Enhancing gravitational-wave burst detection confidence in expanded detector networks with the *BayesWave* pipeline

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PHYS. REV. D 103, 062002 (2021)

Expanded detector networks

The Laser Interferometer Gravitational-Wave Observatory (LIGO) has completed three observing runs (O1, O2, O3) with Virgo joining at the end of O2 and the whole of O3. The Kamioka Gravitational Wave Detector (KAGRA) also began observing at the end of O3. The global gravitational-wave detector network achieves higher detection rates, better parameter estimates, and more accurate sky localisation as number of detectors, $\mathscr{I}$, increases.

BayesWave: unmodelled burst search pipeline

BayesWave [1-3] is a source-agnostic gravitational-wave (GW) burst detection algorithm that reconstructs non-Gaussian, transient features in the data as a sum of sine-Gaussian wavelets (see Figure 1). Model selection in *BayesWave* is done by comparing model evidences via the Bayes factor.

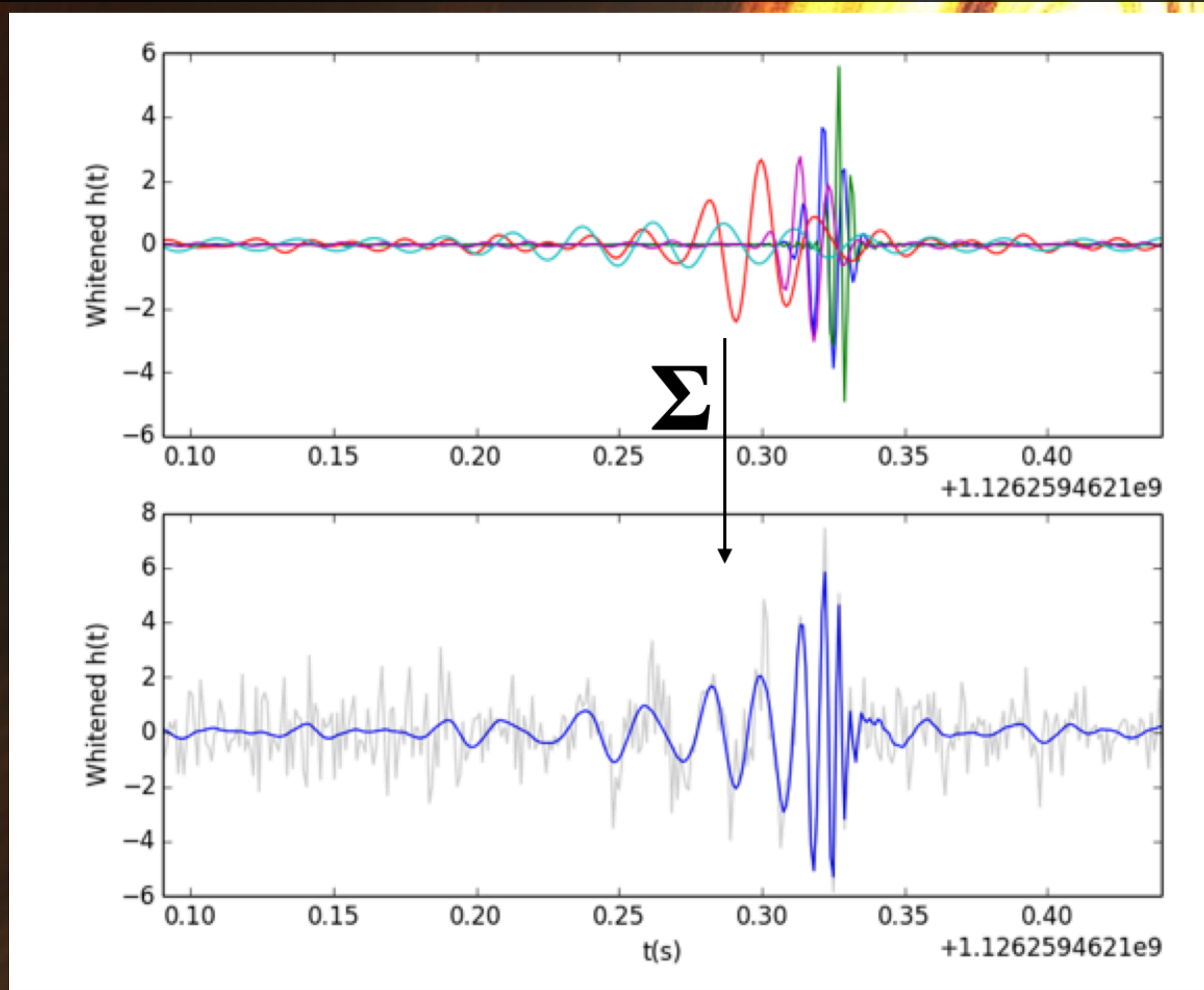

Figure 1: Top panel shows individual sine-Gaussian wavelets, each of different colour, used in the reconstruction of GW150914 in the time domain. Bottom panel shows the resulting waveform (blue) as a sum of all wavelets, overlaid on the actual data (grey). [Image courtesy of Meg Millhouse]

BayesWave and Expanded Detector Networks

Aim: Quantify *BayesWave*'s detection confidence as a function of number of detectors, $\mathscr{I}$. We use the Bayes factor, $\mathscr{B}_{\mathcal{S},\mathcal{G}}$ between the Gaussian-noise plus signal model ($\mathcal{S}$) and the Gaussian noise plus glitch model ($\mathcal{G}$) to measure detection confidence. The three configurations used in this study are: LIGO Hanford-Livingston, (HL), HL-Virgo (HLV) and HLV-KAGRA (HLKV).

Analytic Bayes factor scaling

We use Laplace approximation to estimate the Bayesian evidence and hence the primary scaling of $\ln \mathscr{B}_{\mathcal{S},\mathcal{G}}$ [4]. We find that $\ln \mathscr{B}_{\mathcal{S},\mathcal{G}}$ scales mainly with the $\mathscr{I}$, number of wavelets (N) and signal-to-noise ratio ($\mathrm{SNR}_{\mathrm{net}}$) of the injected waveform:

$$\ln \mathscr{B}_{\mathcal{S},\mathcal{G}} \sim \mathscr{I} N \ln \mathrm{SNR}_{\mathrm{net}}$$

Empirical Bayes factor scaling

Method: Inject 150 phenomenological binary black hole (BBH) waveforms into simulated Gaussian noise coloured by the projected power spectral density (PSD) of LIGO, Virgo and KAGRA for the fourth observing run (O4). We then use *BayesWave* to recover the injections to obtain empirical scaling of $\mathscr{B}_{\mathcal{S},\mathcal{G}}$. The BBHs have equal component masses of $30M_{\odot}$ and are modelled using IMRPhenomD [5].

Results & discussion: Figure 2 shows $\ln \mathscr{B}_{\mathcal{S},\mathcal{G}}$ as a function of $\mathrm{SNR}_{\mathrm{net}}$ for BBH injections recovered using *BayesWave*. All three networks show increasing $\ln \mathscr{B}_{\mathcal{S},\mathcal{G}}$ with increasing $\mathrm{SNR}_{\mathrm{net}}$. However, injections at comparable SNRs are recovered with higher $\ln \mathscr{B}_{\mathcal{S},\mathcal{G}}$ in the larger networks. To test the scaling of $\ln \mathscr{B}_{\mathcal{S},\mathcal{G}}$ with $\mathscr{I}$ alone, we use *BayesWave* to recover a set of ad-hoc sine-Gaussian wavelets ($N = 1$) injected as coherent signals from the three configurations. Figure 3 shows agreement between the analytic and empirical results.

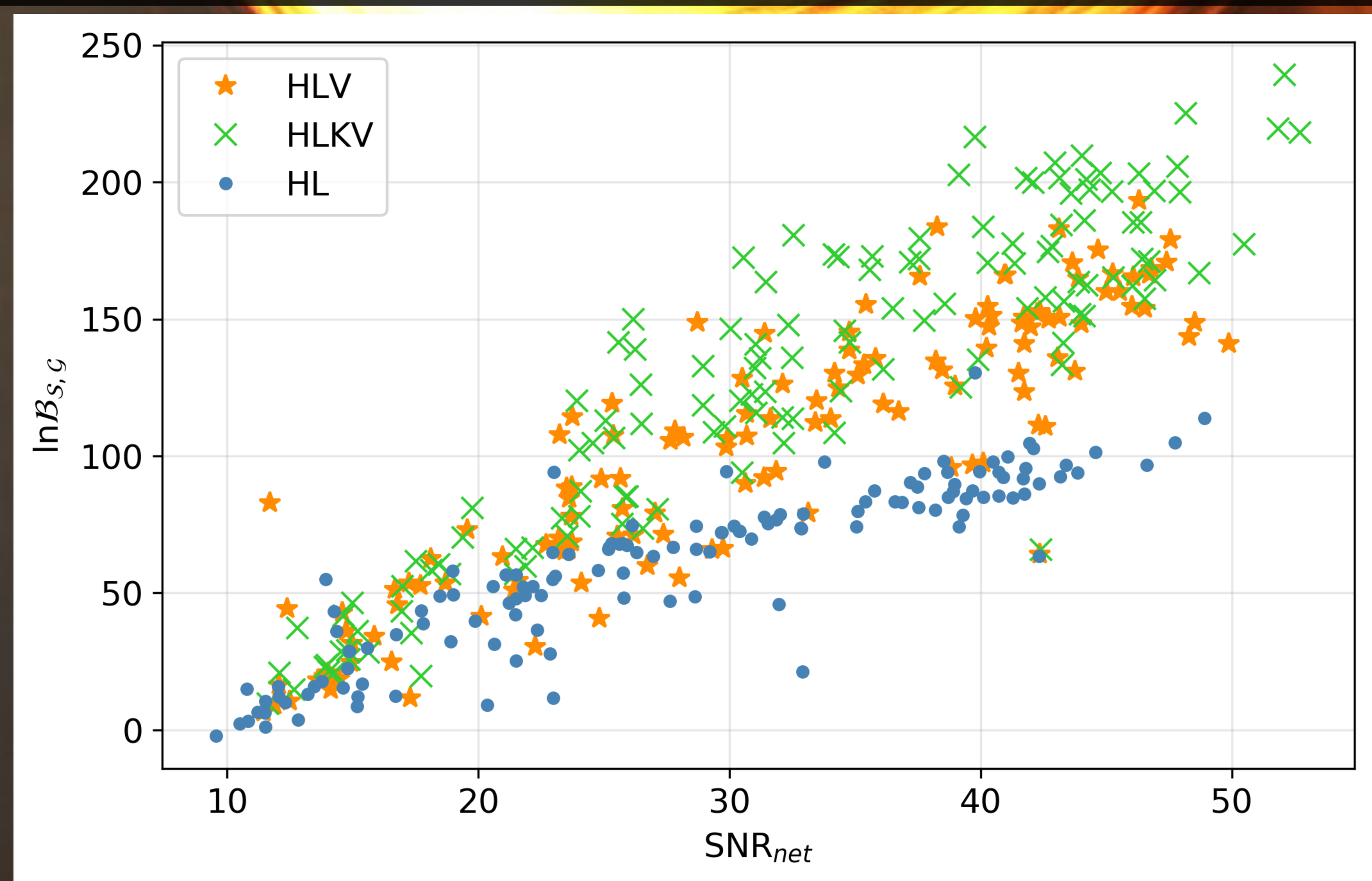

Figure 2: $\ln \mathscr{B}_{\mathcal{S},\mathcal{G}}$ of BBH injection recoveries versus $\mathrm{SNR}_{\mathrm{net}}$. Each data point represents a single BBH injection.

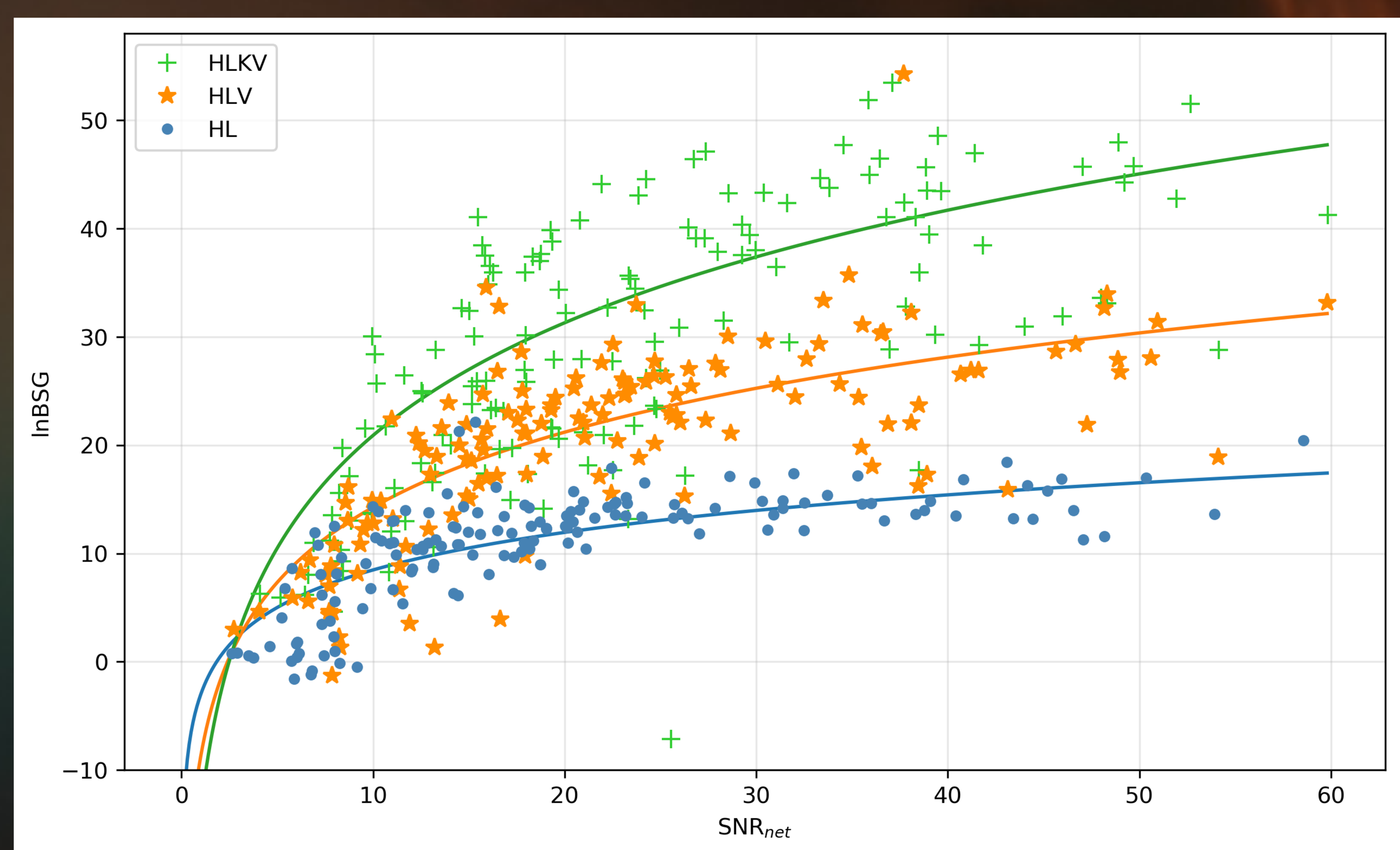

Figure 3: $\ln \mathscr{B}_{\mathcal{S},\mathcal{G}}$ of sine-Gaussian wavelet injection recoveries versus $\mathrm{SNR}_{\mathrm{net}}$. The solid lines with colors corresponding to the data symbols are analytic predictions of $\ln \mathscr{B}_{\mathcal{S},\mathcal{G}}$.

Acknowledgement & References

This material is based upon work supported by the LIGO Laboratory fully funded by the National Science Foundation. Poster background © Mark Myers (OzGrav).

[1] N. Cornish and T. Littenberg, Classical Quantum Gravity 32, 135012 (2015).

[2] N. Cornish et al., Phys. Rev. D 103, 044006 (2021).

[3] BayesWave source code repository, https://git.ligo.org/lscsoft/bayeswave

[4] T. Littenberg et al., Phys. Rev. D 94, 044050 (2016)

[5] S. Husa et al., Phys. Rev. D 93, 044006 (2016).

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