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