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AIP Congress 2022, 12-16 December

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

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Phys. Rev. D 103, 062002

OzGrav

ARC Centre of Excellence for Gravitational Wave Discovery

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Talk Overview

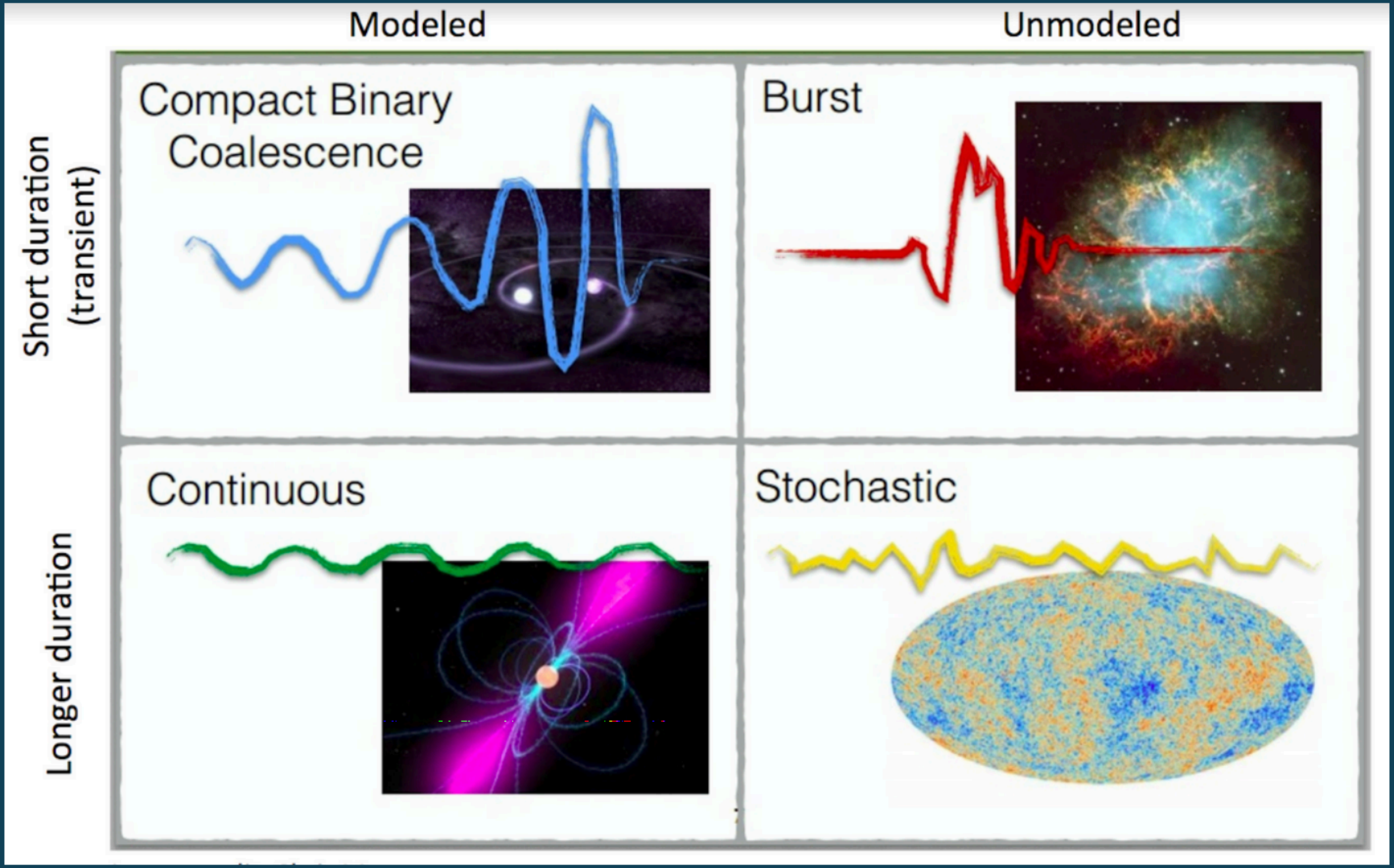
- The global detector network
- Types of GW sources
- Instrumental glitches
- Overview of the *BayesWave pipeline*
- **My work:** Quantifying network performance as a function of number of detectors, $\mathcal{I}$ for *BayesWave* with the Hanford-Livingston (HL), HL-Virgo (HLV) and HL-KAGRA-Virgo (HLKV) networks.
- Ongoing/Future work

Gravitational wave Detectors

- <u>The LIGO Scientific, Virgo and KAGRA (LVK) Collaboration detectors</u>
  (1) Laser Interferometer Gravitational-Wave Observatory (LIGO)
  Hanford and Livingston, United States
  (2) Virgo, Italy
  (3) Kamioka Gravitational wave Detector (KAGRA), Japan.
- Three observing runs O1, O2 and O3.
- 90 detections of Compact Binary Coalescence (CBC)
  - Binary black hole (BBH) mergers
  - Binary neutron stars (BNS) mergers
  - Neutron star-black hole (NSBH) mergers

[Image credits: LIGO Lab Caltech]

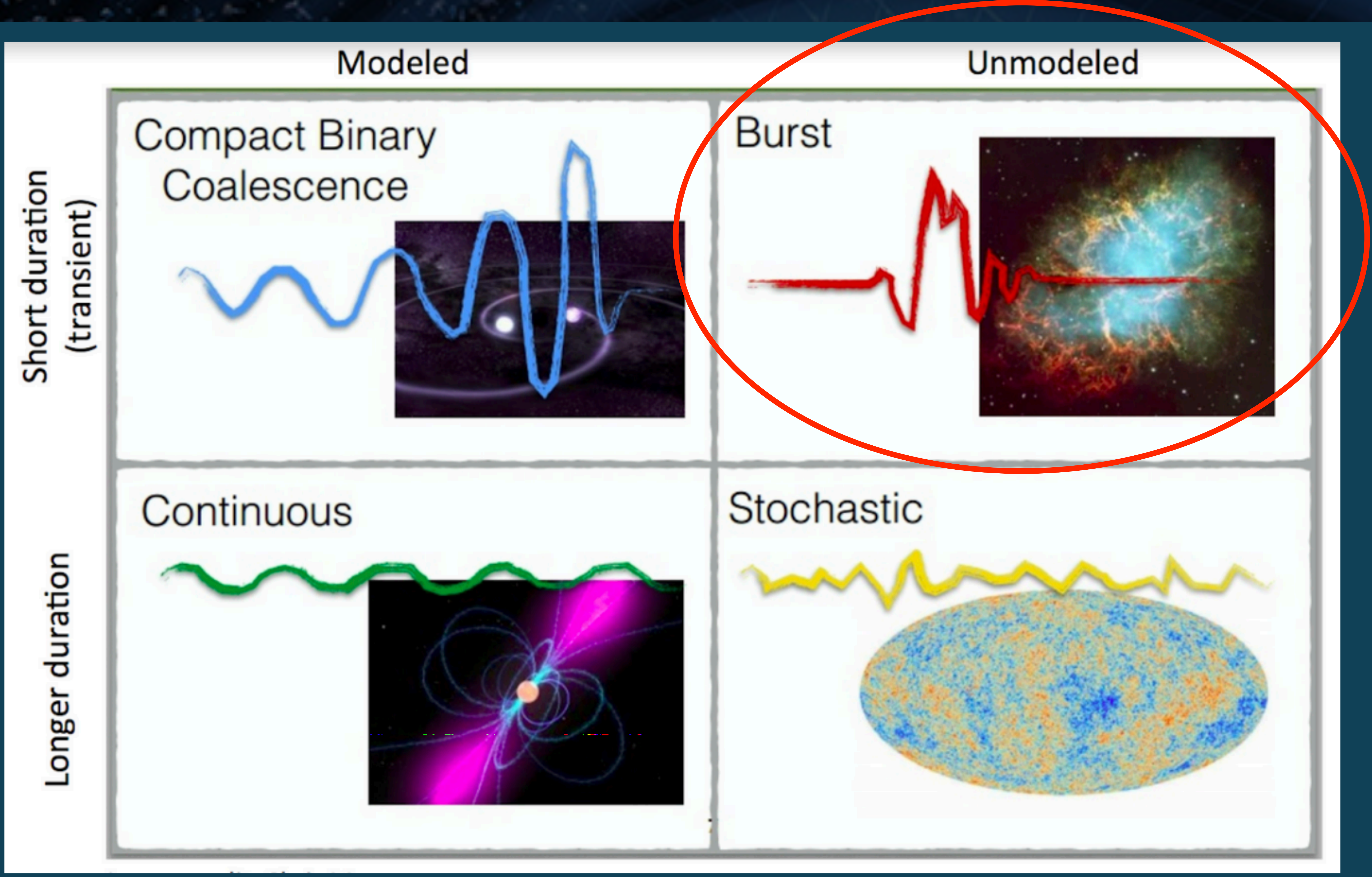
Types of GW Sources



[Chris Messenger]

Slide from Dr. Millhouse

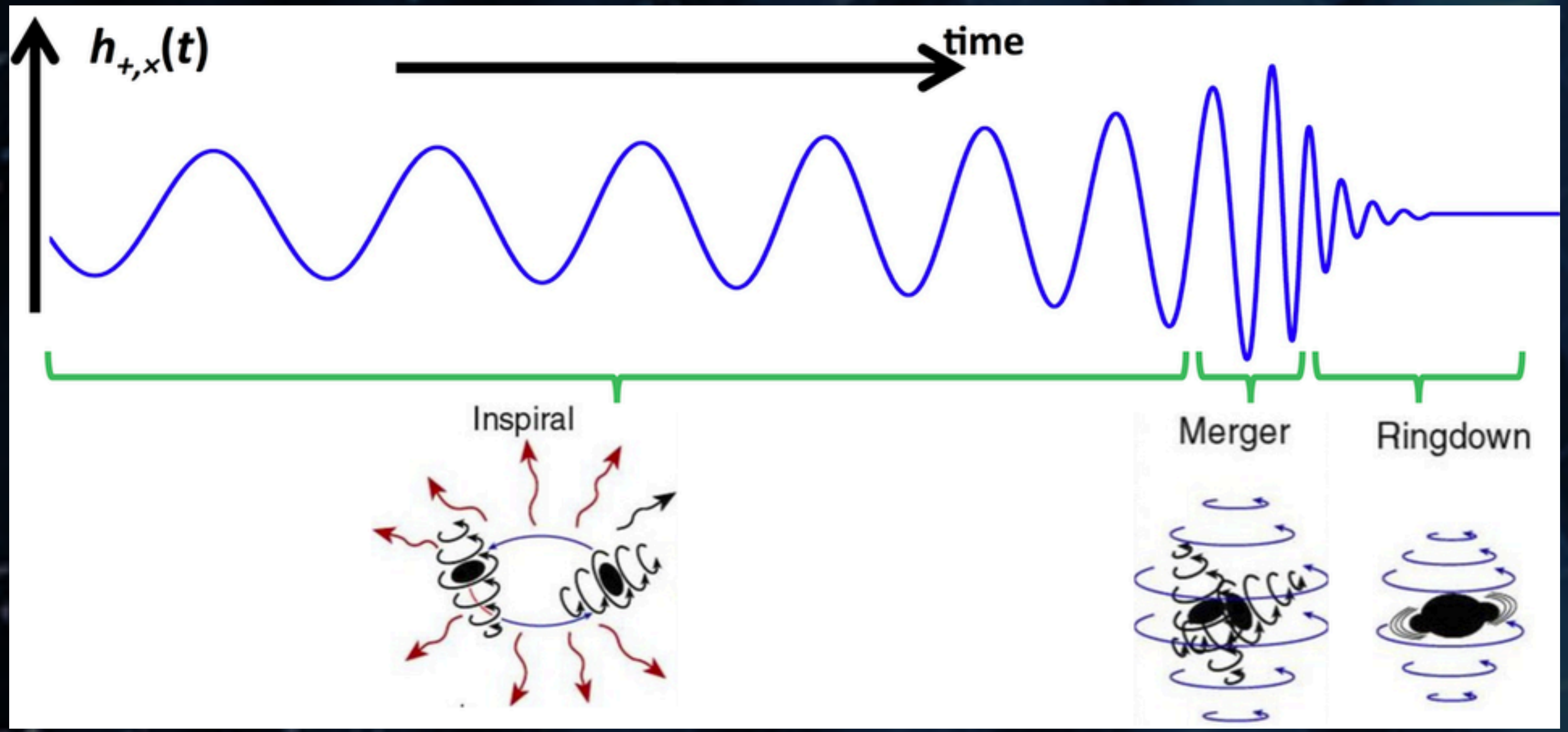
Types of GW Sources



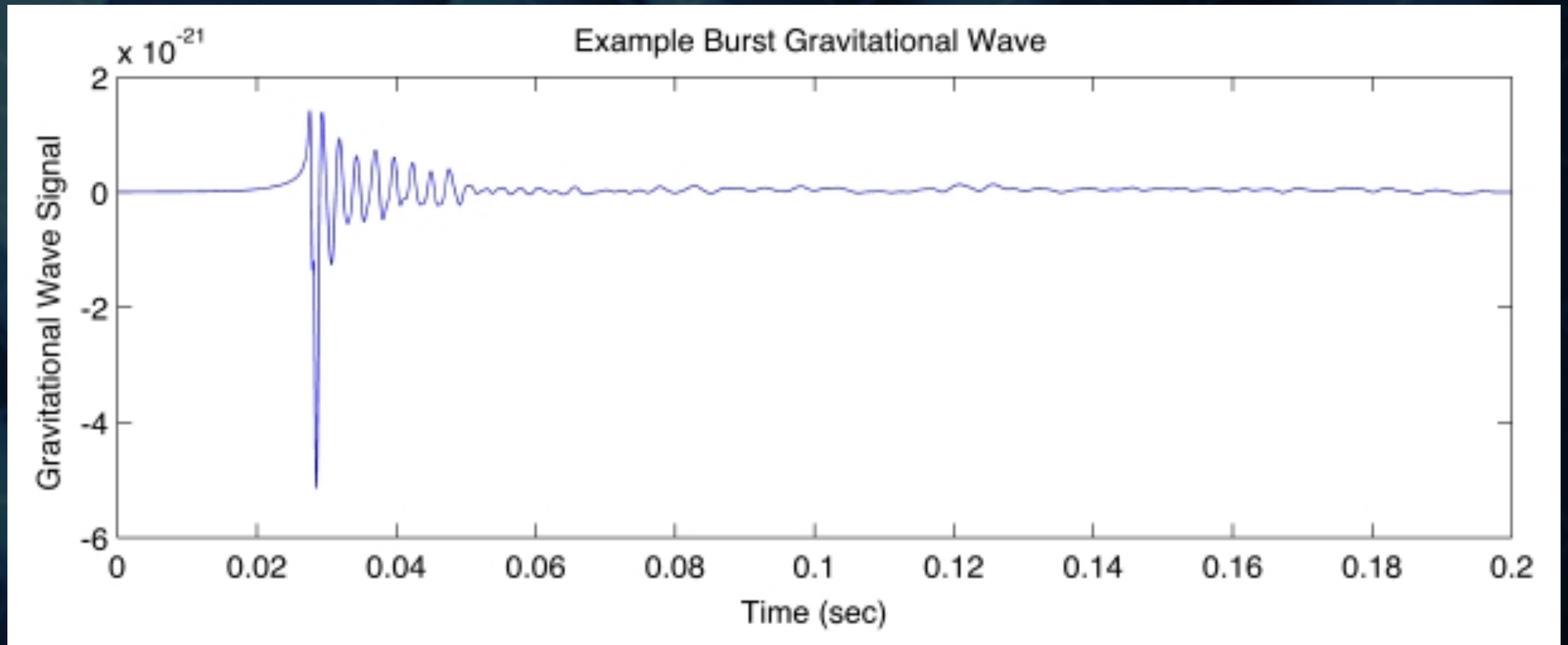
[Chris Messenger]

Why search for "unmodeled" bursts?

- Detection of known potential sources
  - Supernovae (SNe)
  - Gamma-ray Bursts (GRB)
- New discoveries!
  - We may not know the source, but we know what the waveform looks like



[Image: M. Favata/SXS/K. Thorne]



[Image: A. Stuver/LIGO using data from C. Ott, D. Burrows, et al.]

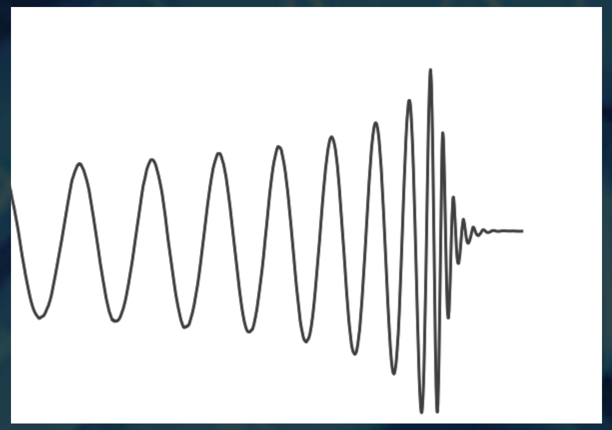
Modelled, well-understood waveforms (CBC)

Sample unmodeled GW burst waveform

GW Detector Data

Data = Signal (maybe) + Noise

$\vec{s}$



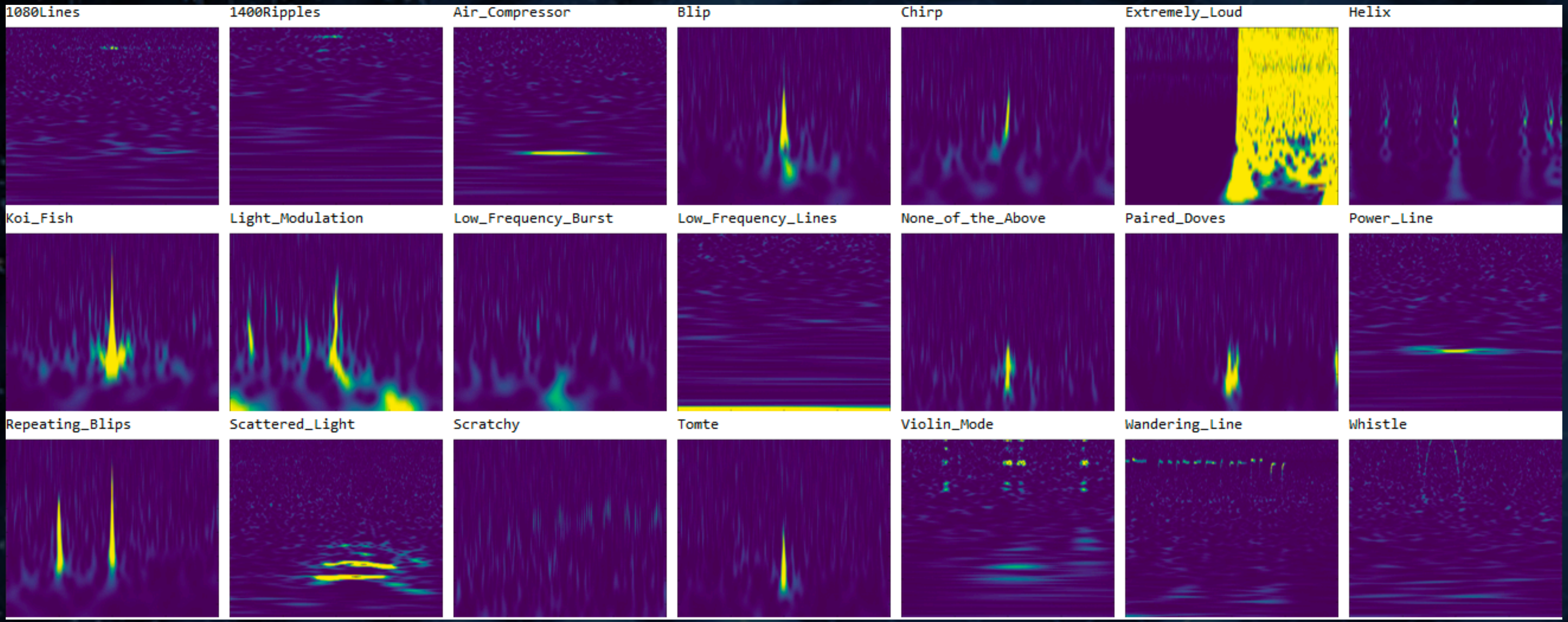
$h(\vec{\theta})$

$\vec{n}$

Noise components:

$$\vec{n} = \vec{n_G} + \vec{g}$$

Glitches



Non-astrophysical and non-Gaussian power spikes in the detector

[Image from Gravity Spy]

BayesWave

- Joint detection of instrumental glitches and GW bursts
- *Wave* = Reconstruction of bursts and glitches through sine-Gaussian (Morlet-Gabor) wavelets.
- Reconstruct non-Gaussian, transient features in the data with no *a priori* assumptions
- *Bayes* = Bayesian model selection
- Variable model complexity (decided by the data!)

BayesWave publications:
Cornish + Littenberg, Class. Quant. Grav 32, 130512 (2015)
Cornish + Littenberg, Phys. Rev. D 97, 104057 (2021)

BayesWave

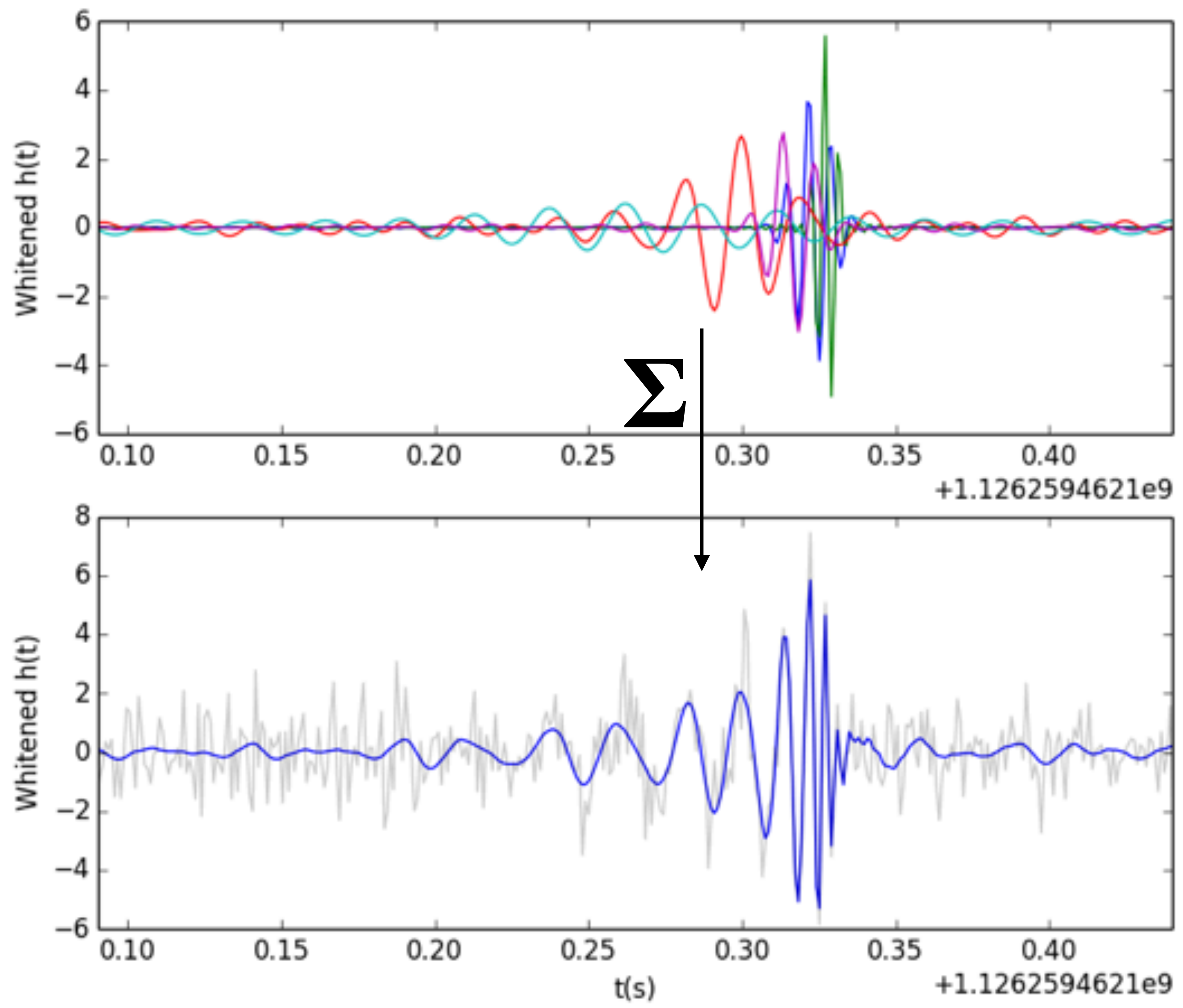
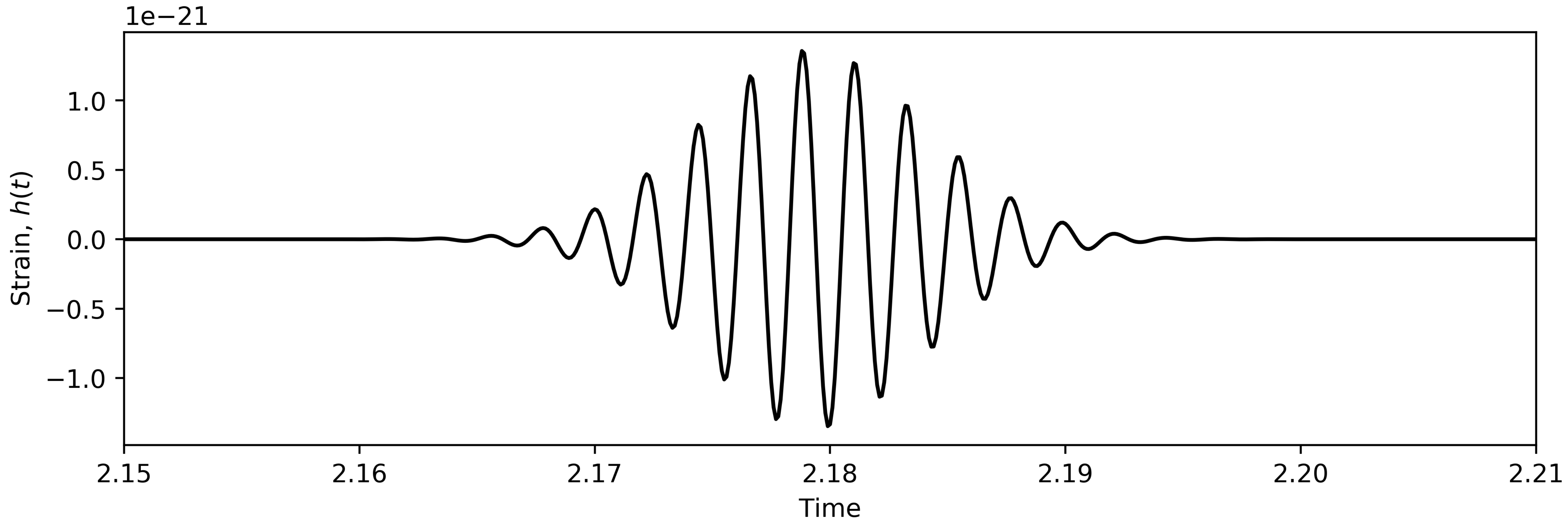


Image courtesy of Dr. Meg Millhouse



Wavelet parameters (Intrinsic parameters)

t_0 - Central time

f_0 - Central frequency

Q - Quality factor

A - Amplitude

ϕ_0 - Phase offset

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Trans-Dimensional Markov chain Monte Carlo (MCMC)

- **Purpose:**

  To explore different model spaces and their respective parameter spaces

  To estimate posterior distribution of models that fit the data
- Monte Carlo:

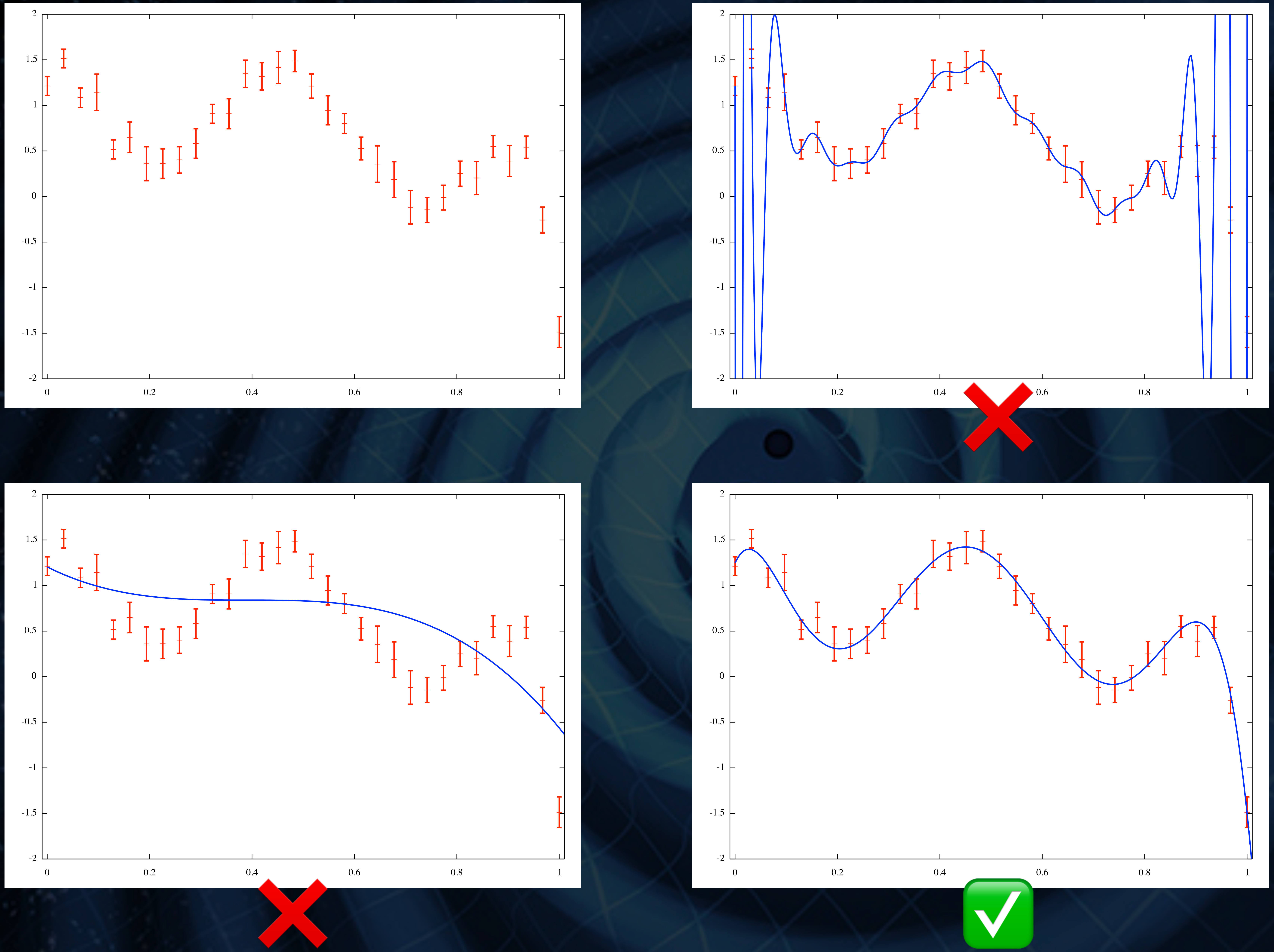
  Random drawing of samples from a proposal distribution
- Markov Chain:

  The next step in the chain depends entirely on the current state
- Trans-Dimensional:

  Model has varying dimensions (i.e. varying number of wavelets)

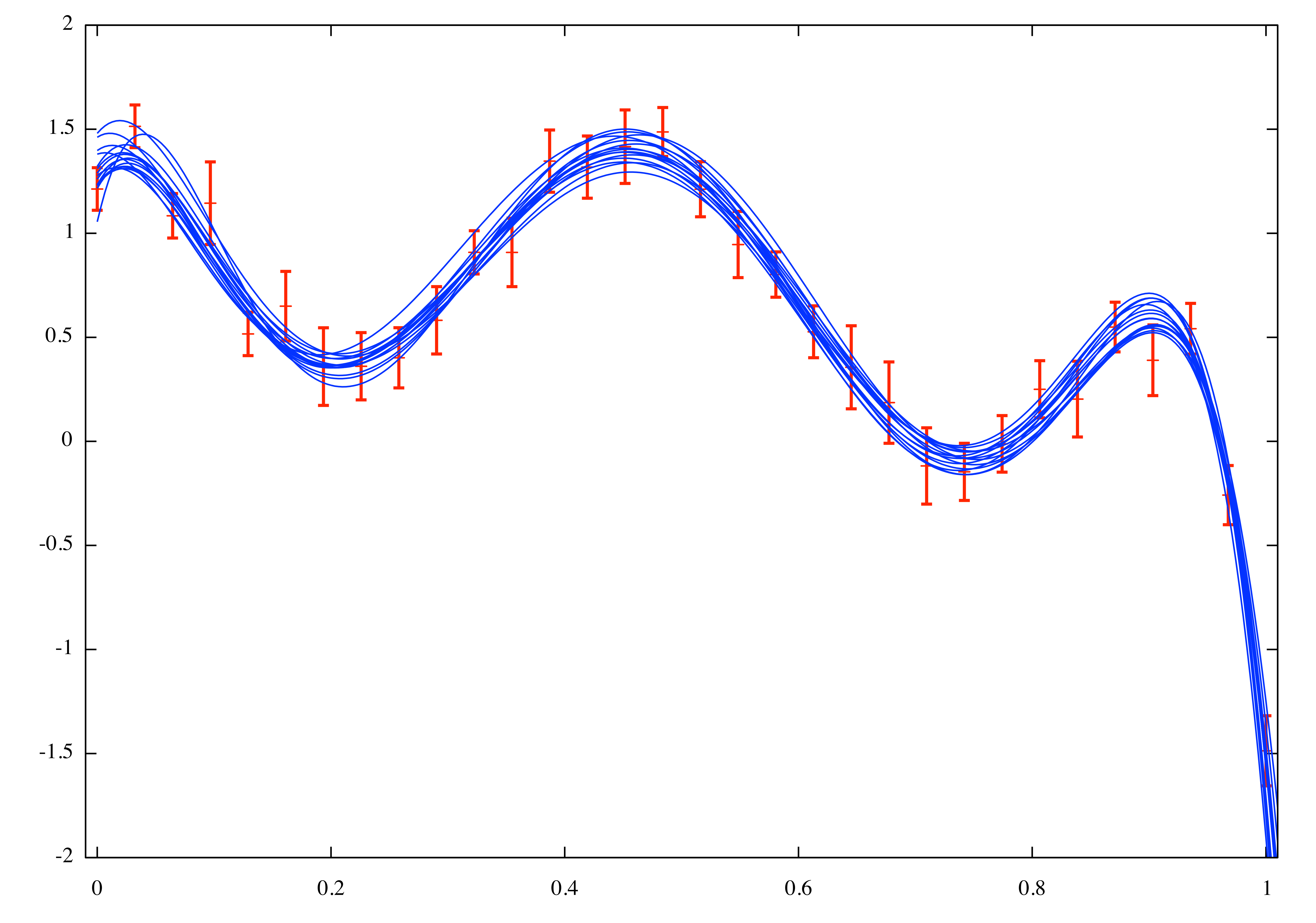
[Image: Phil Gregory]

Trans-Dimensional?



[Images: N. Cornish]

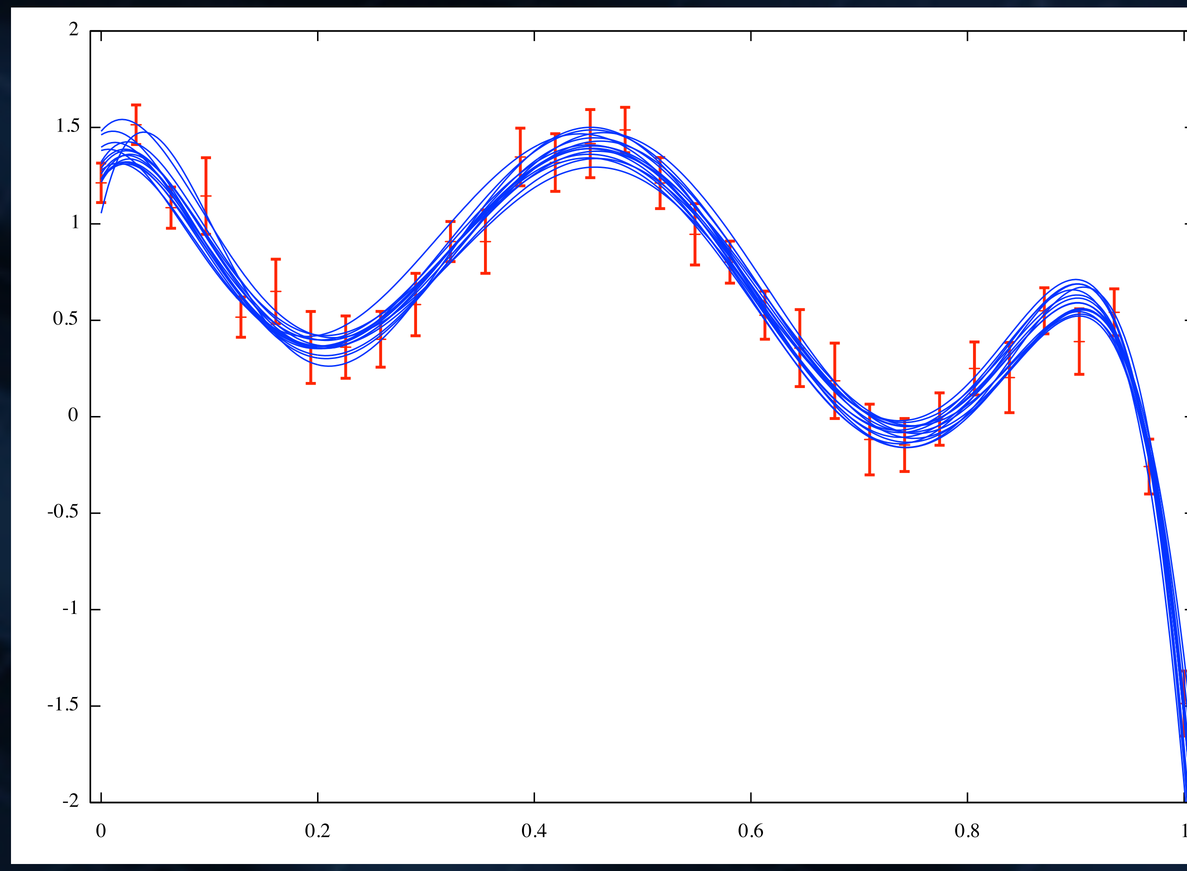
Posterior distribution of suitable fits

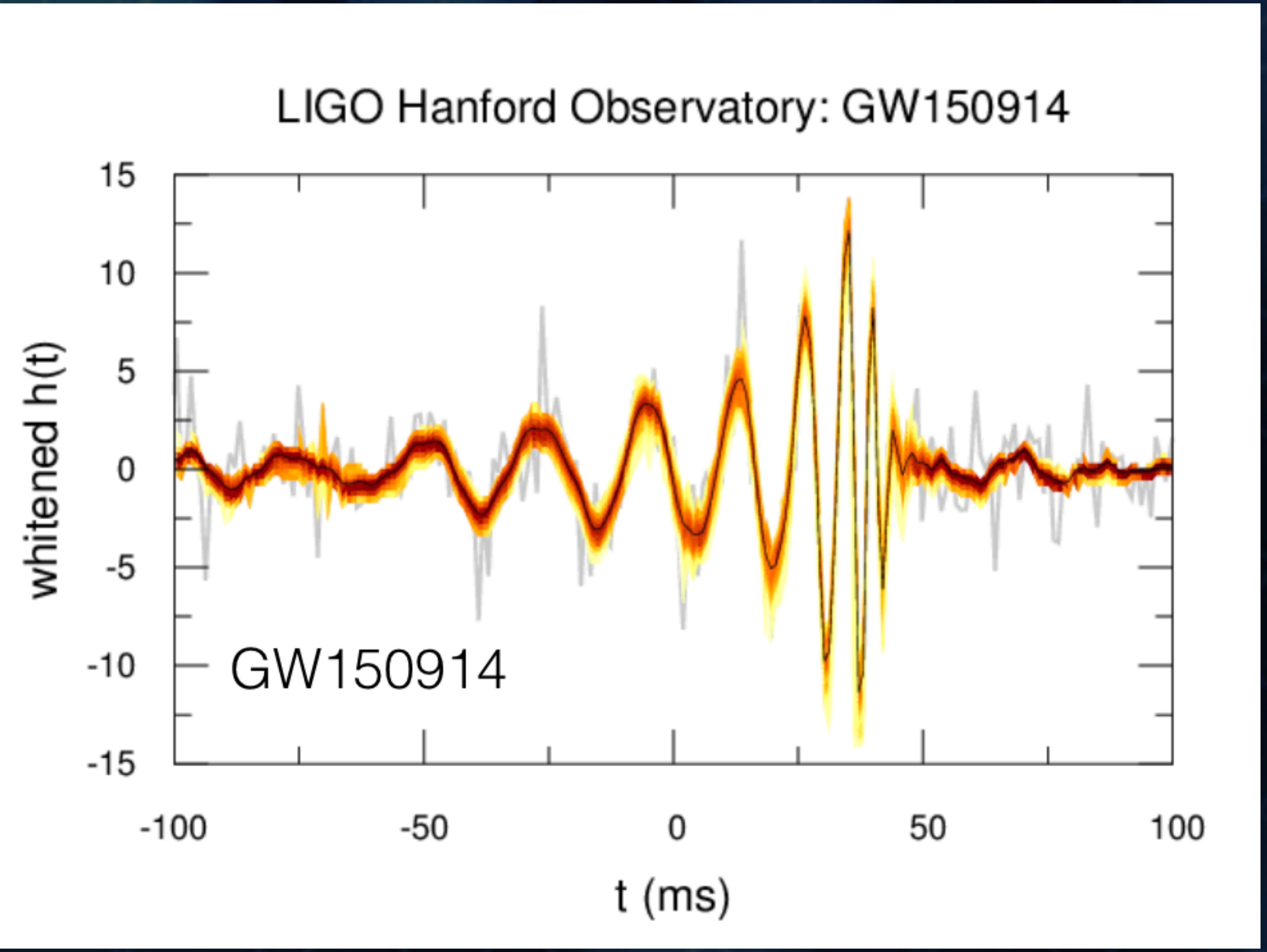


[Images: N. Cornish]

BayesWave Waveform Posterior

- At each MCMC iteration, we get:
  - (i) Number of wavelets, *N*
  - (ii) Parameters of each of the *N* wavelets
- At each iteration, we can construct waveform model by summing all the *N* wavelets
- Waveform Posterior:
  Combine waveform models across all iterations





[Image courtesy of Jonah Kanner, Tyson Littenberg, and Meg Millhouse]

BayesWave Waveform Posterior

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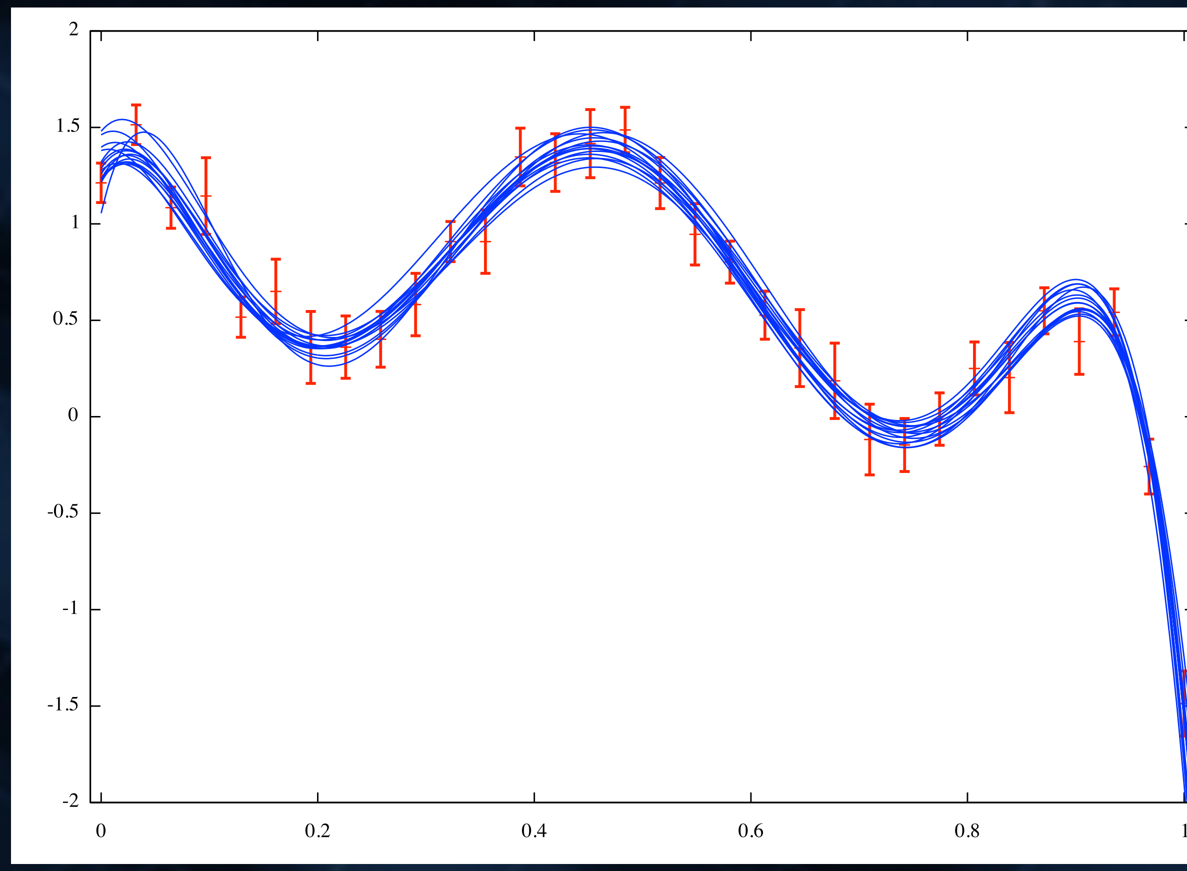

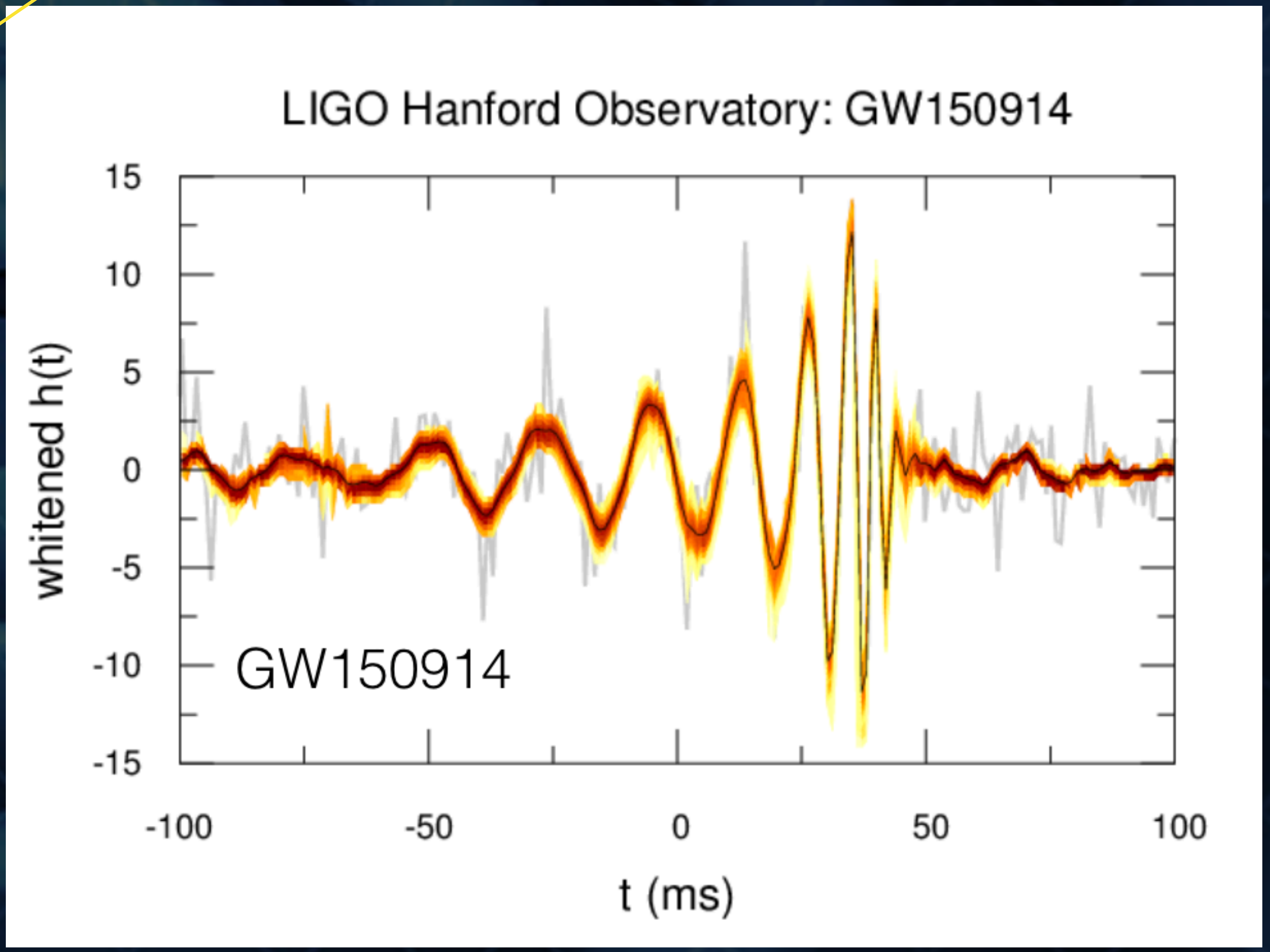

[Image courtesy of Jonah Kanner, Tyson Littenberg, and Meg Millhouse]

BayesWave models

- Attempts to fit the data using 3 independent models:
  - Gaussian noise only
  - Gaussian noise + Instrumental glitch, $\mathcal{G}$
  - Gaussian noise + GW signal, $\mathcal{S}$

- But which one best fits the data?

Bayes Factor for Model Selection

$$\text{Bayes Factor} = \text{Evidence Ratio}$$

$$\text{i.e. } \mathscr{B}_{\mathcal{S},\mathcal{G}} = \frac{p(\vec{s}\,|\,\mathcal{S})}{p(\vec{s}\,|\,\mathcal{G})}$$

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$\mathscr{S}$: gaussian noise + signal model

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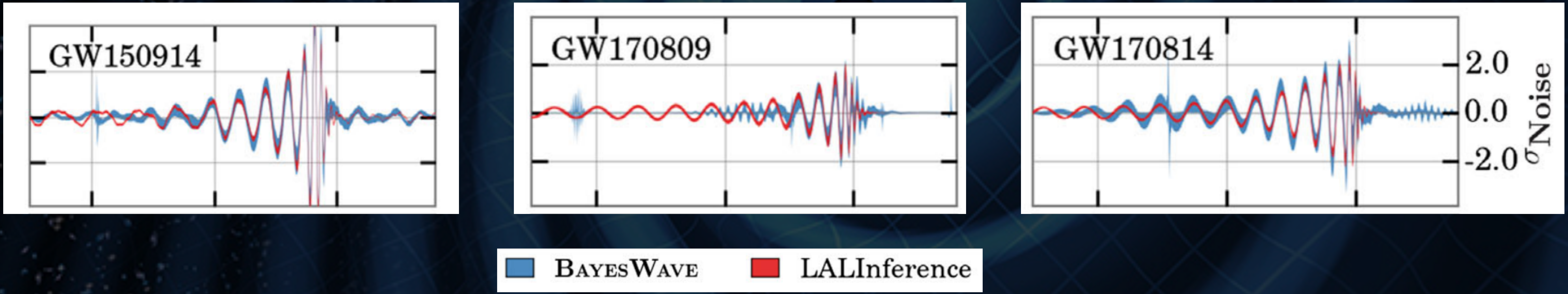
If $\mathscr{B}_{\mathscr{S},\mathscr{G}} > 1 \Rightarrow$ $\mathscr{S}$ is more strongly supported by data than $\mathscr{G}$

BayesWave and Burst Searches

- Used in follow-up searches for GW events in O1, O2 and O3
  To assess consistency with matched-filter (model-based) searches
- Also used as a follow-up to background (non-astrophysical) events found by coherent WaveBurst (cWB) to increase detection confidence



GWTC-1: Phys. Rev. X 9, 031040 (2019),
GWTC-2: Phys. Rev. X 11, 021053 (2021),
GWTC-3: arXiv:2111.03606

Aim of study

YS. C. Lee et al. (2021), Phys. Rev. D 103, 062002

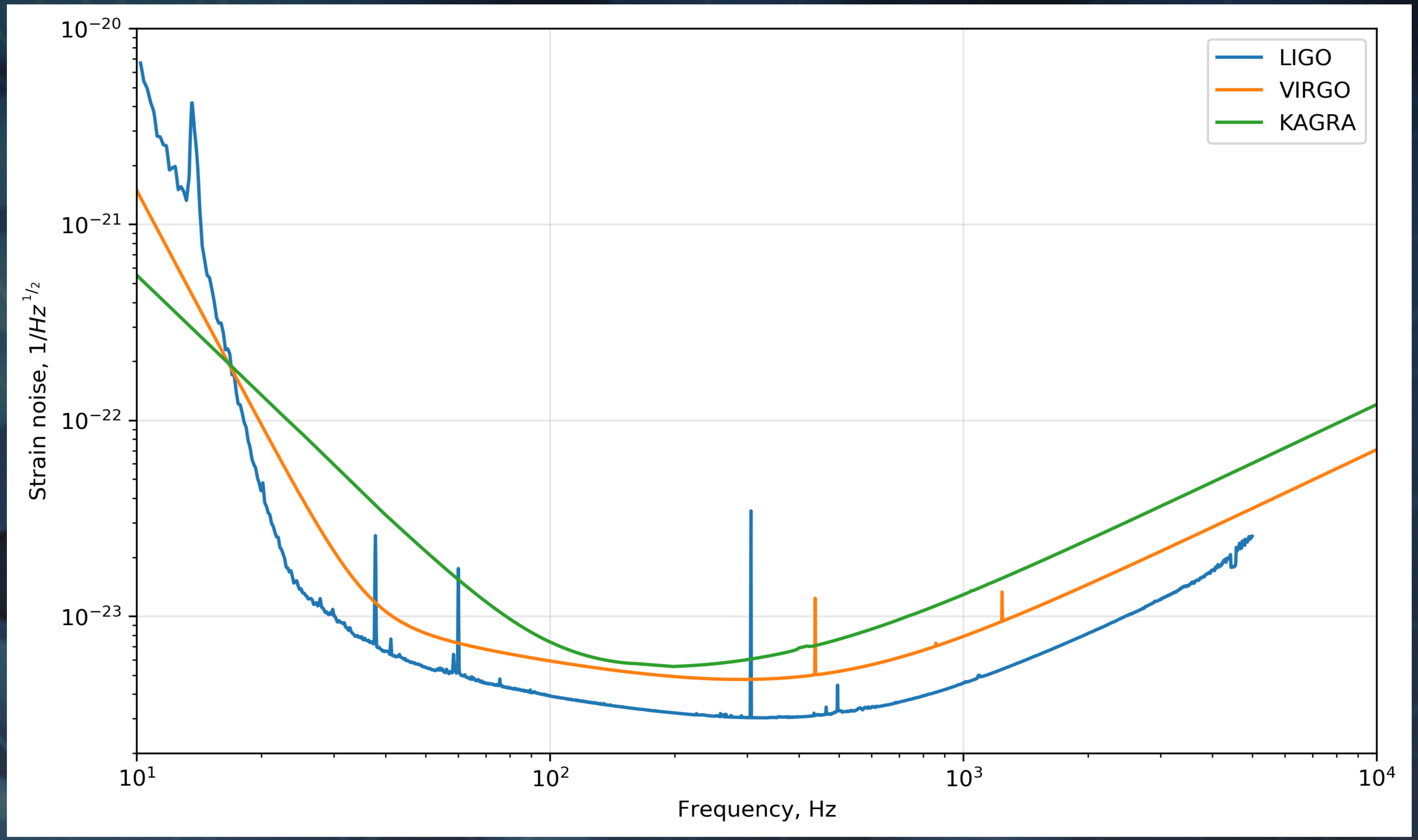
To evaluate network performance of *BayesWave* as a function of number of detectors, $\mathscr{I}$

Detection confidence - Figure of Merit:

Signal versus Glitch model Bayes Factor, $\mathscr{B}_{\mathscr{S},\mathscr{G}}$

Method overview

- Derive analytic scaling of $\mathscr{B}_{\mathscr{S},\mathscr{G}}$ with $\mathscr{I}$ following Littenberg et al. 2016 (Phys. Rev. D, 94, 044050)
- Using *BayesWave* to recover 150 injected BBH waveforms from simulated Gaussian noise at projected LIGO, Virgo and KAGRA sensitivities for O4



Noise curves from: Observing scenarios paper
https://dcc.ligo.org/LIGO-T2000012/public

Multi-detector Bayes Factor Scaling

Previous work: "Enabling high confidence detections of gravitational wave bursts"

Littenberg, T. B., Kanner, J. B., Cornish, N. J., et al. 2016, Phys. Rev. D, 94, 044050

$$\ln \mathcal{B}_{\mathcal{S},\mathcal{G}} \simeq (\mathcal{I}-1)\left[\frac{5N}{2} + N\ln(V_\lambda) - \sum_{n=1}^{N} \ln\left(\bar{Q}_n\right) + 5N\ln\left(\frac{\mathrm{SNR}_{\mathrm{net}}}{\sqrt{N}}\right)\right] - \frac{5}{2}\mathcal{I}N\ln(\mathcal{I}) + \left(2 + \ln\frac{\sqrt{\det C_\Omega}}{V_\Omega}\right).$$

SNR_{net} : Injected SNR

$\mathcal{I}$: Number of detectors in the network

N : Number of wavelets used in *BayesWave* reconstruction

Main Scaling

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

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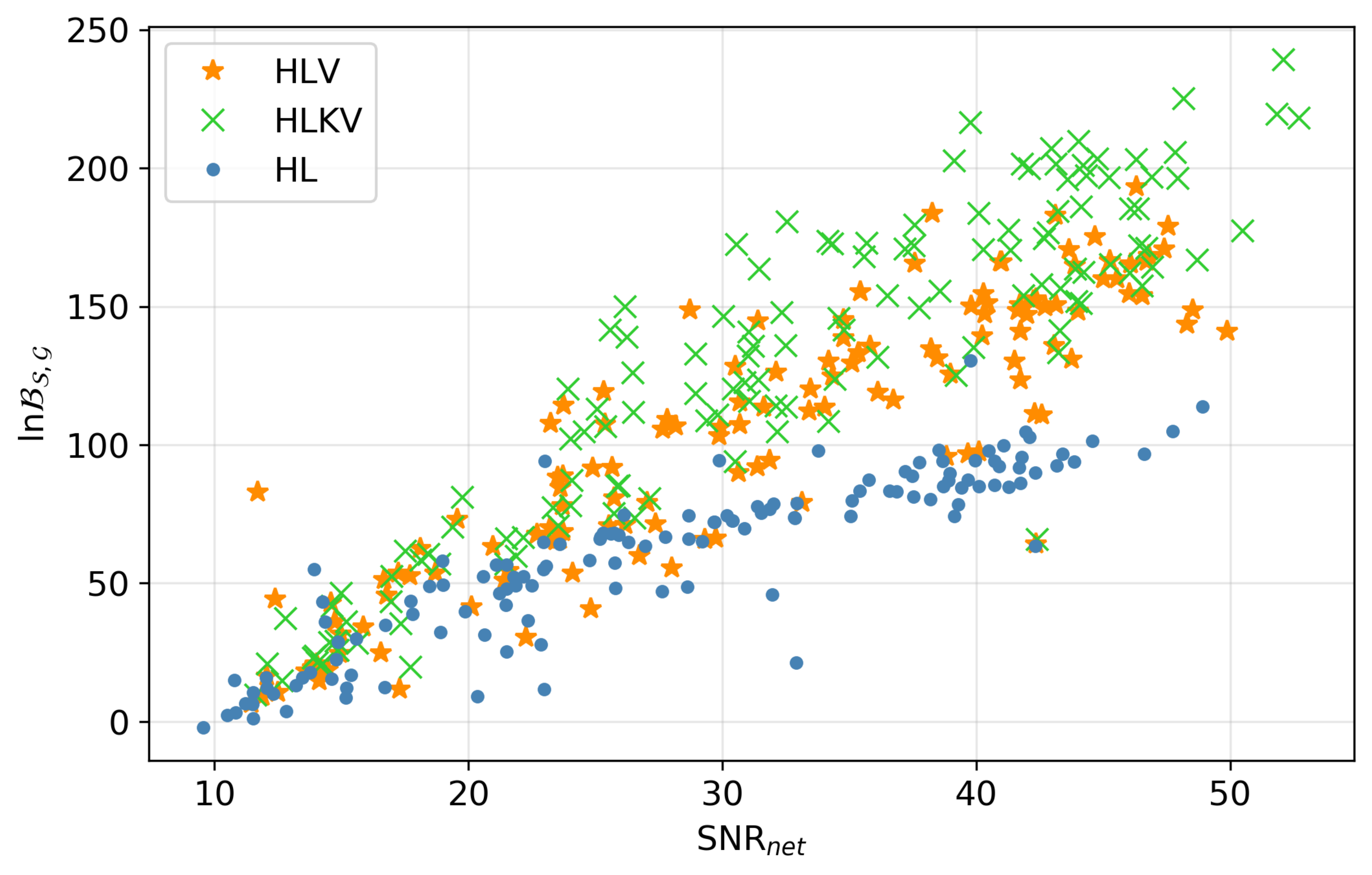
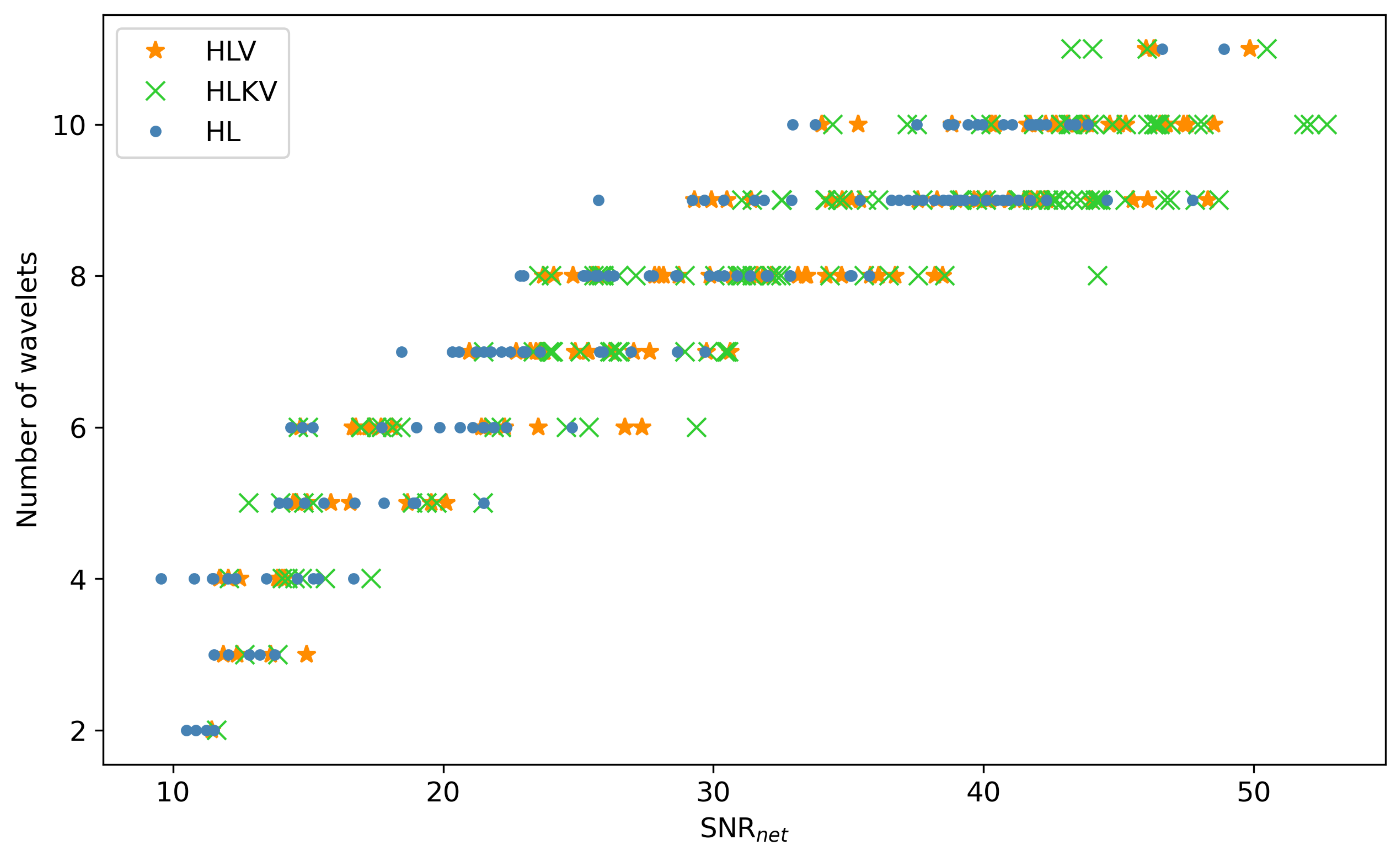
Bayes Factor Comparison

Assessing detection confidence with different detector configurations





Agrees with $\ln \mathcal{B}_{\mathcal{S},\mathcal{G}} \sim \mathcal{O}[\mathcal{I} N \ln \mathrm{SNR}_{\mathrm{net}}]$

KEY RESULT: Phys. Rev. D 103, 062002

Ongoing work:
BayesWave's detection confidence in presence of instrumental glitches??

(1) Glitches negatively impact detection confidence of GW burst searches

(2) Unmodelled burst searches like *BayesWave:*

More sensitive to glitches compared to modelled searches

(3) Expanding global detector network:

More detector, higher SNR, better detection confidence…

BUT…..more glitches!

(4) So how does the increased glitch rate affect detection?

Will larger, and hence glitchy-er, detector networks still perform better?

<u>ANSWER COMING (VERY) SOON!</u>

<u>Follow-up study to:</u> YS. C. Lee et al. (2021), Phys. Rev. D 103, 062002

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Summary

- **Analytic results:**

  Showed that $\log \mathscr{B}_{\mathcal{S},\mathcal{G}} \sim \mathcal{O}(\mathcal{I} N \log SNR_{net})$

  i.e. Bayes Factor scales with the number of detectors

- **Empirical results:**

  Higher $\mathscr{B}_{\mathcal{S},\mathcal{G}}$ (detection confidence) in the HLV and HLKV networks, compared to HL

  i.e. agreement with analytic results

- **Future work:**

  Overall performance of *BayesWave* in the presence of instrumental glitches

Phys. Rev. D 103, 062002