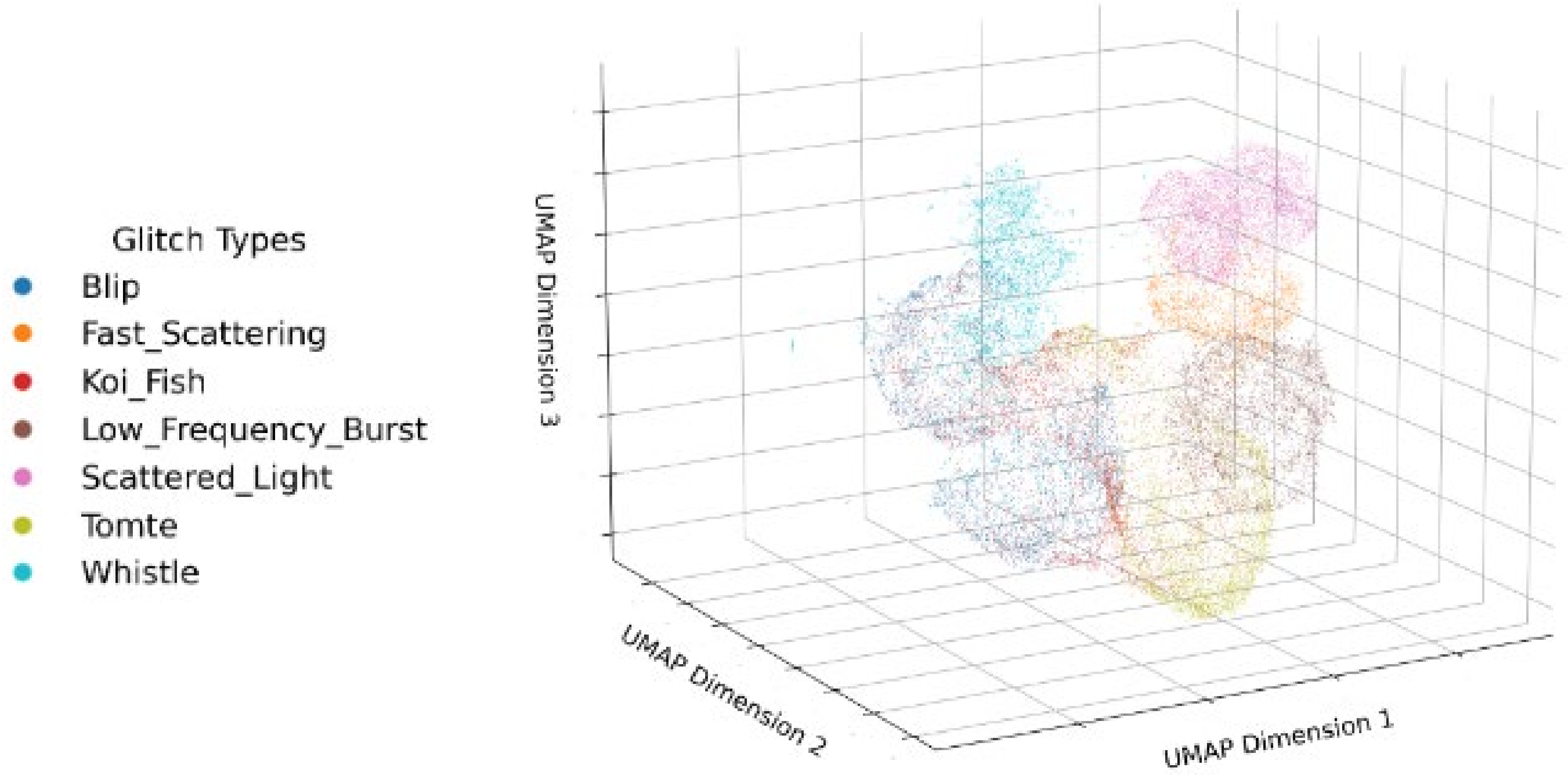
Validating reconstructions with U-Map



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LIGO O3 signal reconstruction

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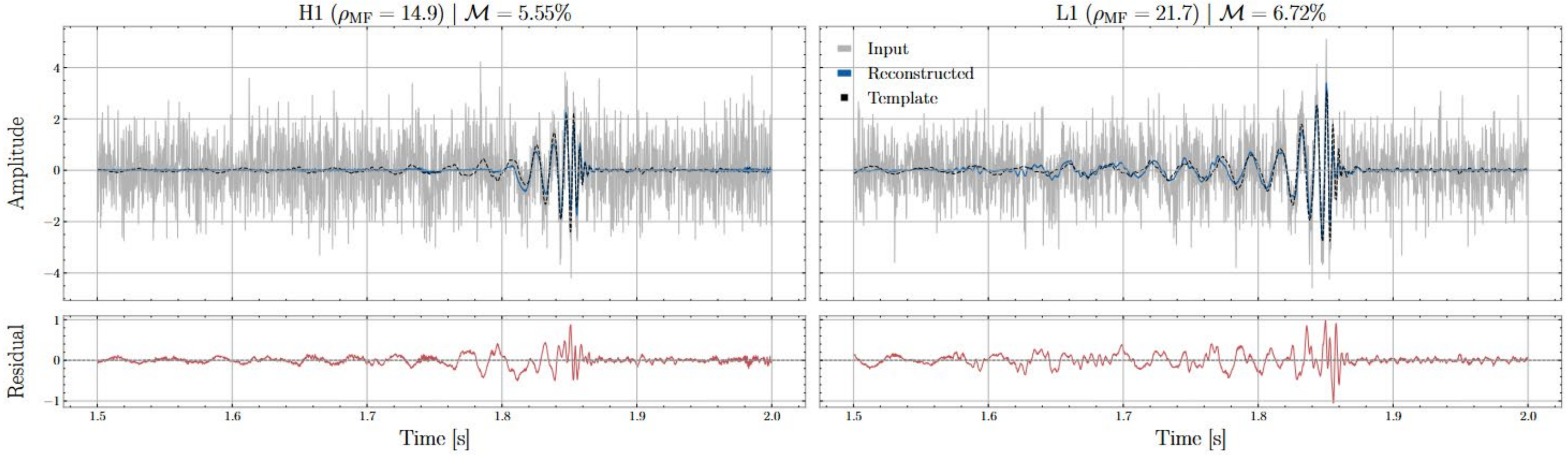
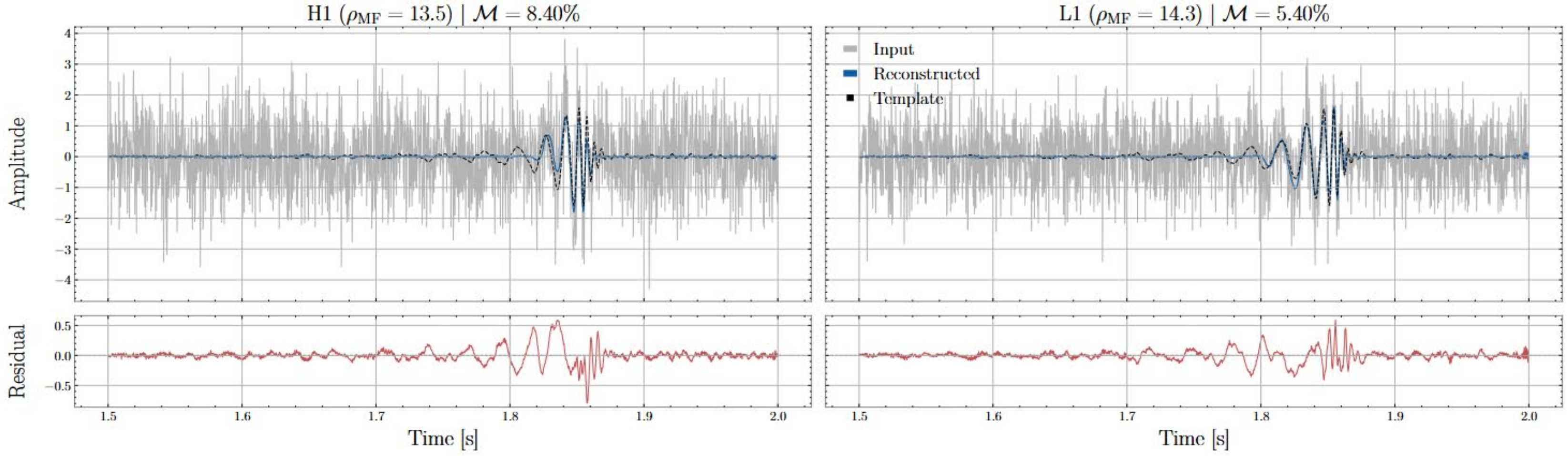
Signal reconstruction…



(b) *GW200129_065458*



(c) *GW200224_222234*

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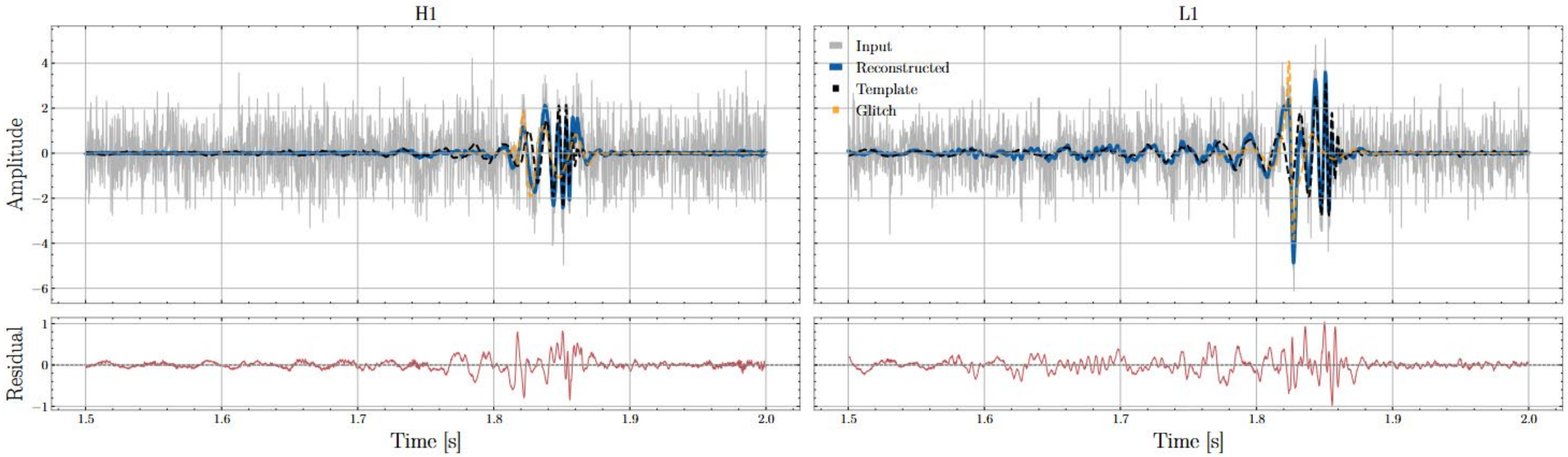
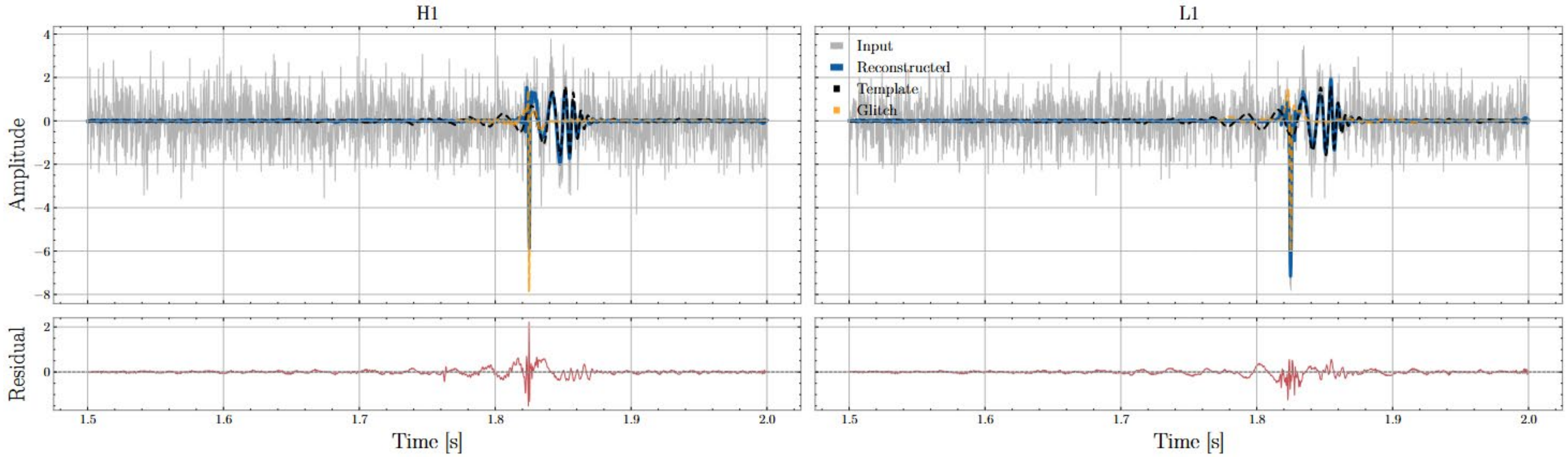
… and with injected glitches



(b) *GW200129_065458*



(c) *GW200224_222234*

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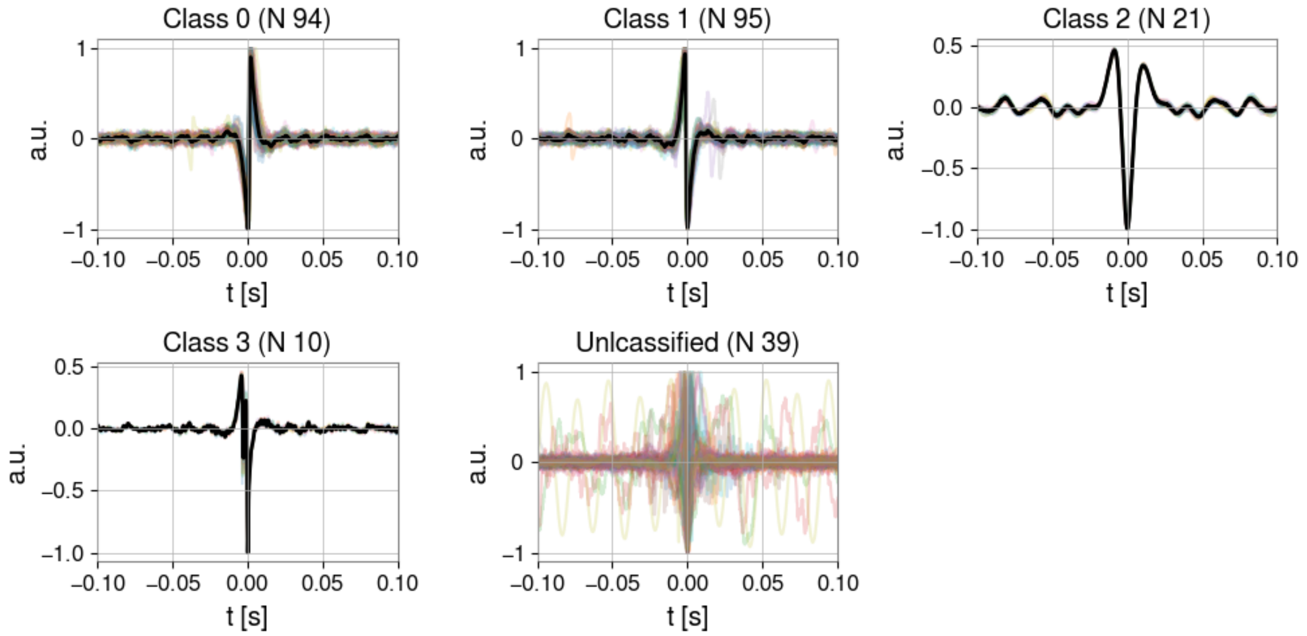
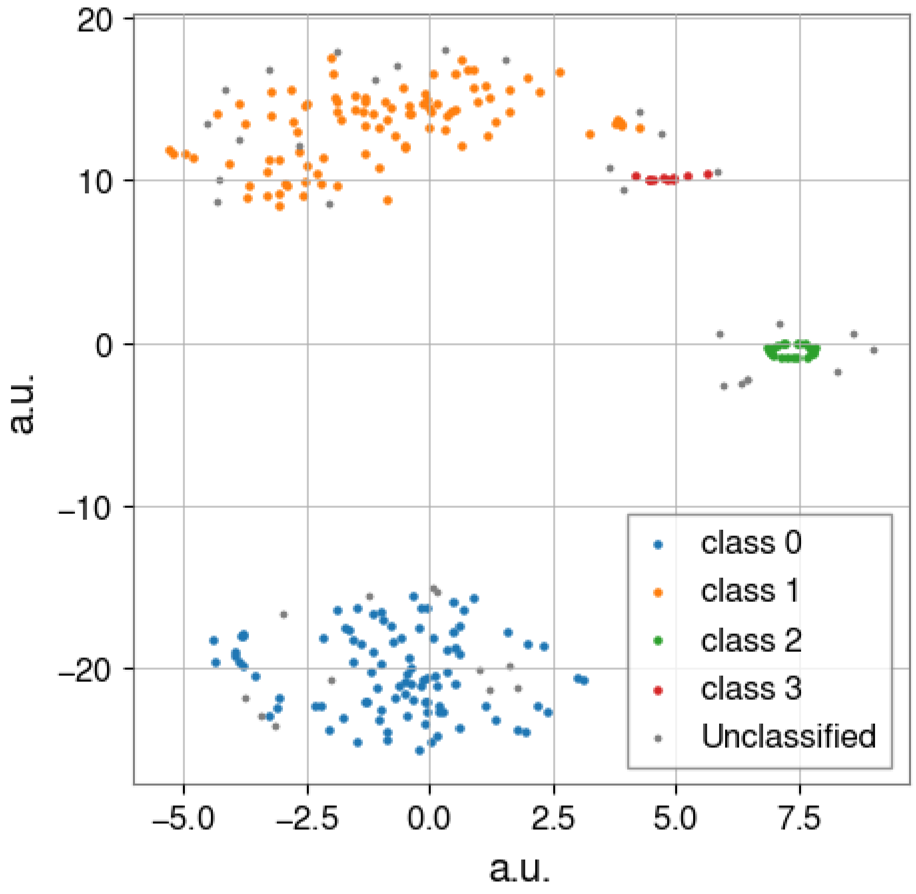
Virgo Applications





Credit: Luca Negri, https://logbook.virgo-gw.eu/virgo/?r=66895

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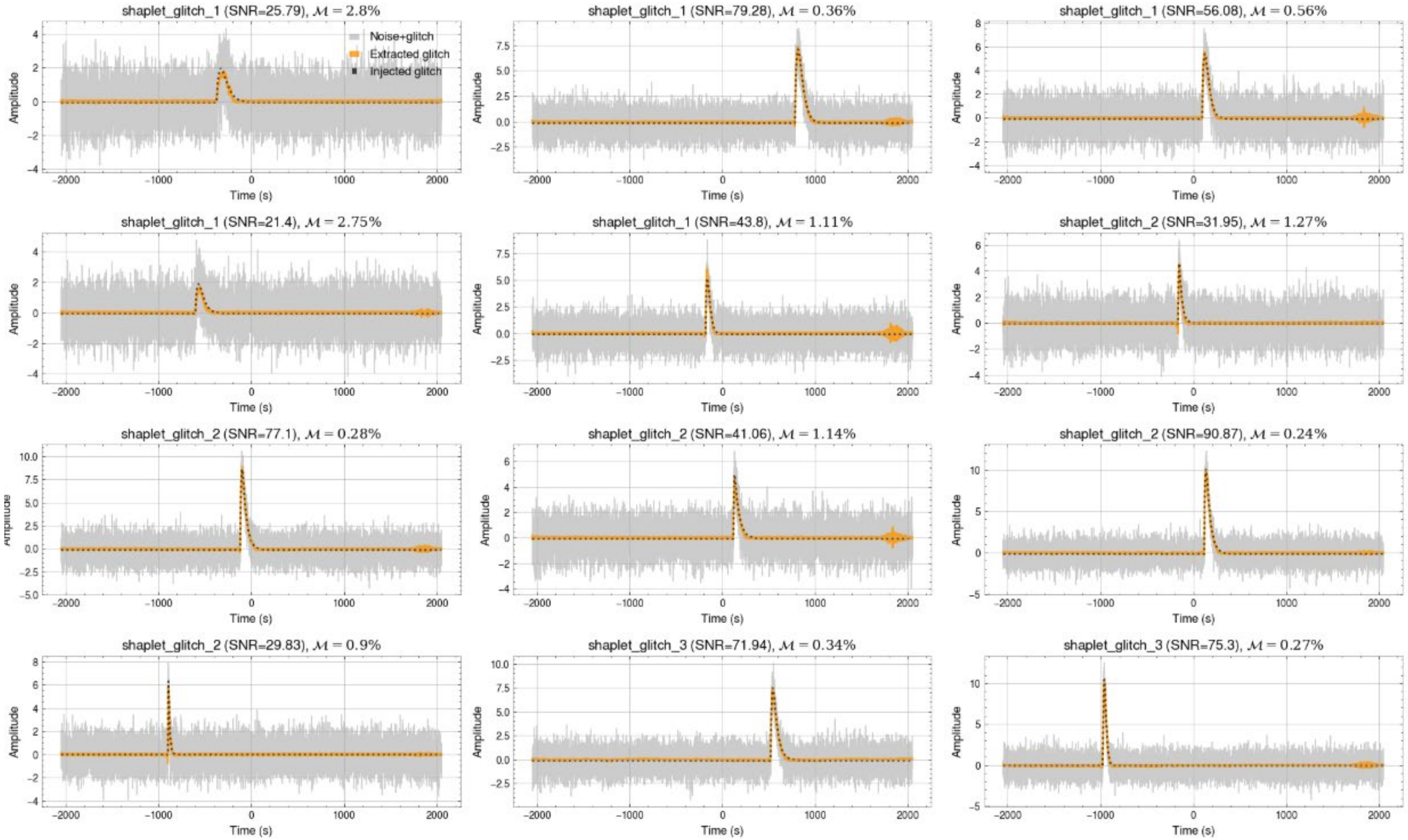
LISA Applications



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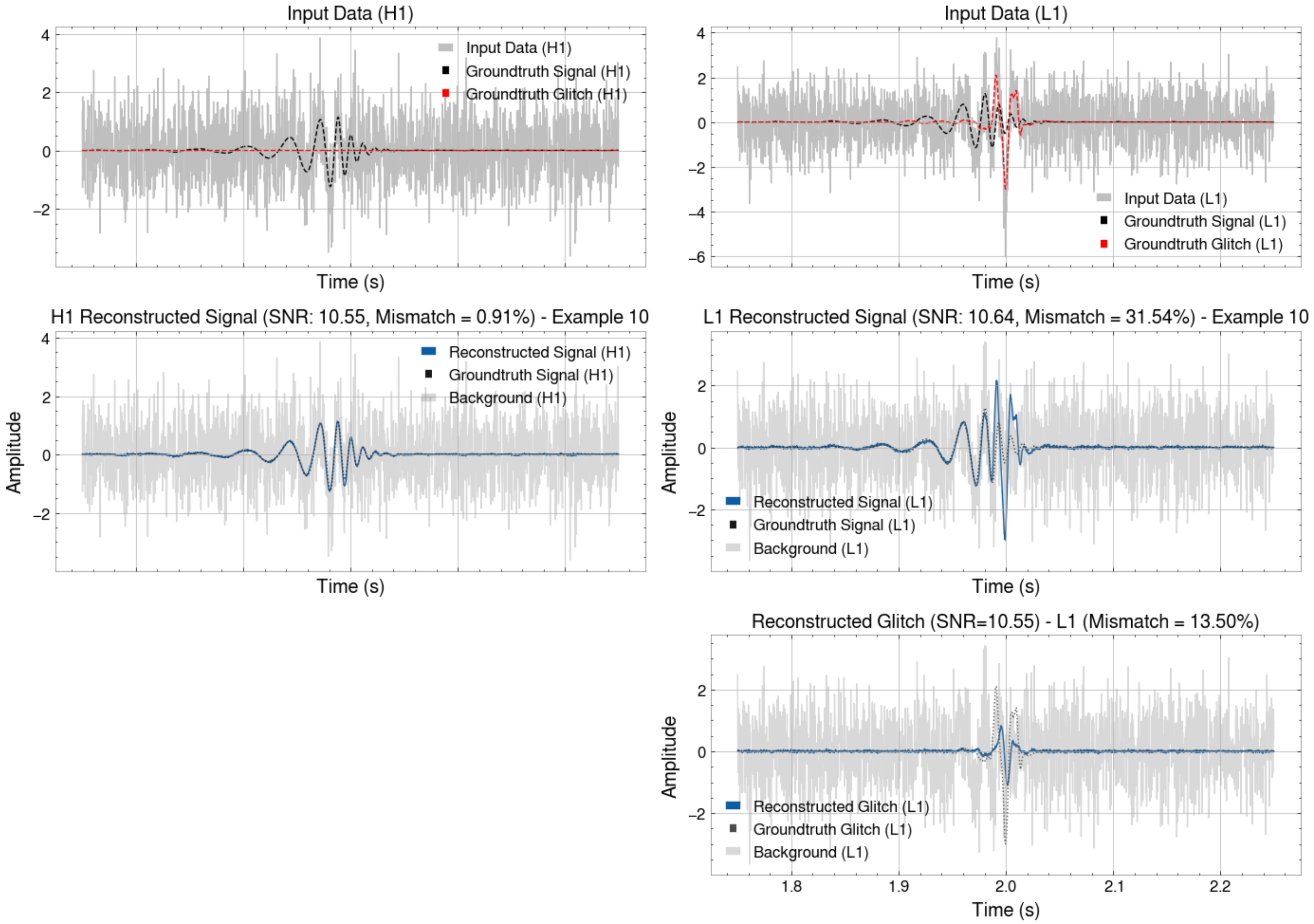
What about signal+glitch separation?



Summary

- DeepExtractor: **agnostic** time-domain **reconstruction** of signals and glitches
  - Foundation model for GW denoising/reconstruction?
  - Applicable to other domains?
- **Interpolatation** to unseen classes
  - Trained with diverse **combinations** of **proxy glitch** classes
  - **Transfer learning** on **real noise** required
- Surpass BayesWave glitch recovery performance
  - **x10,000 speedup**
  - Learned **deterministic** mapping **vs RJMCMC**
  - Online applications
- Limitations: **loud** and **quiet** signals and glitches

Future Work

- Package coming soon…
  - Time-domain O3 glitch catalogue (LIGO-Virgo)
- Overlapping signals and glitches
  - 2G era:
    - Multi-detector network
    - Signal Models – IMRPhenomXPHM
  - 3G era:
    - Einstein Telescope Null Stream
- Testing PE with DeepExtractor glitch mitigation
- Uncertainty estimation

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Paper & Code & Questions

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This material is based upon work supported by NSF's LIGO Laboratory which is a major facility fully funded by the National Science Foundation.

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Appendix

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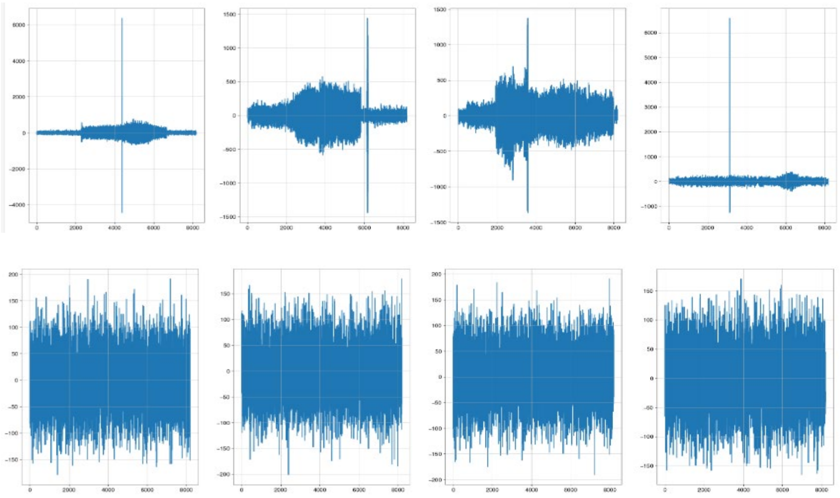
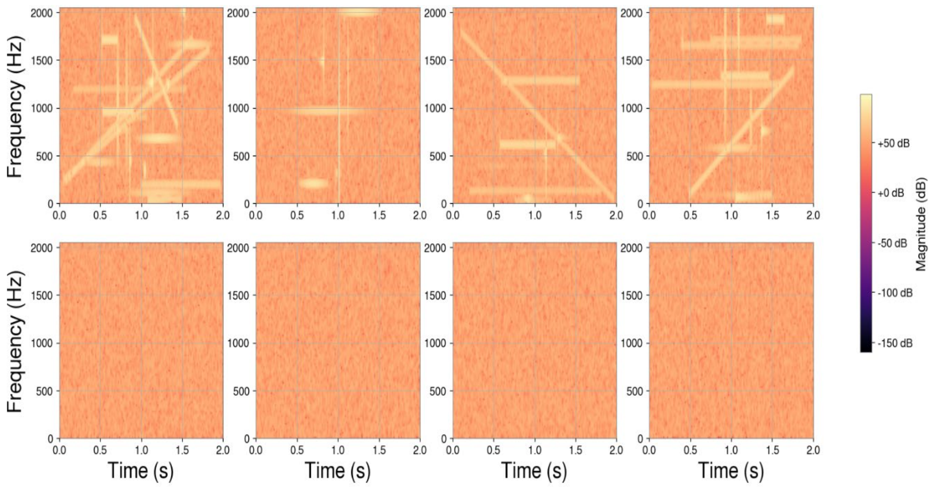
Training Examples: 1D vs 2D

We learn to map this....

...to this!



Time-domain (1D)



Spectrogram-domain (2D) via short-time-Fourier-transform (STFT)

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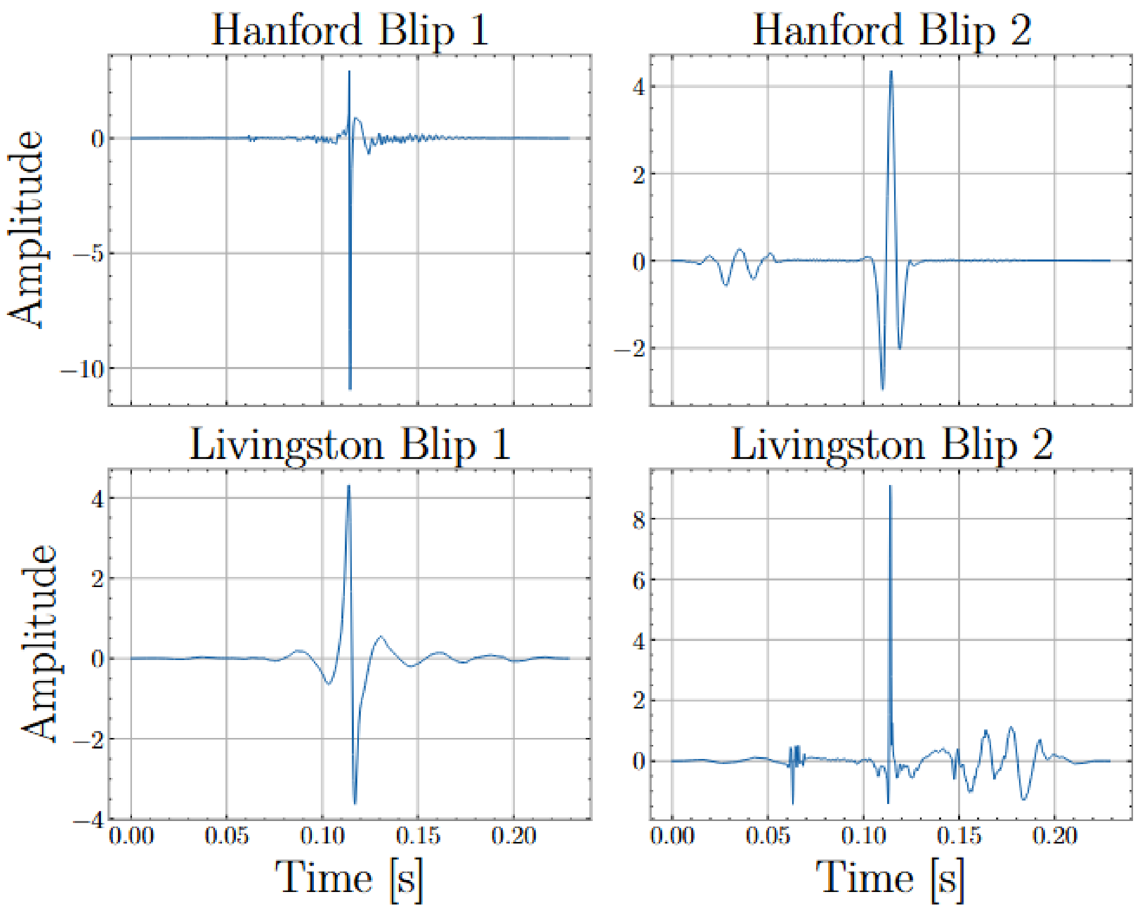
Gengli examples



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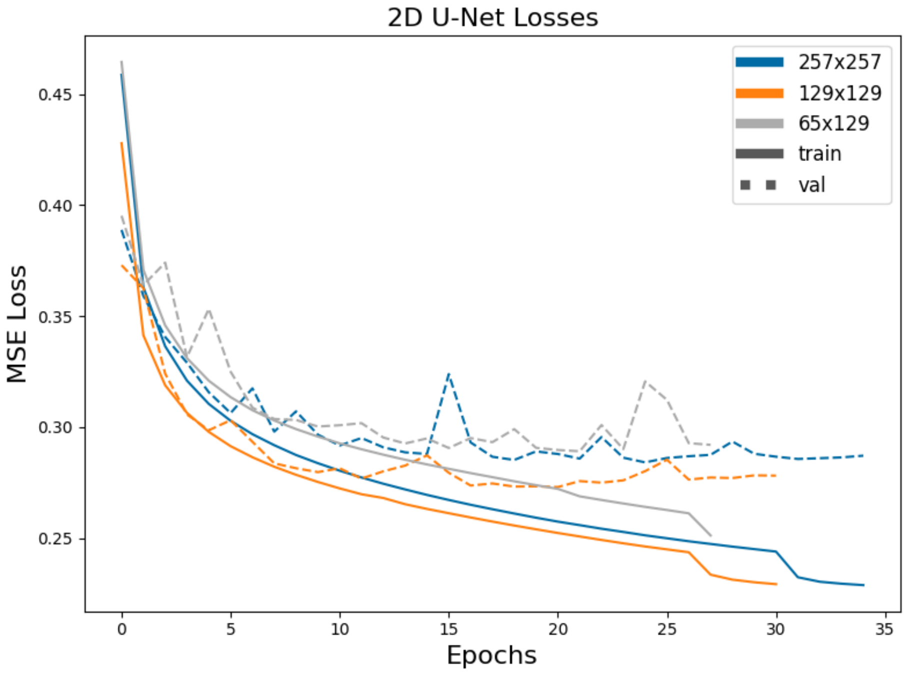
Model and training details

Number of trainable parameters

1. 1D U-Net: 11M
   - (5min/epoch)
2. 2D U-Net (**DeepExtractor**): 31M
   - (6min/epoch)
3. 1D DnCNN: 125k
   - (6min/epoch)
4. 1D Autoencoder: 9M
   - (7min/epoch)

Training scheme

1. **Initial learning rate:** 10^{-4}
2. **ReduceLROnPlateau**: 4 epochs of no improvement
3. **Early stopping**: 10 epochs of no improvement



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Simulated Experiments

(Deep-learning comparison)

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Results – Simulated experiments

Spectrogram resolution eg. 257x257

Glitch Type	UNET1D	DnCNN1D	Autoencoder1D	Autoencoder2D	DeepEx. (65x129)	DeepEx. (129^2)	DeepEx. (257^2)
chirp	$2.0^{+2.1}_{-0.8}$	$26.1^{+20.8}_{-13.9}$	$2.3^{+2.4}_{-0.9}$	$41.2^{+20.1}_{-9.3}$	$1.9^{+1.7}_{-0.6}$	$1.1^{+0.9}_{-0.4}$	$\mathbf{0.8}^{+0.7}_{-0.3}$
sine	$1.7^{+2.8}_{-0.6}$	$23.5^{+27.6}_{-11.5}$	$1.9^{+3.7}_{-0.7}$	$41.1^{+20.2}_{-9.7}$	$1.7^{+1.8}_{-0.6}$	$0.8^{+1.0}_{-0.2}$	$\mathbf{0.5}^{+0.7}_{-0.1}$
sine_gaussian	$1.4^{+1.8}_{-0.6}$	$8.9^{+13.5}_{-3.3}$	$1.6^{+2.0}_{-0.7}$	$40.2^{+16.3}_{-11.3}$	$1.7^{+1.8}_{-0.8}$	$0.6^{+0.7}_{-0.2}$	$\mathbf{0.4}^{+0.6}_{-0.1}$
gaussian_pulse	$0.4^{+0.4}_{-0.2}$	$3.8^{+3.8}_{-1.7}$	$0.6^{+0.7}_{-0.3}$	$37.7^{+13.9}_{-11.5}$	$1.8^{+2.1}_{-0.8}$	$0.6^{+0.7}_{-0.2}$	$\mathbf{0.4}^{+0.4}_{-0.2}$
ringdown	$0.6^{+0.8}_{-0.2}$	$5.2^{+4.3}_{-2.1}$	$0.9^{+1.0}_{-0.4}$	$39.3^{+15.0}_{-9.5}$	$2.2^{+2.4}_{-1.0}$	$0.9^{+0.8}_{-0.4}$	$\mathbf{0.7}^{+0.6}_{-0.3}$
gengli_H1	$1.0^{+1.0}_{-0.3}$	$3.8^{+3.3}_{-1.4}$	$1.2^{+1.1}_{-0.4}$	$36.6^{+13.0}_{-9.0}$	$2.7^{+2.0}_{-1.1}$	$1.2^{+0.8}_{-0.4}$	$\mathbf{0.9}^{+0.7}_{-0.3}$
gengli_L1	$1.2^{+0.7}_{-0.4}$	$4.0^{+2.8}_{-1.1}$	$1.3^{+0.9}_{-0.4}$	$36.1^{+10.9}_{-7.6}$	$2.8^{+2.1}_{-1.1}$	$1.2^{+0.9}_{-0.3}$	$\mathbf{1.1}^{+0.7}_{-0.4}$
cdvgan_blip	$1.2^{+1.0}_{-0.4}$	$4.5^{+3.9}_{-1.7}$	$1.4^{+1.1}_{-0.5}$	$36.2^{+15.6}_{-9.1}$	$2.9^{+2.6}_{-1.0}$	$1.2^{+0.9}_{-0.4}$	$\mathbf{0.9}^{+0.8}_{-0.2}$
cdvgan_tomte	$1.0^{+0.7}_{-0.3}$	$4.5^{+3.4}_{-1.7}$	$1.2^{+0.8}_{-0.4}$	$38.0^{+12.4}_{-10.7}$	$2.6^{+2.5}_{-1.0}$	$1.0^{+0.7}_{-0.3}$	$\mathbf{0.9}^{+0.6}_{-0.3}$
cdvgan_bbh	$1.0^{+1.1}_{-0.3}$	$4.6^{+5.2}_{-1.5}$	$1.1^{+1.2}_{-0.3}$	$34.6^{+17.7}_{-6.7}$	$2.7^{+2.4}_{-0.9}$	$1.2^{+1.0}_{-0.5}$	$\mathbf{0.8}^{+0.9}_{-0.2}$
cdvgan_simplex	$1.8^{+1.4}_{-0.6}$	$5.2^{+5.4}_{-1.6}$	$2.0^{+1.6}_{-0.7}$	$36.9^{+16.1}_{-7.6}$	$3.5^{+3.5}_{-1.1}$	$1.8^{+1.4}_{-0.5}$	$\mathbf{1.6}^{+1.2}_{-0.5}$
cdvgan_uniform	$1.6^{+1.1}_{-0.5}$	$5.3^{+3.9}_{-1.9}$	$1.7^{+1.3}_{-0.5}$	$38.1^{+13.3}_{-10.0}$	$3.1^{+3.3}_{-1.1}$	$1.6^{+1.0}_{-0.5}$	$\mathbf{1.4}^{+0.9}_{-0.5}$
Total	$1.2^{+1.1}_{-0.4}$	$5.9^{+6.9}_{-2.4}$	$1.4^{+1.3}_{-0.5}$	$37.9^{+15.2}_{-9.2}$	$2.5^{+2.3}_{-0.9}$	$1.1^{+0.9}_{-0.4}$	$\mathbf{0.9}^{+0.7}_{-0.3}$

Median mismatch (%) between injected and extracted glitches over 512 samples from each class. Bounds represent 1σ confidence interval.

Main Findings

1. 2D model on high resolution STFT is best
2. Reconstruct a sample ≈ 0.1s (CPU)

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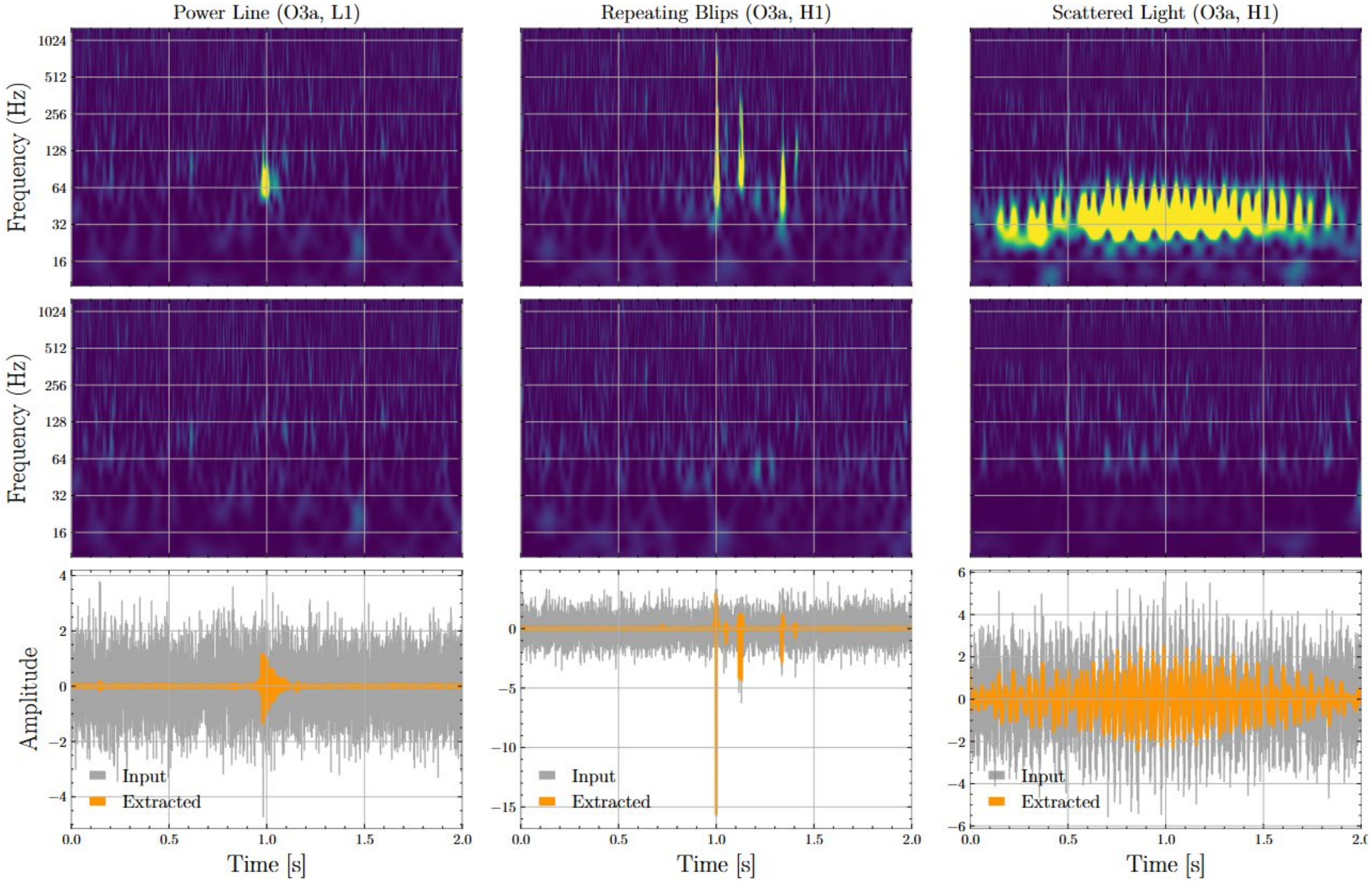
Gravity Spy Examples 3

Input

Output

Reconstruction



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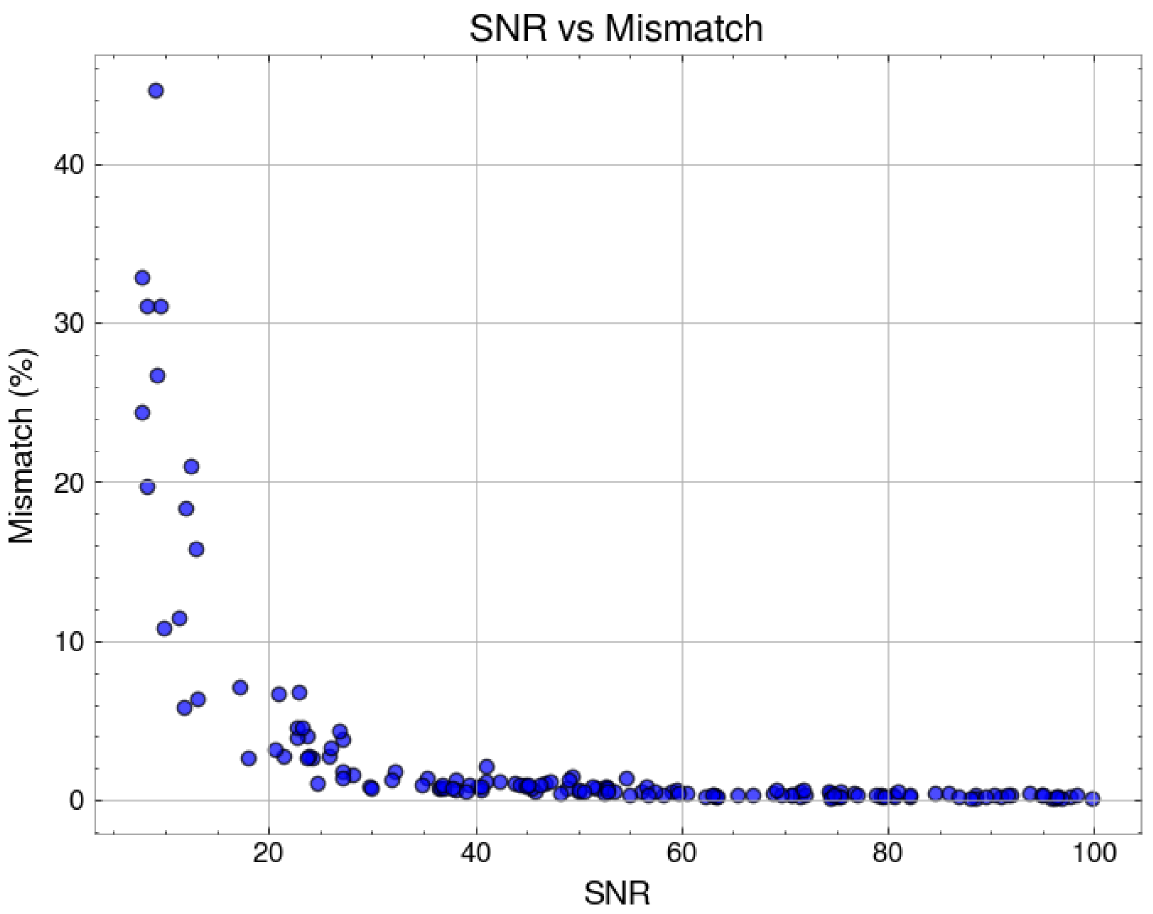
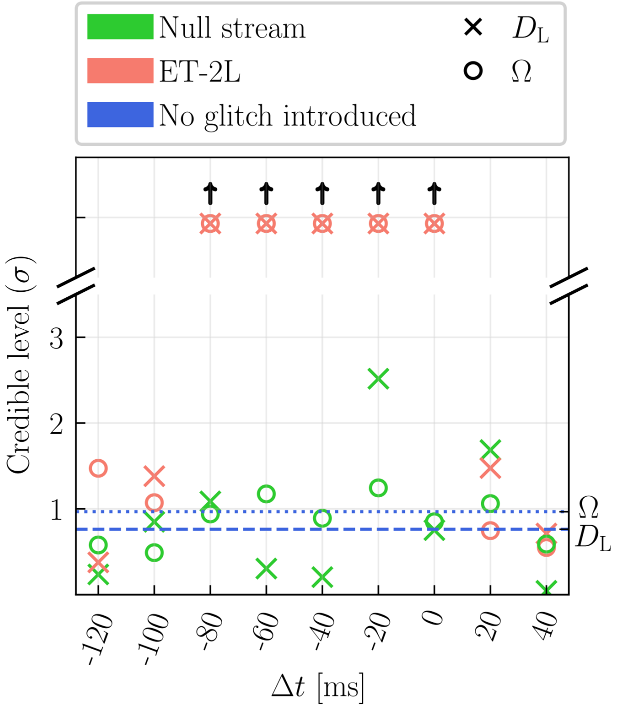
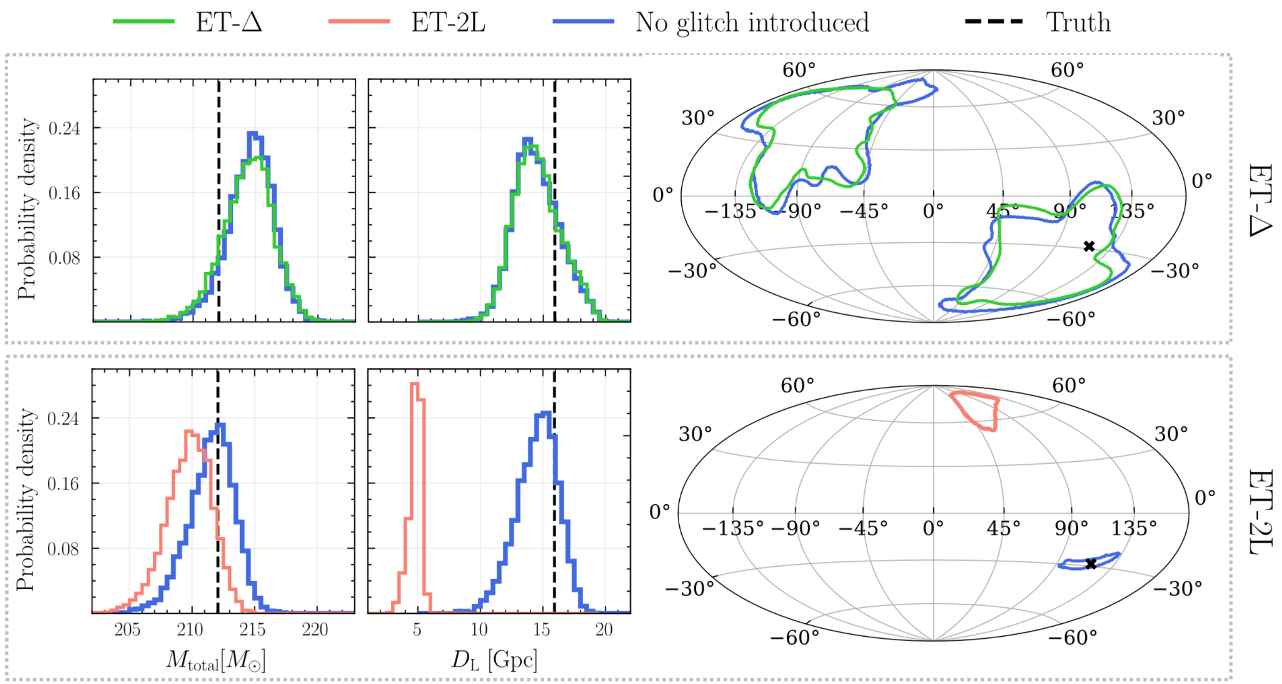
Nikhef

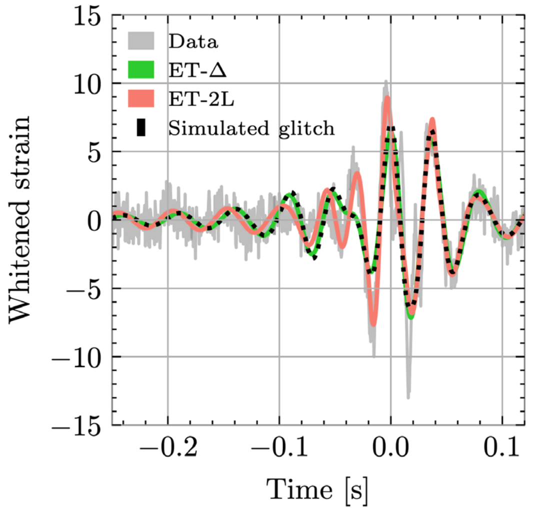
SNR vs Mismatch



ET Δ vs 2L







Narola et. al: https://arxiv.org/pdf/2411.15506

Applicable to other domains?

- Relevant for denoising problems where:
  - Background can be measured accurately
  - Target is unmodelled (proxy signals)

- Astrophysics
  - CATO background estimation?

- Particle Physics
  - Pile-up removal?