9th Wernher von Braun Memorial Symposium
October 25 – 27, 2016

Improving the Efficiency of Gravitational Wave Detection

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The discovery of the binary black hole merger GW150914 in September of last year signaled the birth of a new observational field of gravitational-wave astronomy. Work is now underway to improve the detectors and the analysis tools in anticipation of the second observing run (O2) scheduled to begin later this year. BayesWave is a "burst" (short-duration transient signal) detection algorithm that uses Bayesian model selection to distinguish between signals and instrument artifacts. Here we describe ongoing development activities to improve the algorithm based on lessons learned in O1.

Gravitational Waves & LIGO

Gravitational Waves

- Ripples in space-time caused by accelerating masses
- Predicted by Einstein in 1915
- First direct measurement on Sept. 14, 2015 by LIGO/Virgo Scientific Collaborations [PRL **116**, 061102 (2016)]

LIGO

- Pair of identical 4km-long gravitational wave detectors in the U.S.
- Detectors located in Hanford, WA and Livingston, LA
- Use laser interferometry to measure changes in distance due to passing gravitational waves.

Bayesian Inference/Role of Priors

Bayes' Theorem for data analysis:

- Infer posterior distribution p(**h** | **s,** M) of waveform (h) given data (s) and model (M).
- Choose likelihood p(**s** | **h**, M) and prior p(**h** | M)
- Compute evidence p(**s** | M)

$$p(\mathrm{h}|\mathrm{s}, M) = \frac{p(\mathrm{h}|M)p(\mathrm{s}|\mathrm{h}, M)}{p(\mathrm{s}|M)}$$

Models under consideration:

- Model S: Gravitational wave signal.
- Model G: Short-duration instrument artifact, or "glitch."
- Model N: Stationary Gaussian noise.

Choice of priors:

- Start with "uninformative" priors (e.g. uniform distributions)
- Posterior from past experiment become priors for new experiment
- **Our aim is to develop priors for glitches in LIGO data**
  - Improve detection efficiency (our model will better understand noise)
  - Can be used to inform efforts to understand cause of glitches

BayesWave Algorithm

[Class. Quant. Grav, 32, 13 (2015), Phys Rev D91, 084034 (2015)]

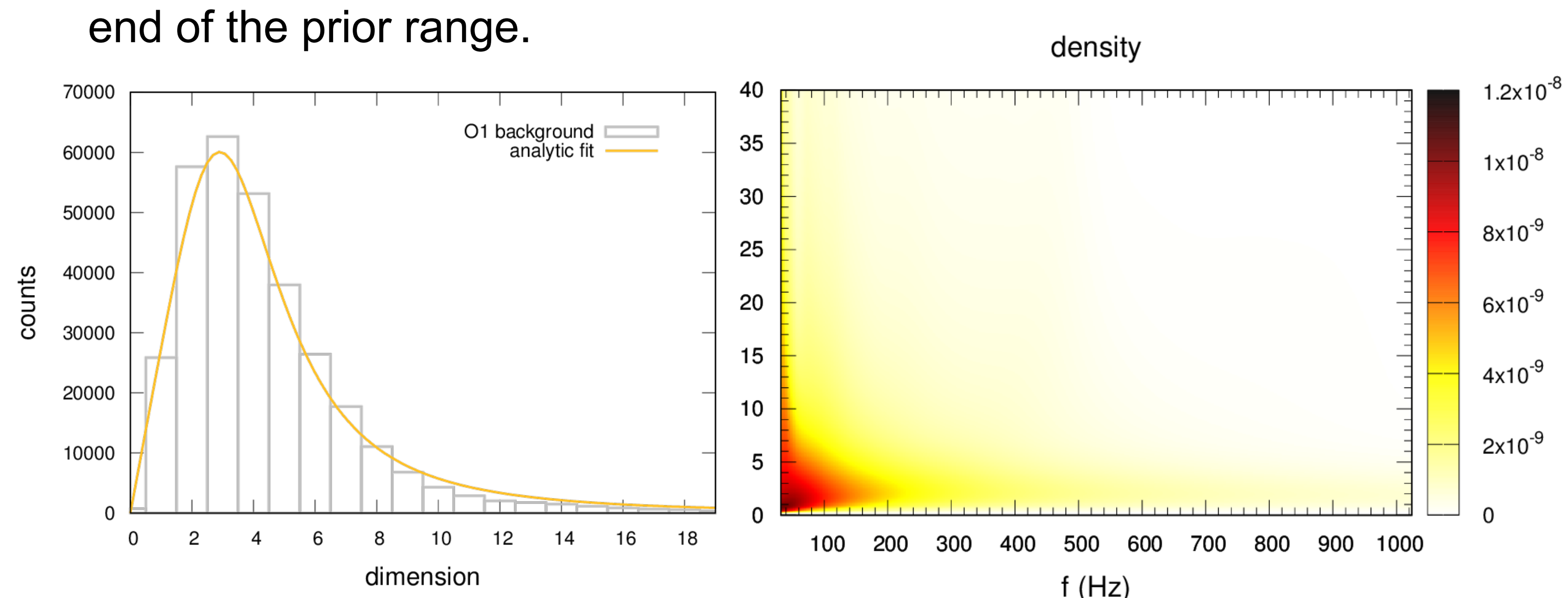
- Use Parallel Tempered Markov Chain Monte Carlo algorithm to compute Bayesian Evidence for each model
- Model glitches as linear combination of wavelets *independent* in each LIGO detector

$$\Psi\left(t; A, f_0, Q, t_0, \phi_0\right) = A e^{-(t-t_0)^2/\tau^2}\cos\left(2\pi f_0\left(t-t_0\right)+\phi_0\right)$$

- Model signals as linear combination of wavelets *coherent* across LIGO network.
- Number of wavelets used is determined using trans-dimensional (reversible jump) MCMC
- Candidates are ranked by the Bayes factor (B), i.e. ratio of signal-model evidence to glitch-model evidence.
- In O1 we used uniform priors on the number of wavelets, and the wavelet parameters (particularly f_0 and Q)

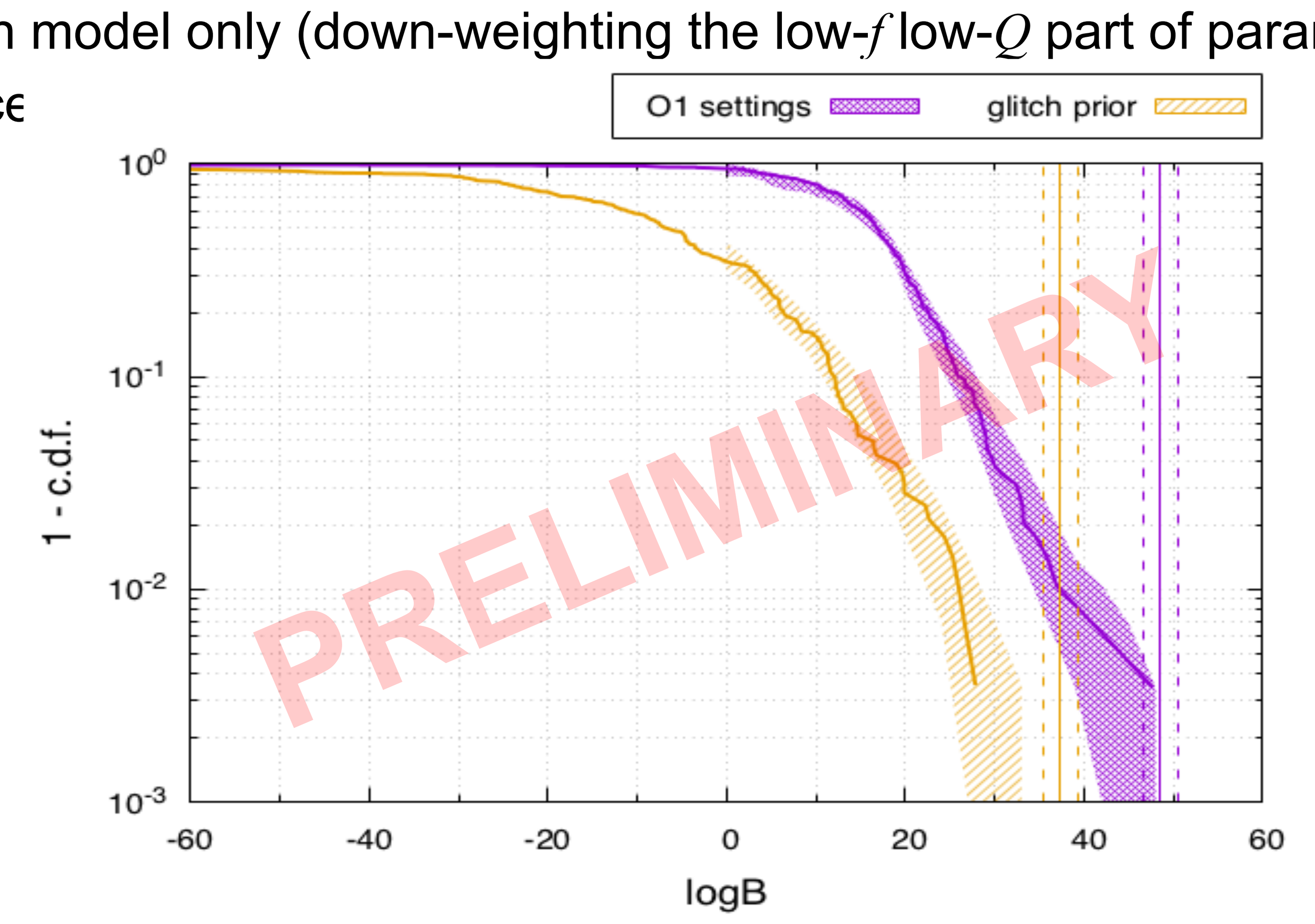
Developing and Testing Priors

- In O1, most glitches that affected the BayesWave search used a small number of wavelets and had f_0 and Q values typically at the low end of the prior range.



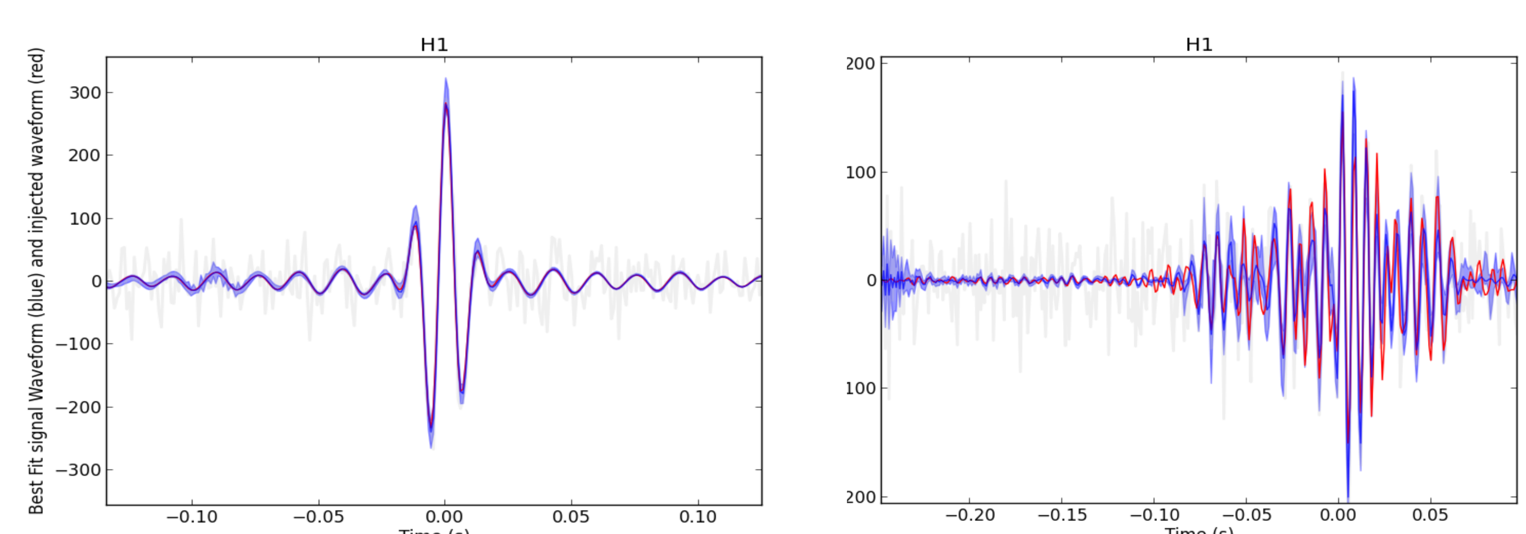
Left panel: histogram of median wavelet number for background events during O1 (gray) and normalized, analytic fit to distribution used for prior (gold). Right panel: 2-dimensional probability density of wavelet Q *vs.* f parameters, smoothed with a Gaussian kernel.

- Adopt number of wavelets prior for all models, use $p(f,Q)$ as prior for glitch model only (down-weighting the low-f low-Q part of parameter space



Background distribution of glitches for BayesWave using the O1 settings (purple) and the new priors (gold) as a function of the ranking statistic: the natural log of the Bayes factor between the signal- and glitch-models. Vertical lines show Bayes factors for black hole mergers like GW150914. Shaded regions represent 90% probability contours. Using the O1 settings, GW150914-like signals are more significant in the BayesWave search.

- Testing new priors on simulated burst signals is ongoing to see how changes influence the recovery of other signal morphologies



Two examples of test signals. Left: Sine-Gaussian waveform similar to basis functions used by BayesWave. Right: Gaussian-enveloped, band-limited, white noise. Red represents simulated signal, blue bands contain 90% probability for reconstructed waveforms.

Acknowledgments

We acknowledge the support of NSF LIGO grant, award PHY-1307020.

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