Machine Learning for Gravitational Wave data analysis

Physics of Data workshop

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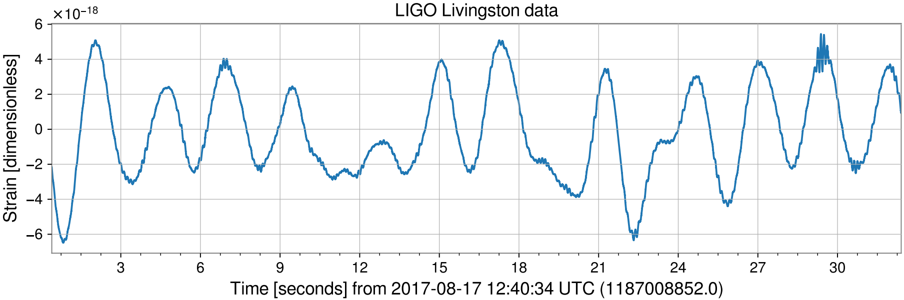
Virgo interferometer

Bare interferometer data



Describing Gaussian noise

We can completely characterize Gaussian noise through its **power** or **amplitude** spectral density:

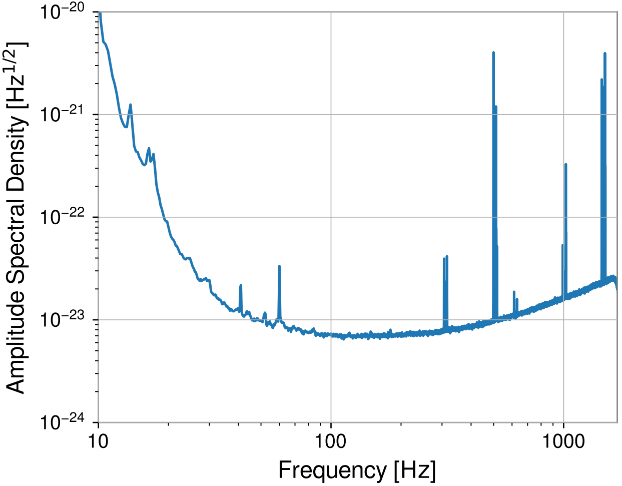
$$\mathrm{PSD}(f) = S_n(f) = \lim_{T\to\infty} \frac{\left|\widetilde{d}(f)\right|^2}{T}\,, \tag{1}$$

$$\mathrm{ASD}(f) = \sqrt{\mathrm{PSD}(f)}\,, \tag{2}$$

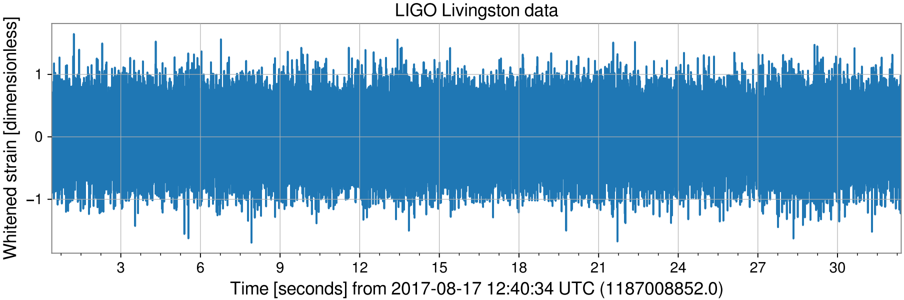
and then we can whiten the signal as

$$\widetilde{d}_w(f) = \frac{\widetilde{d}(f)}{\sqrt{S_n(f)}}\,. \tag{3}$$

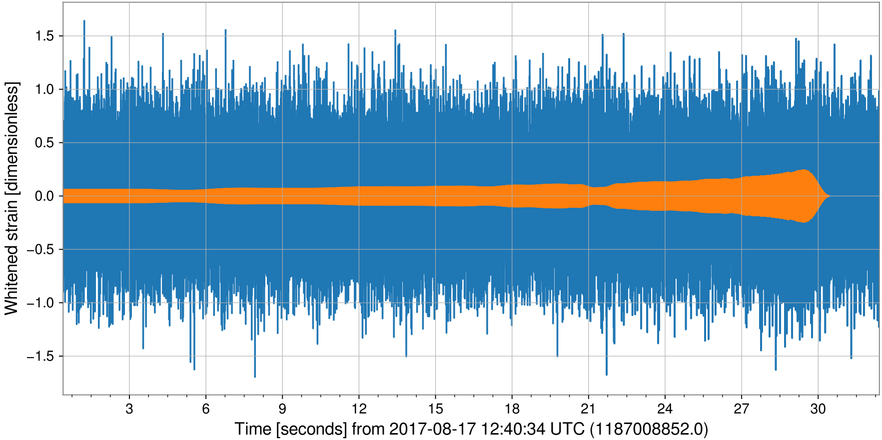
Amplitude spectral density



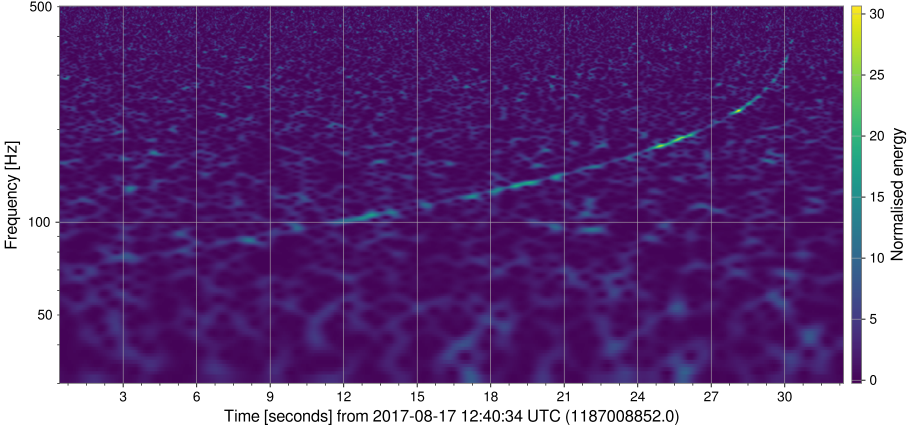
Whitened, bandpassed data



The signal is small



Q-transform


500
100
50
Frequency [Hz]
3
6
9
12
15
18
21
24
27
30
Time [seconds] from 2017-08-17 12:40:34 UTC (1187008852.0)
30
25
20
15
10
5
0
Normalised energy

Signal parametrization

The strain at the detector is modelled as $s(t) = h_\theta(t) + n(t)$, where:

- the noise $n(t)$ is taken to be stationary, with zero mean, and Gaussian with power spectral density $S_n(f)$;
- the signal $h_\theta(t)$ can depend on:
  - intrinsic parameters: total mass $M = m_1 + m_2$, mass ratio $q = m_1 / m_2$, spins $\vec{\chi}_1$ and $\vec{\chi}_2$, tidal polarizabilities Λ_1 and Λ_2;
  - extrinsic parameters: luminosity distance D_L, inclination ι...

The Wiener distance

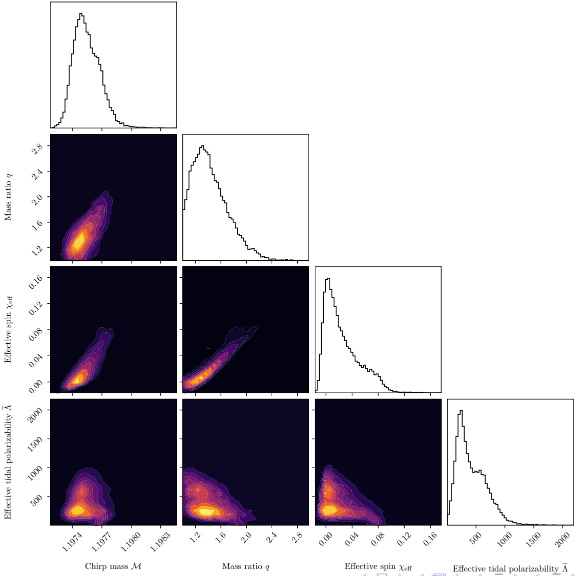
The likelihood used in parameter estimation reads:

$$\Lambda(s|\theta) \propto \exp\left((h_\theta|s) - \frac{1}{2}(h_\theta|h_\theta) \right), \tag{4}$$

where $(a|b)$ is the Wiener product:

$$(a|b) = 4\,\mathrm{Re} \int_0^\infty \frac{\widetilde{a}^*(f)\widetilde{b}(f)}{S_n(f)}\,\mathrm{d}f = 4\,\mathrm{Re} \int_0^\infty a_w^*(f) b_w(f)\,\mathrm{d}f\ . \tag{5}$$

A posterior distribution: GW170817



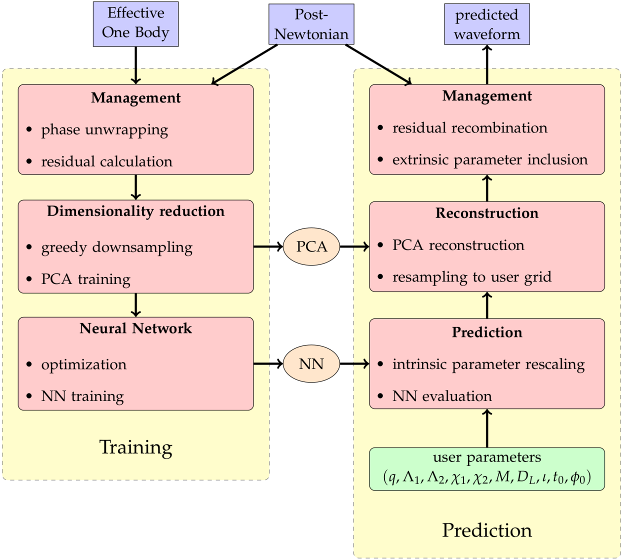
Theoretical signal models

The main strategies for the generation of theoretical waveforms are:

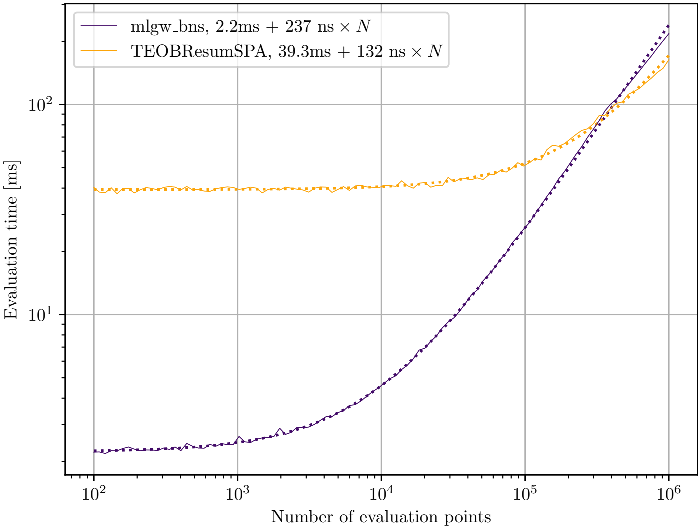
- numerical relativity;
- effective one body;
- post-Newtonian.

Other methods mix and match these: hybrid waveforms, phenomenological models, **surrogates**.

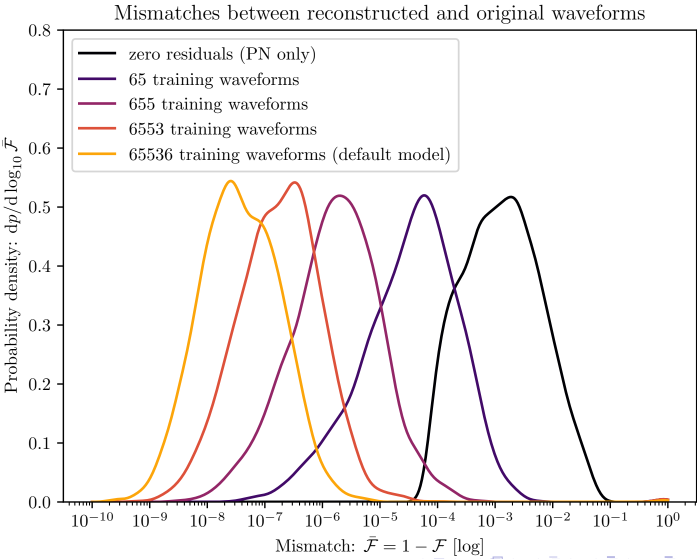
mlgw_bns structure



Evaluation time



Fidelity


Mismatches between reconstructed and original waveforms
zero residuals (PN only)
65 training waveforms
655 training waveforms
6553 training waveforms
65536 training waveforms (default model)
Probability density: $\mathrm{d}p/\mathrm{d}\log_{10}\bar{\mathcal{F}}$
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
10^{-10} 10^{-9} 10^{-8} 10^{-7} 10^{-6} 10^{-5} 10^{-4} 10^{-3} 10^{-2} 10^{-1} 10^{0}
Mismatch: $\bar{\mathcal{F}} = 1 - \mathcal{F}$ [log]

More information

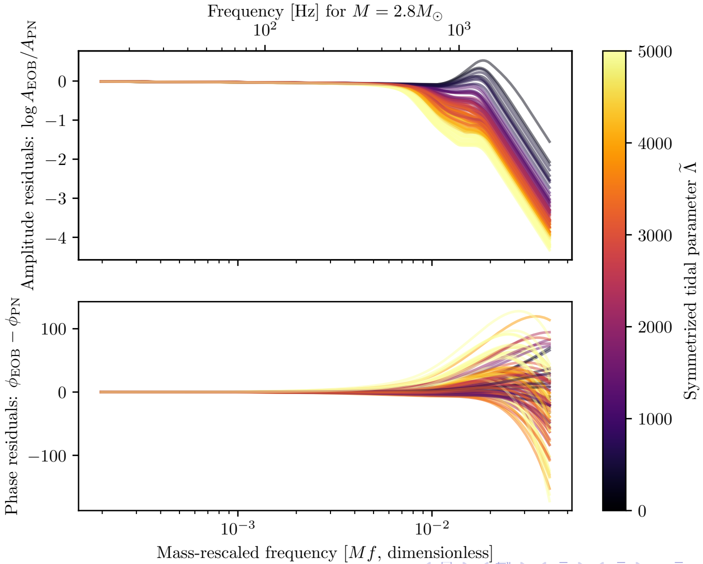
- Learn about GW data analysis at `gw-openscience.org`;
- documentation for `mlgw_bns` is available at `mlgw-bns.readthedocs.io`;
- scripts and source for this presentation are available at `github.com/jacopok/pod-workshop`.

Technologies

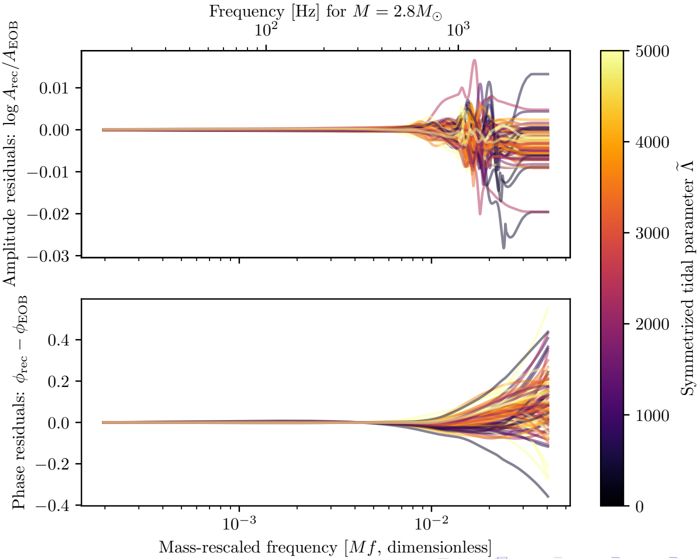
`mlgw_bns` is implemented as a `python` package, and it makes use of

- `scikit-learn` for the neural network (upgrading to `pytorch`);
- `optuna` for the hyperparameter optimization;
- `pytest` and `tox` for automated testing;
- `numba` for just-in-time compilation and acceleration.

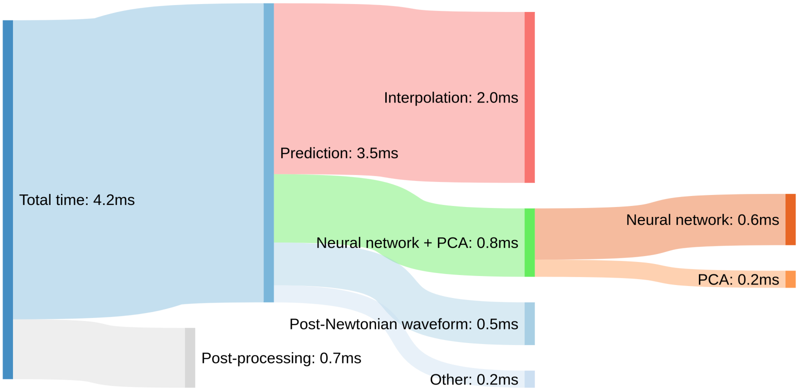
Original residuals



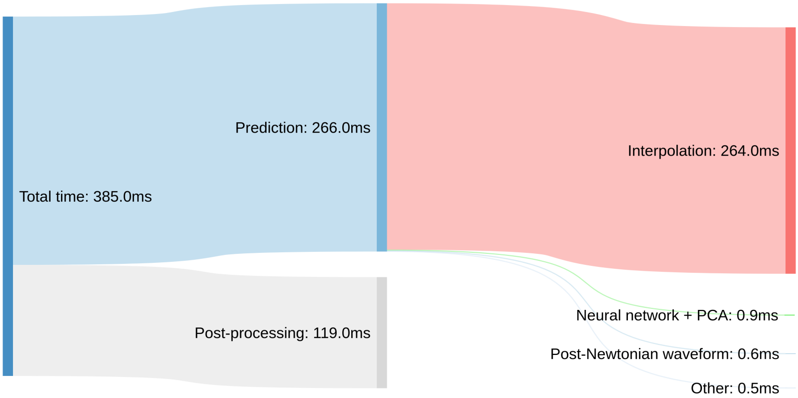
Reconstruction residuals



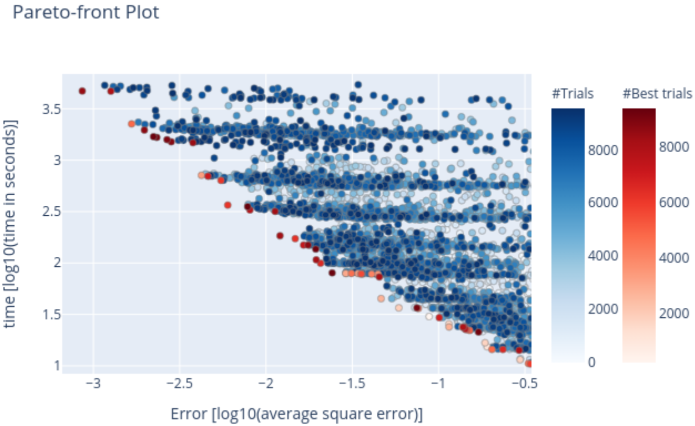
Profiling the evaluation: 8×10^3 interpolation points



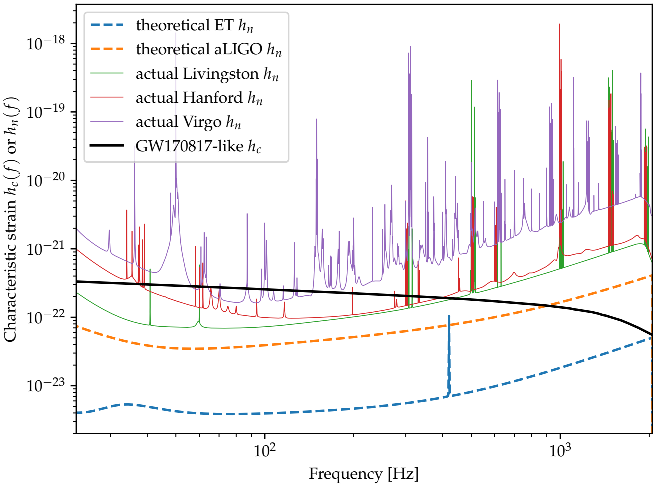
Profiling the evaluation: 2×10^6 interpolation points



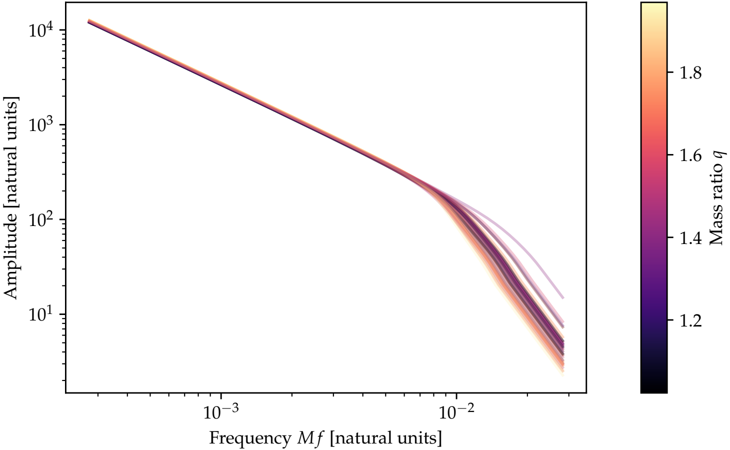
Hyperparameter optimization



Power Spectral densities and GW170817

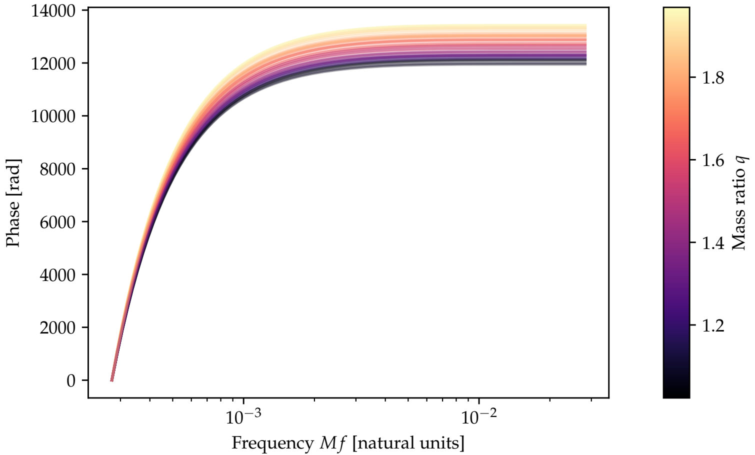


Amplitudes



10^4
10^3
10^2
10^1
Amplitude [natural units]
10^{-3}
10^{-2}
Frequency Mf [natural units]
1.8
1.6
1.4
1.2
Mass ratio q

Phases


14000
12000
10000
8000
6000
4000
2000
0
Phase [rad]
10^{-3}
10^{-2}
Frequency Mf [natural units]
1.8
1.6
1.4
1.2
Mass ratio q