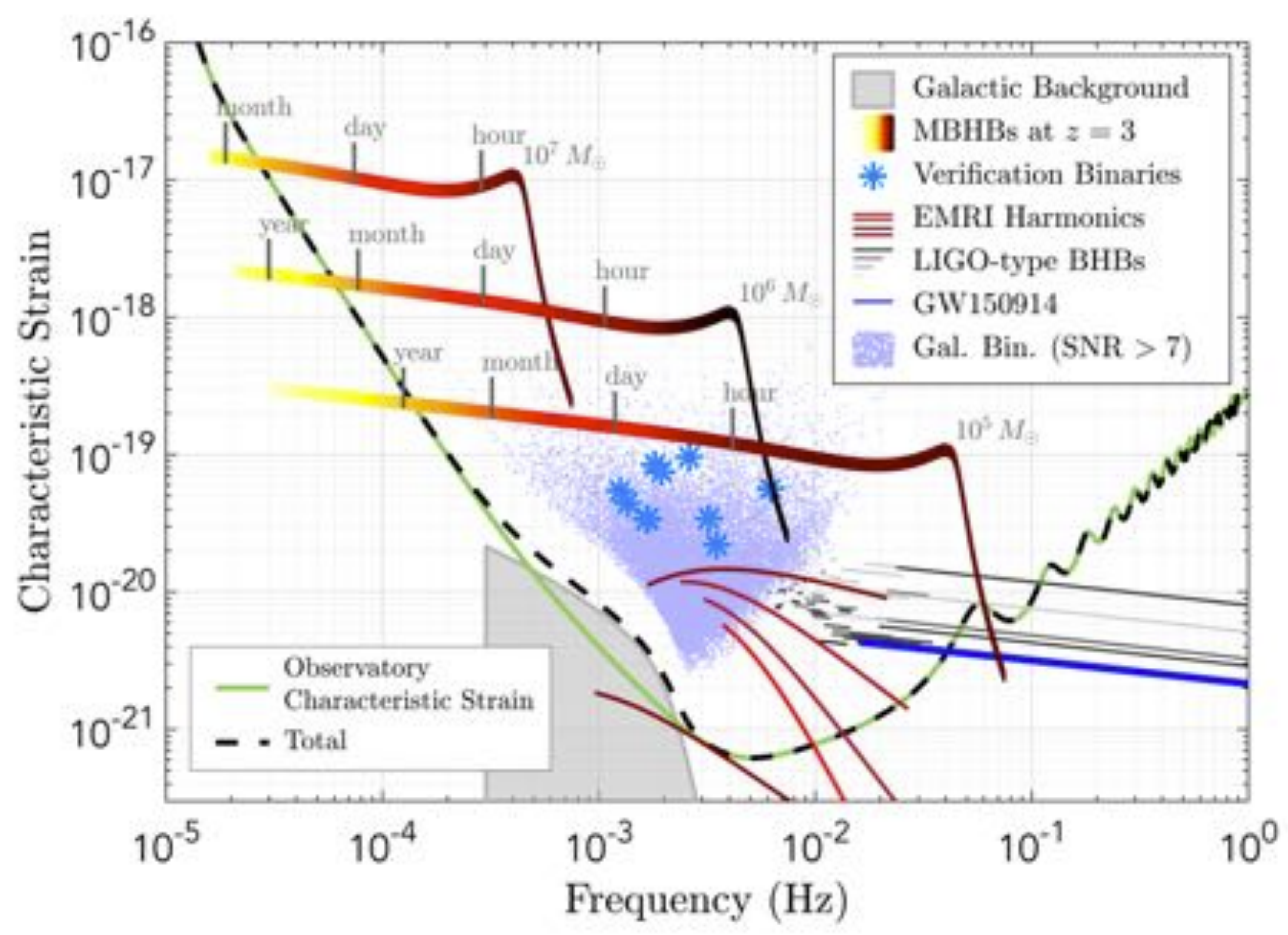
Ultra-compact Binary Analysis with LISA

Tyson B. Littenberg [NASA/MSFC]
in collaboration with N. Cornish, T. Robson [MSU]

Galactic Binaries in LISA Data



Credit: LISA Mission Proposal for L3 submitted to ESA

The Galactic Binary Problem

While individual sources are relatively simple

- Thousands of individually resolvable systems

- Large dynamic range

- Unknown noise level

- Over-fitting = contamination in catalog

- Under-fitting = excess noise for other sources

this is a hard (c.f. interesting) problem!

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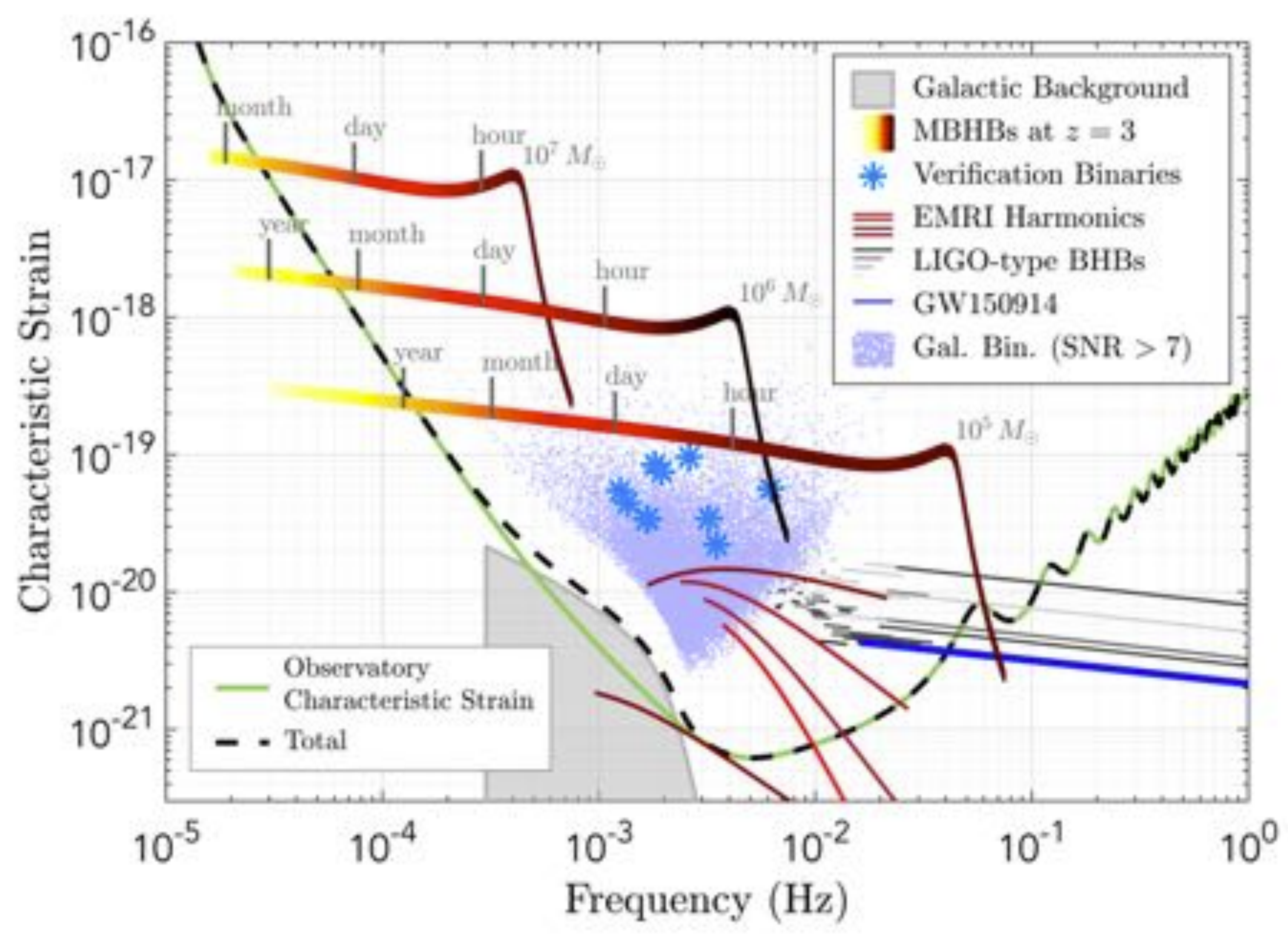

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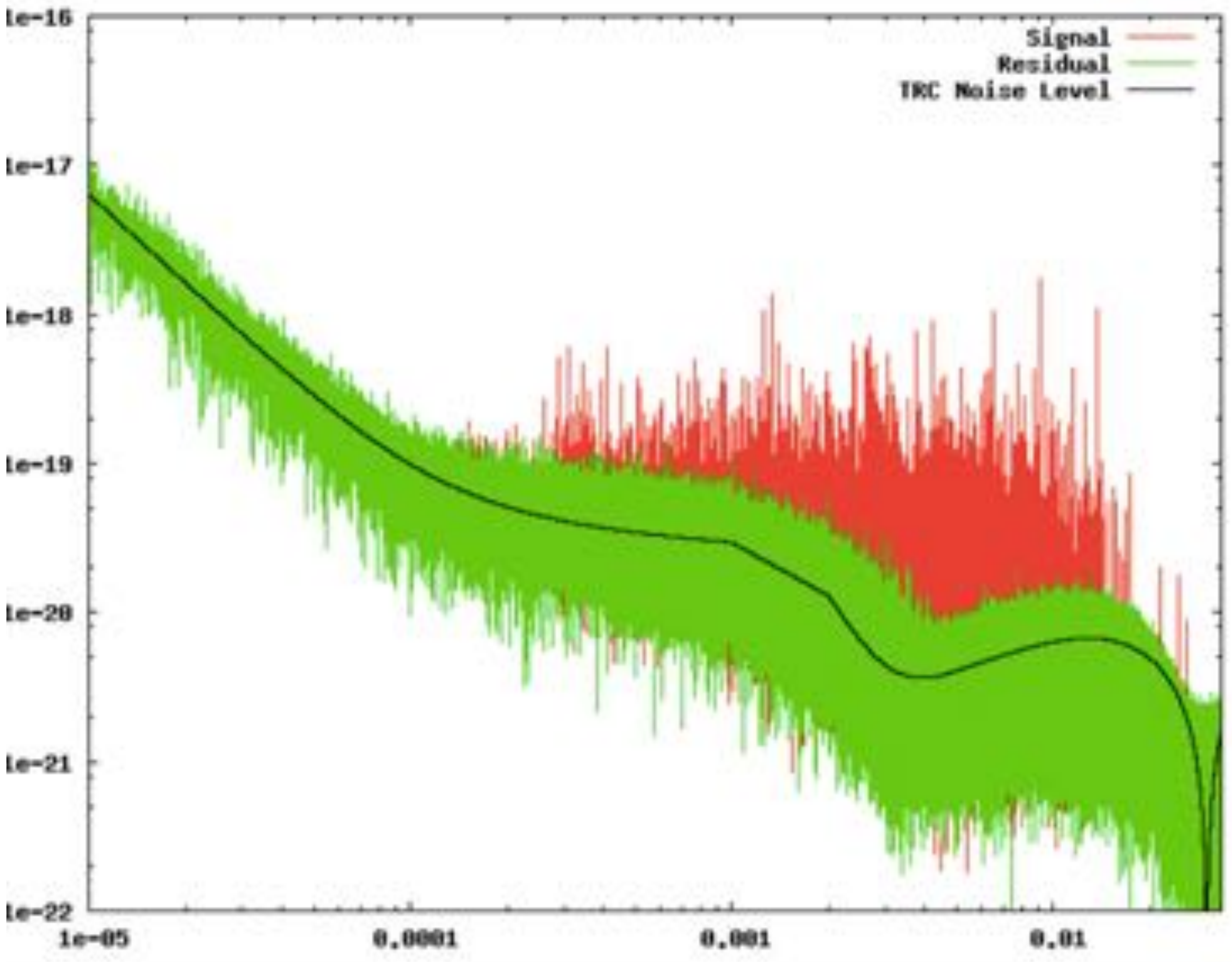

Credit: Crowder et al (MT/JPL) in response to MLDC 2

Crowder & Cornish, PRD **75**, 2007

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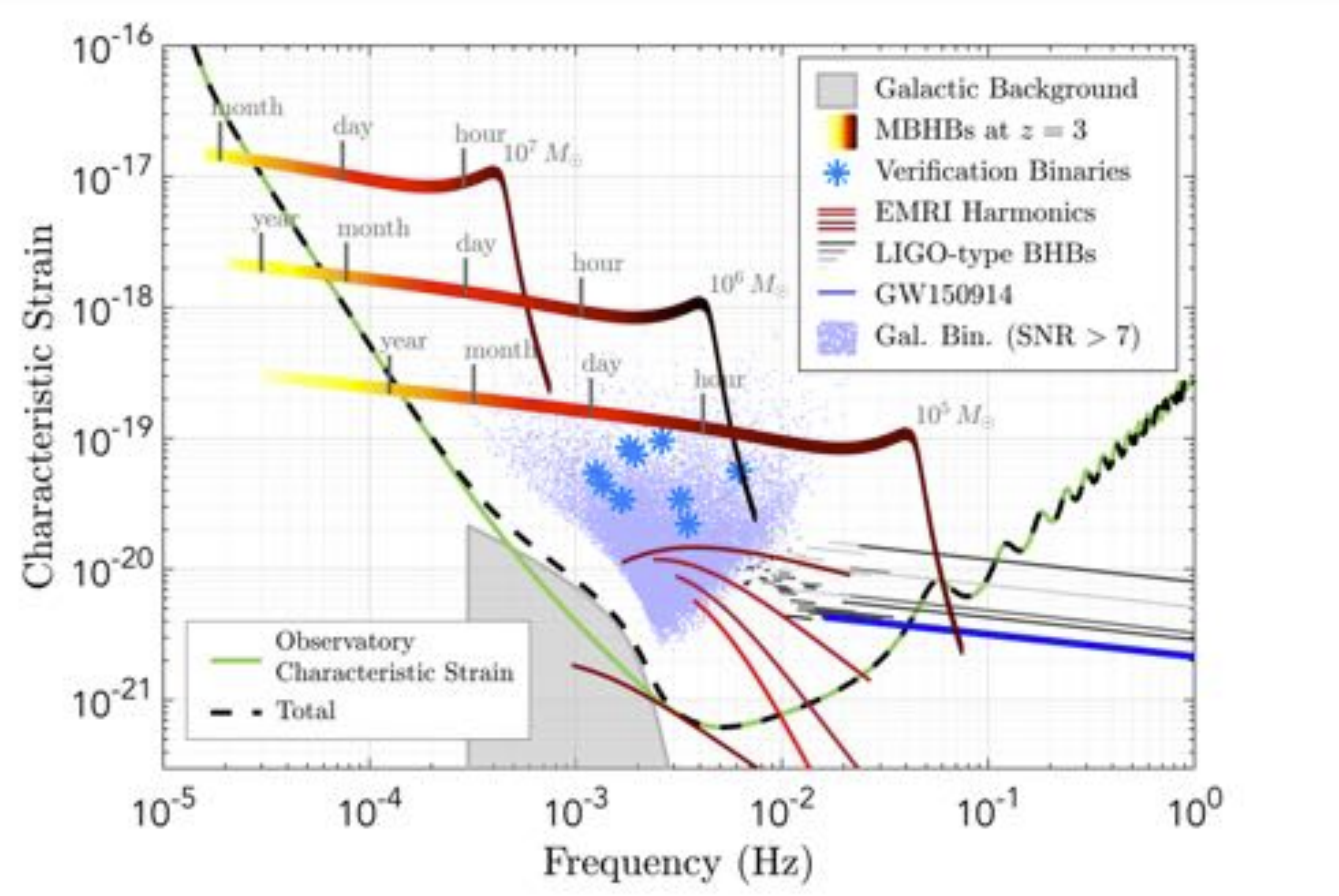

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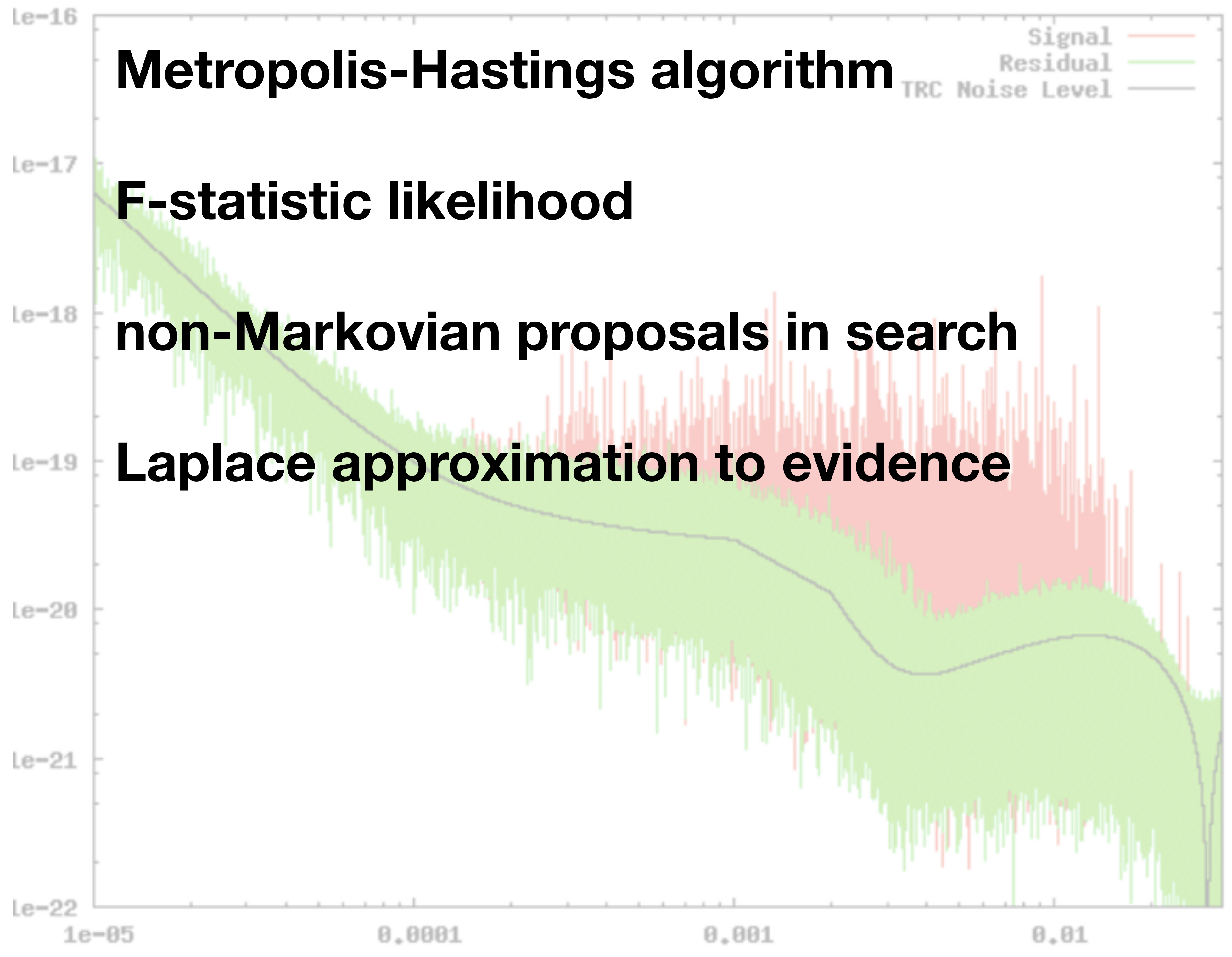

Metropolis-Hastings algorithm

F-statistic likelihood

non-Markovian proposals in search

Laplace approximation to evidence

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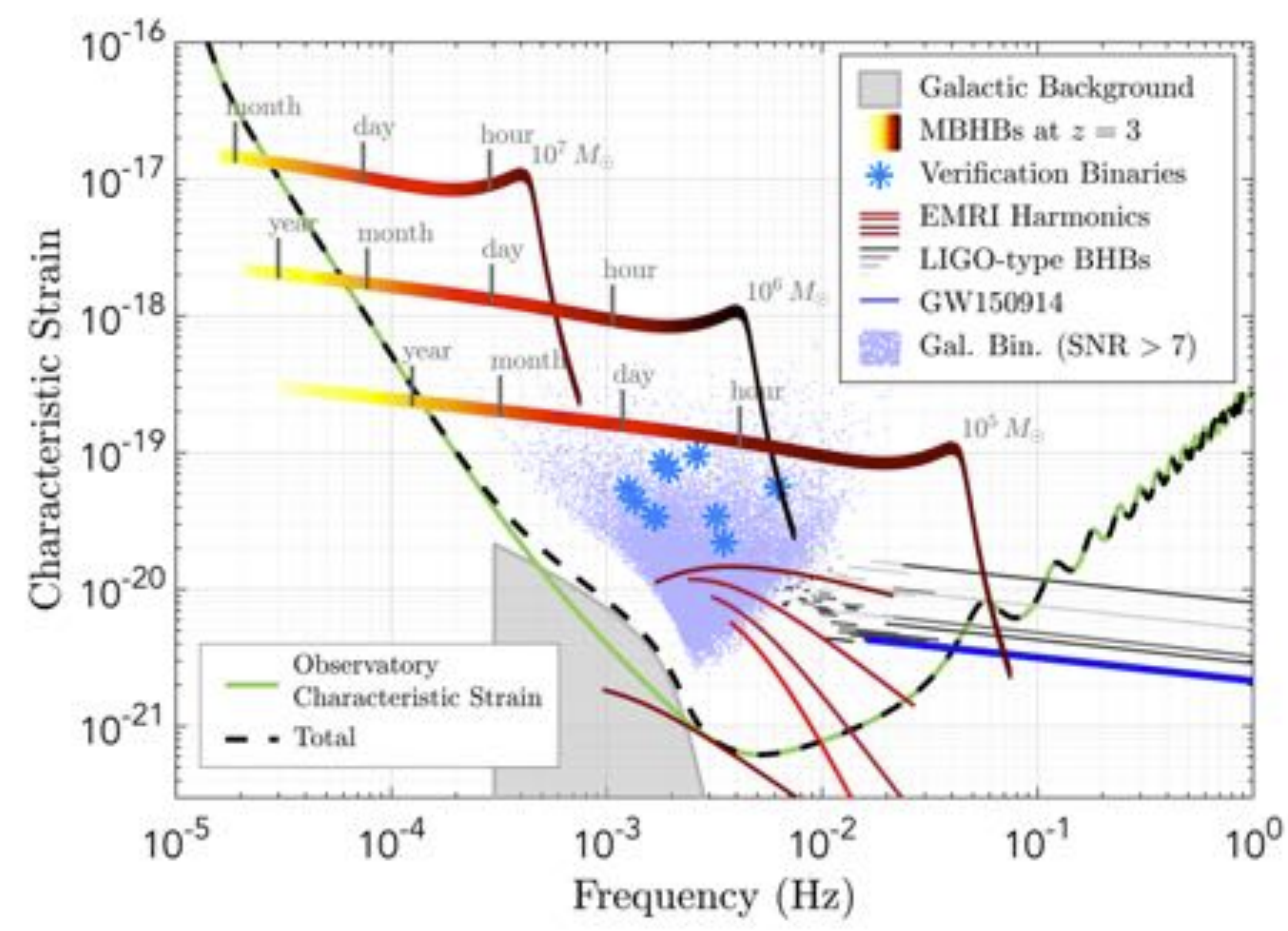

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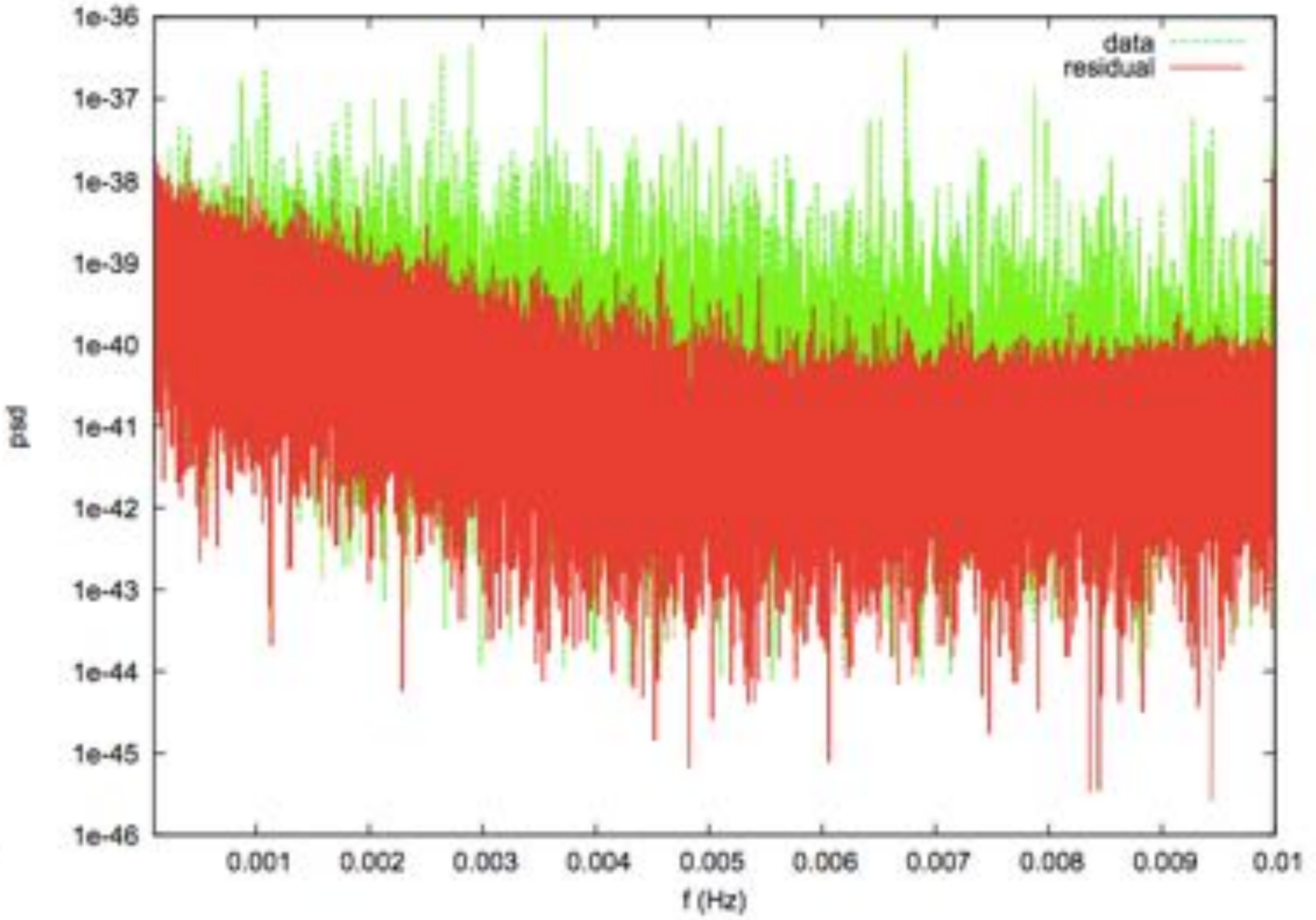

Credit: Littenberg, PRD 84, 2011 in response to MLDC 4

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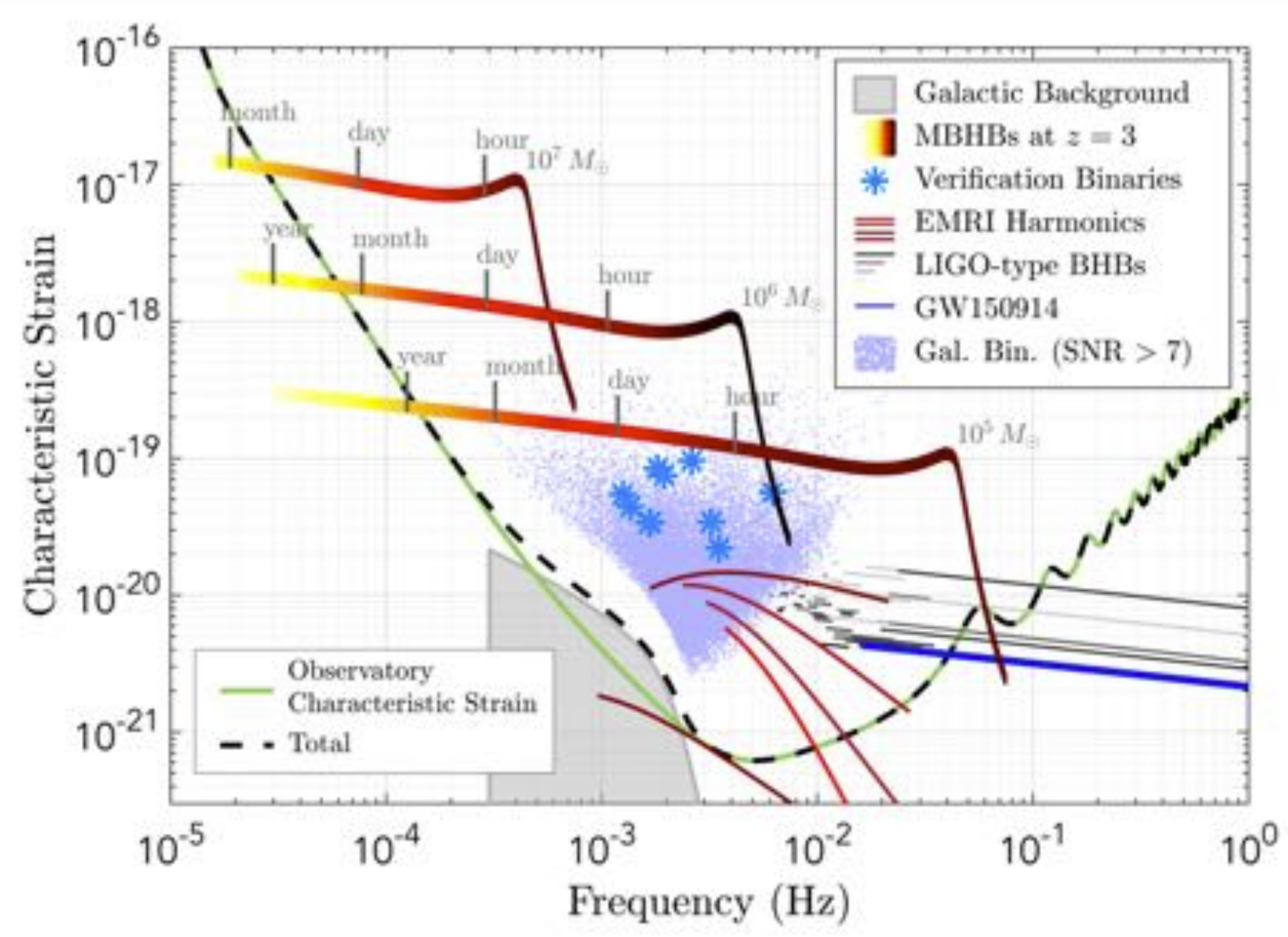

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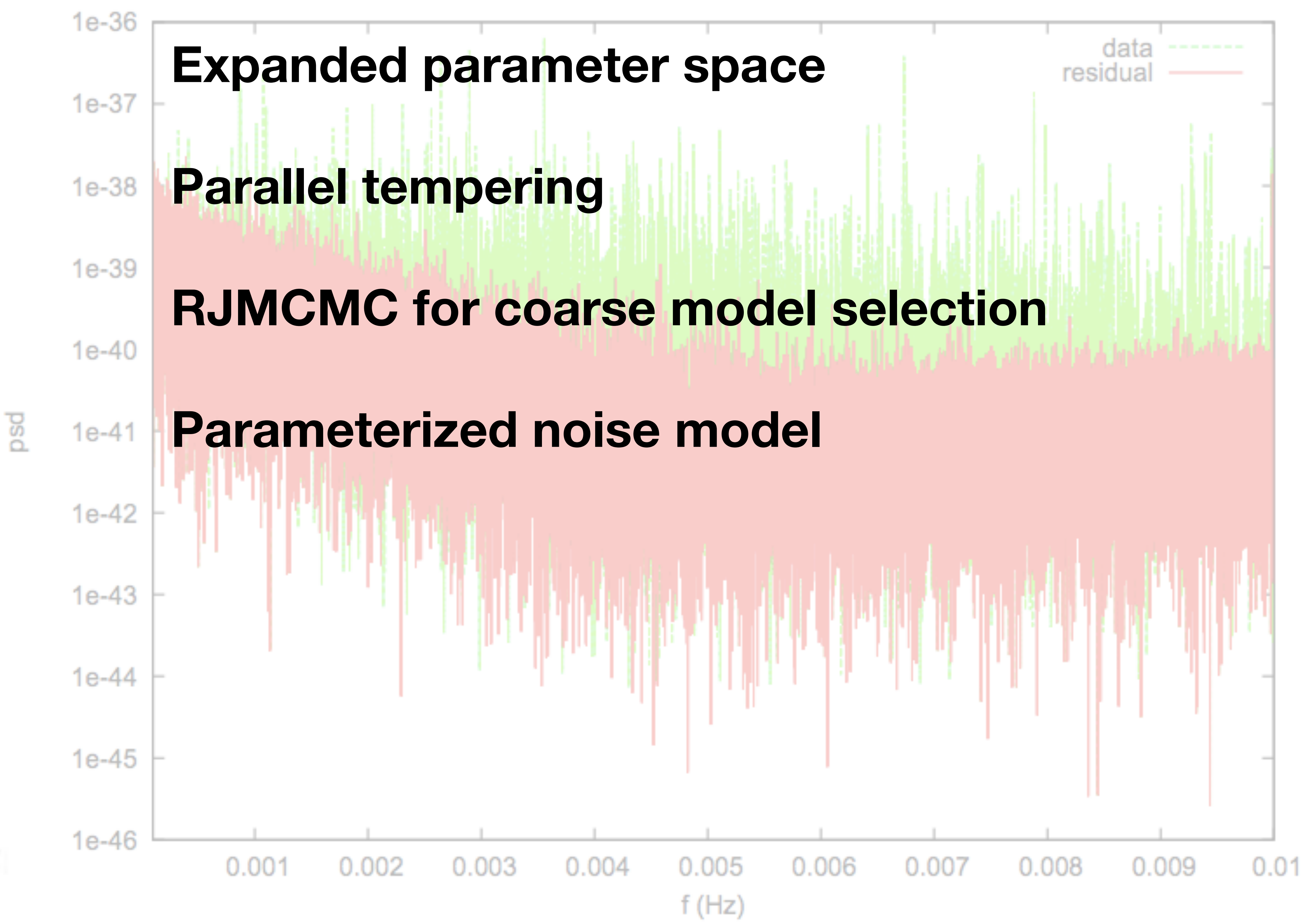


Expanded parameter space

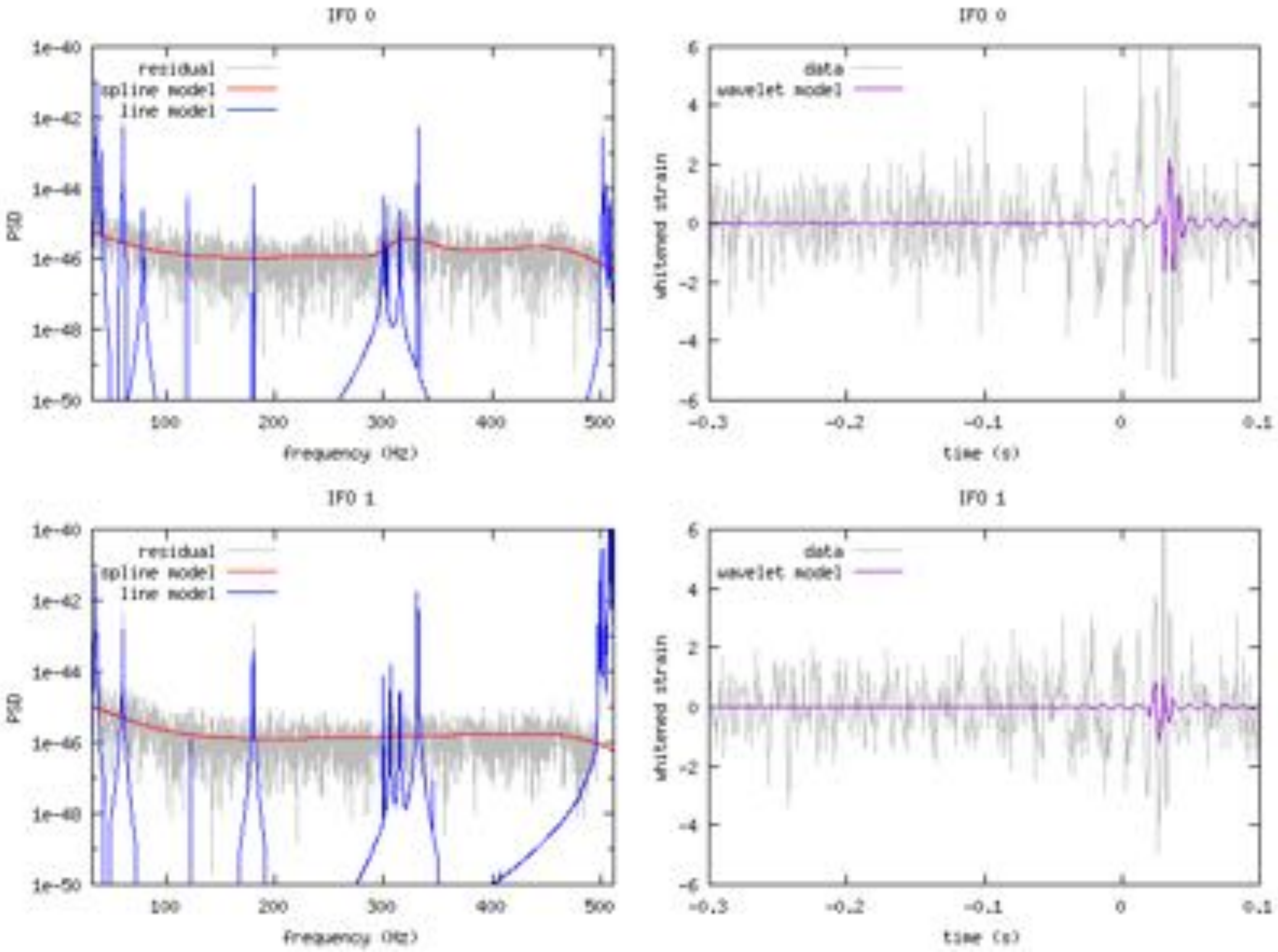
Parallel tempering

RJMCMC for coarse model selection

Parameterized noise model

Credit: Littenberg, PRD 84, 2011 in response to MLDC 4

RJMCMC in GW Astronomy



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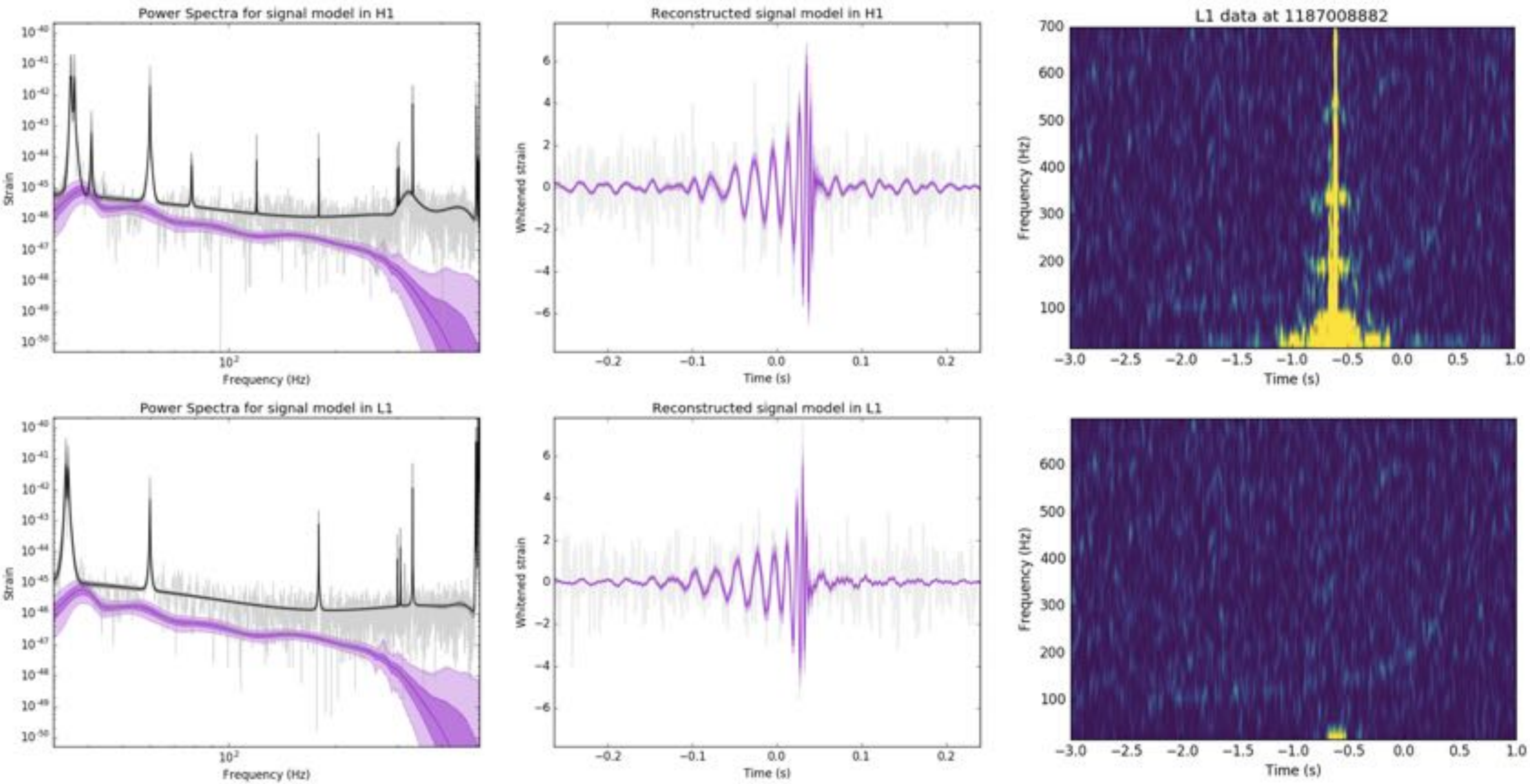
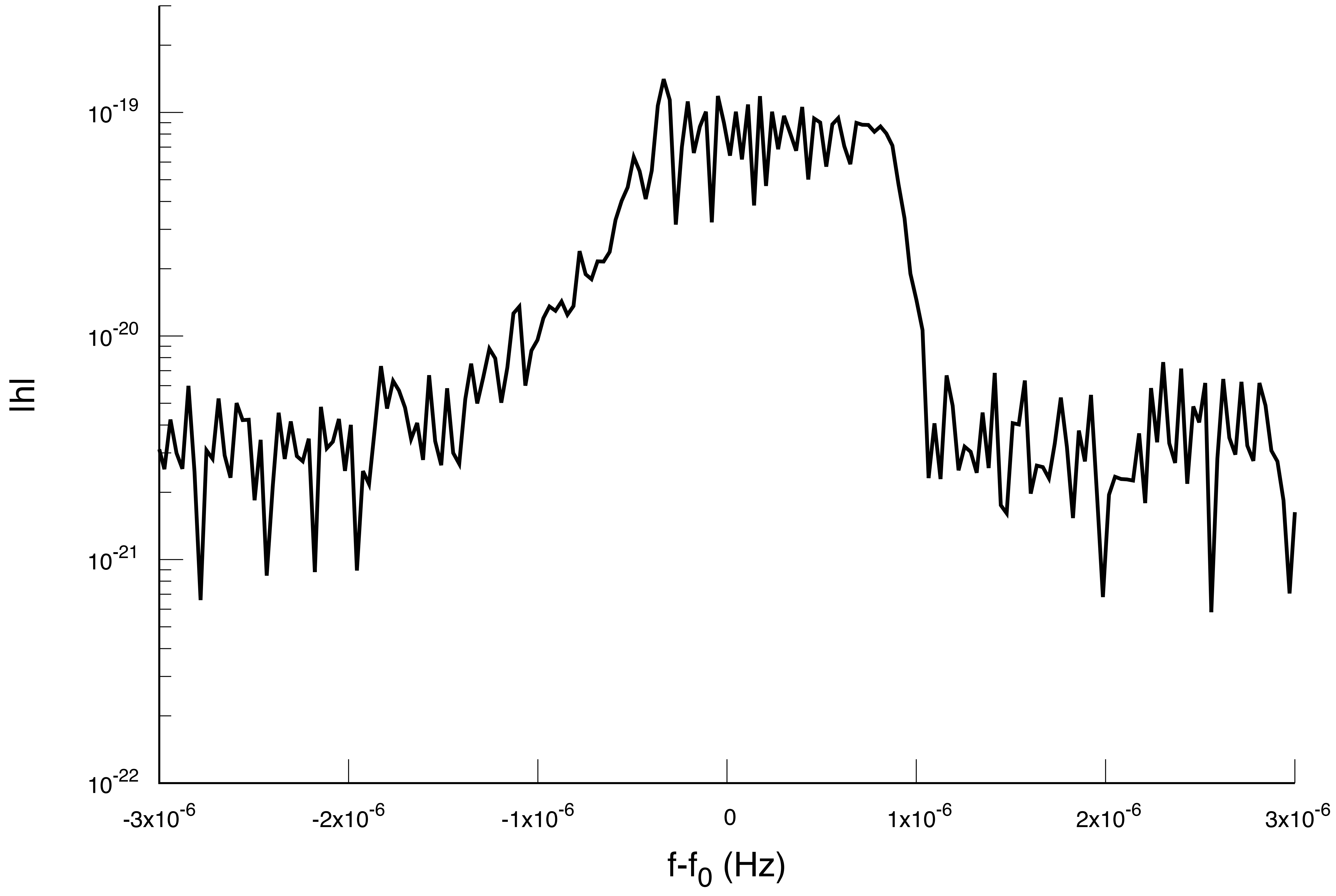


Model Everything…



Data model

$$d(f) = \sum_i^N h_i(f; \vec{\theta}) + n(f), \;\; \langle |n(f)|^2 \rangle = \frac{T}{2} S_n(f; \vec{\eta})$$

Parameters

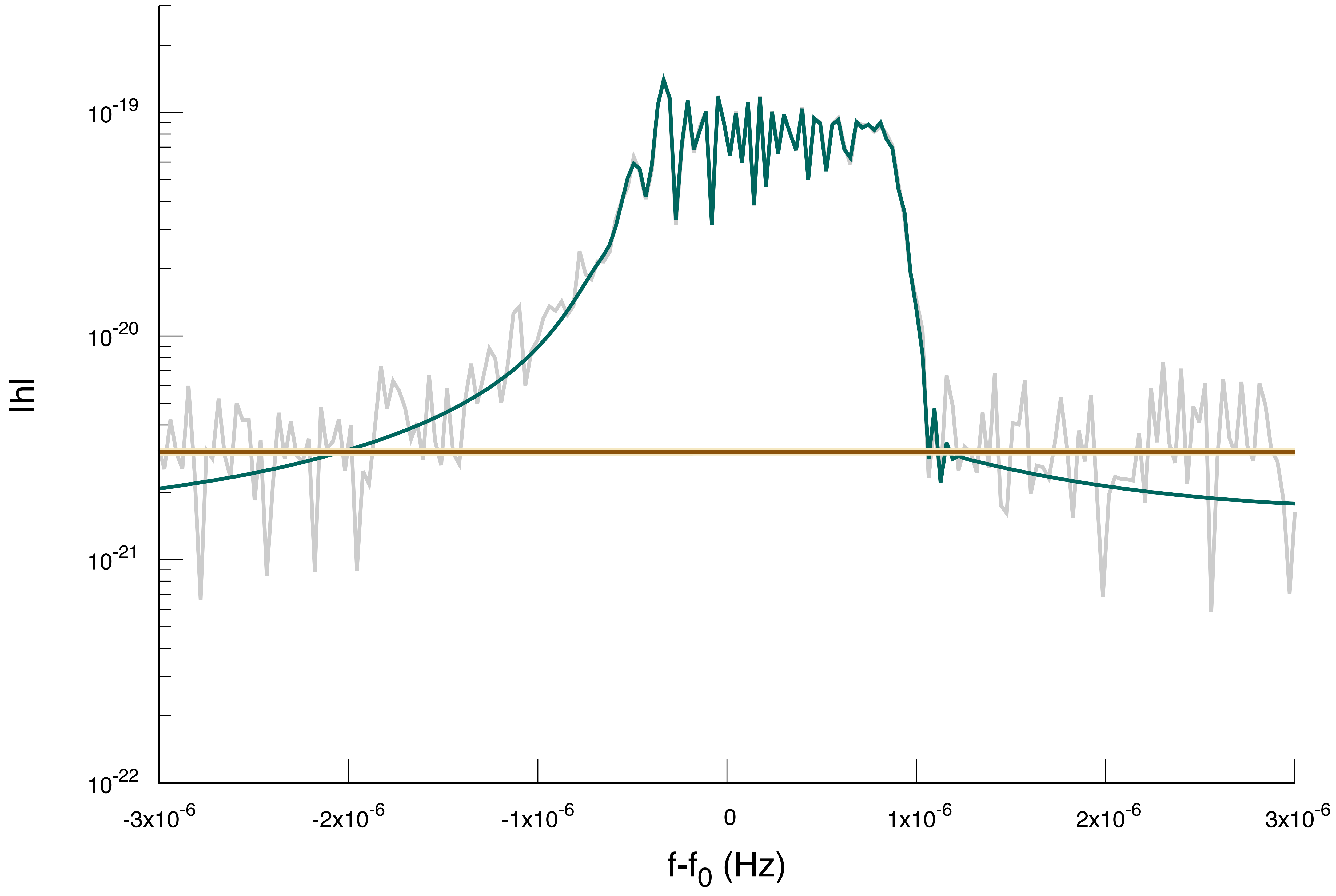
$$\vec{x} \rightarrow \{N \times \vec{\theta}, \vec{\eta}\}$$

Likelihood

$$\ln p(d|\vec{x}) \propto -\frac{1}{2} \sum_f \left(\frac{|d(f) - h_i(f; \vec{\theta})|^2}{\frac{T}{2} S_n(f; \vec{\eta})} + \ln S_n(f; \vec{\eta}) \right)$$

Model Everything…

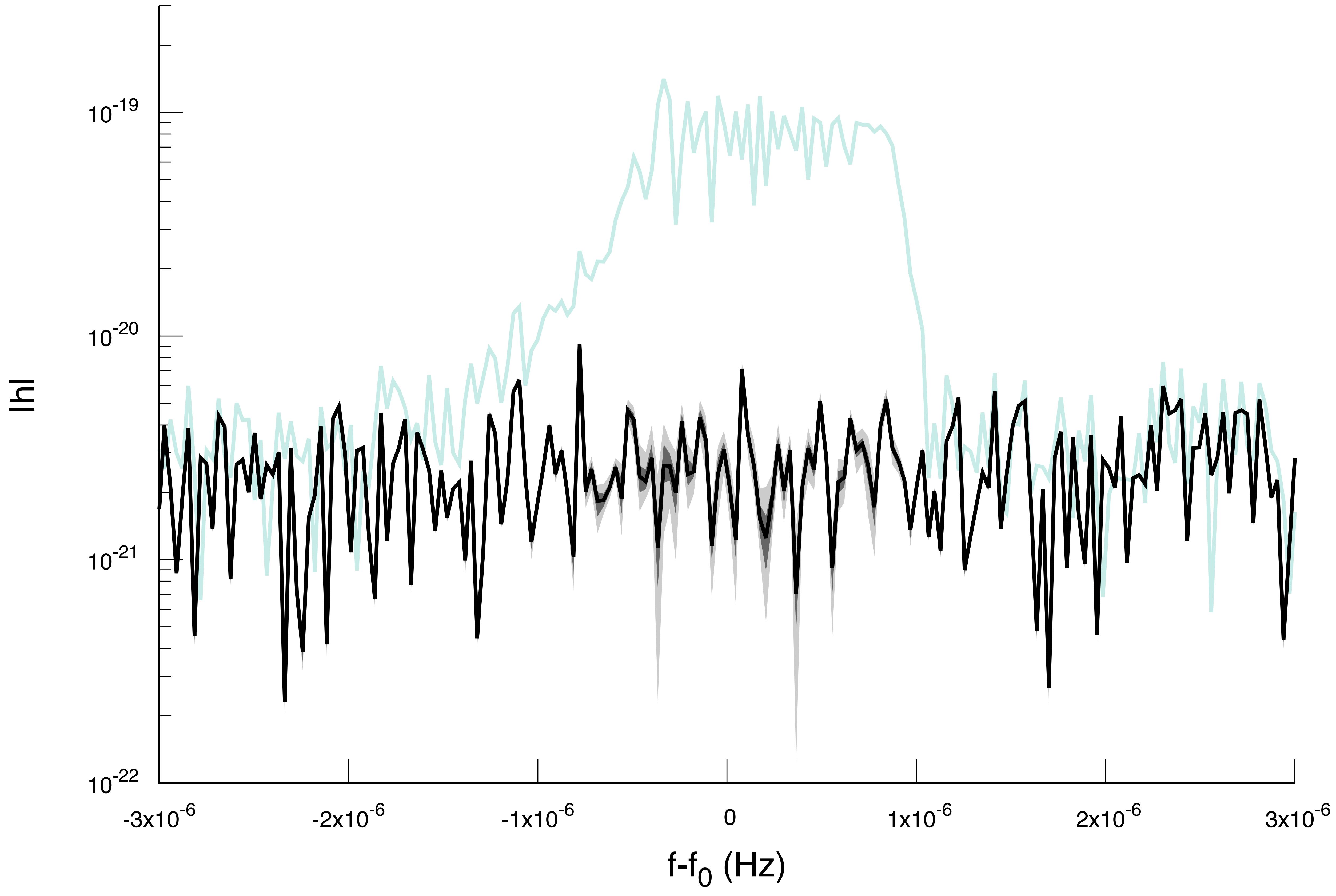
Decompose data into signal and noise contributions



Model Everything…

Decompose data into signal and noise contributions

Output residuals with uncertainties…

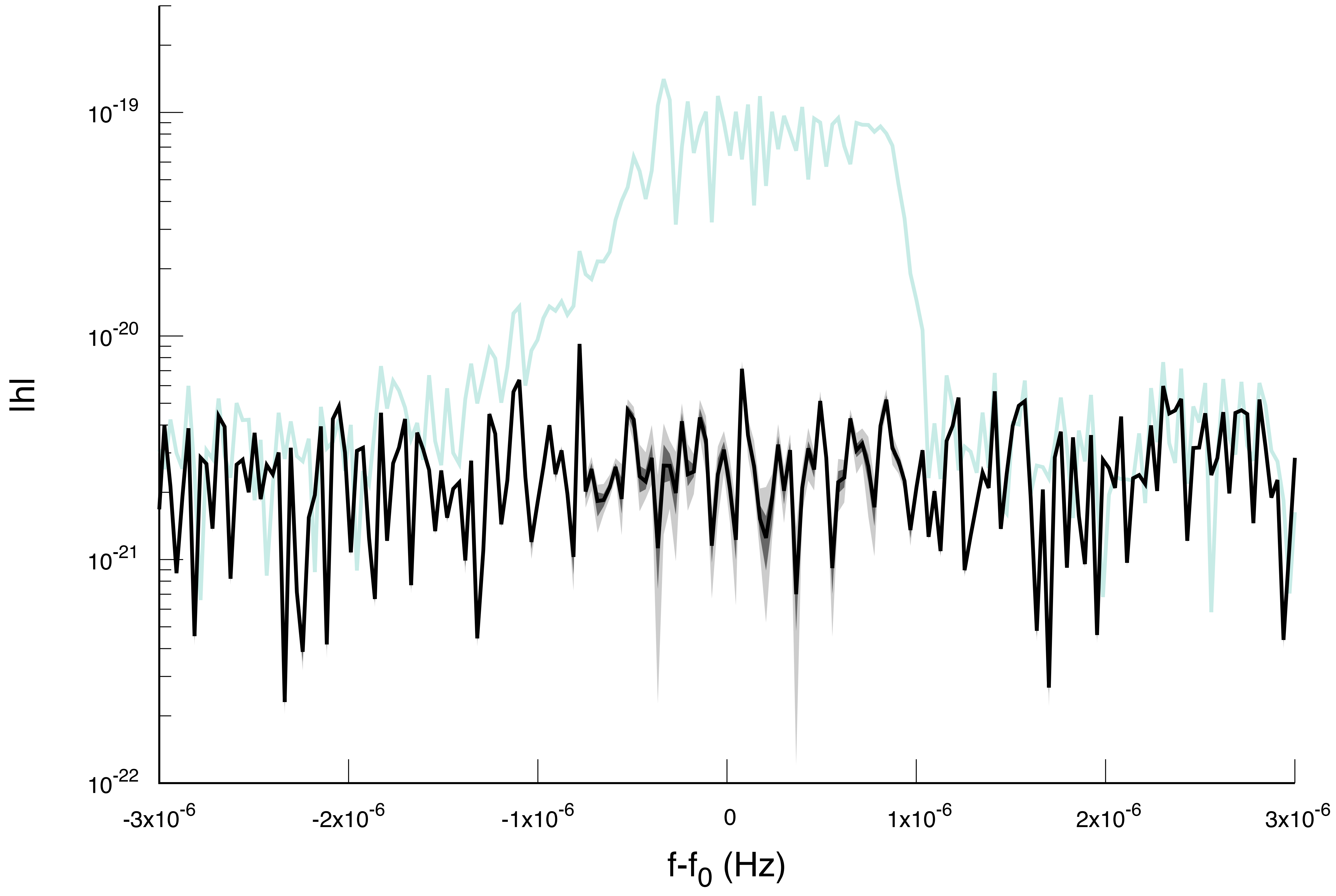


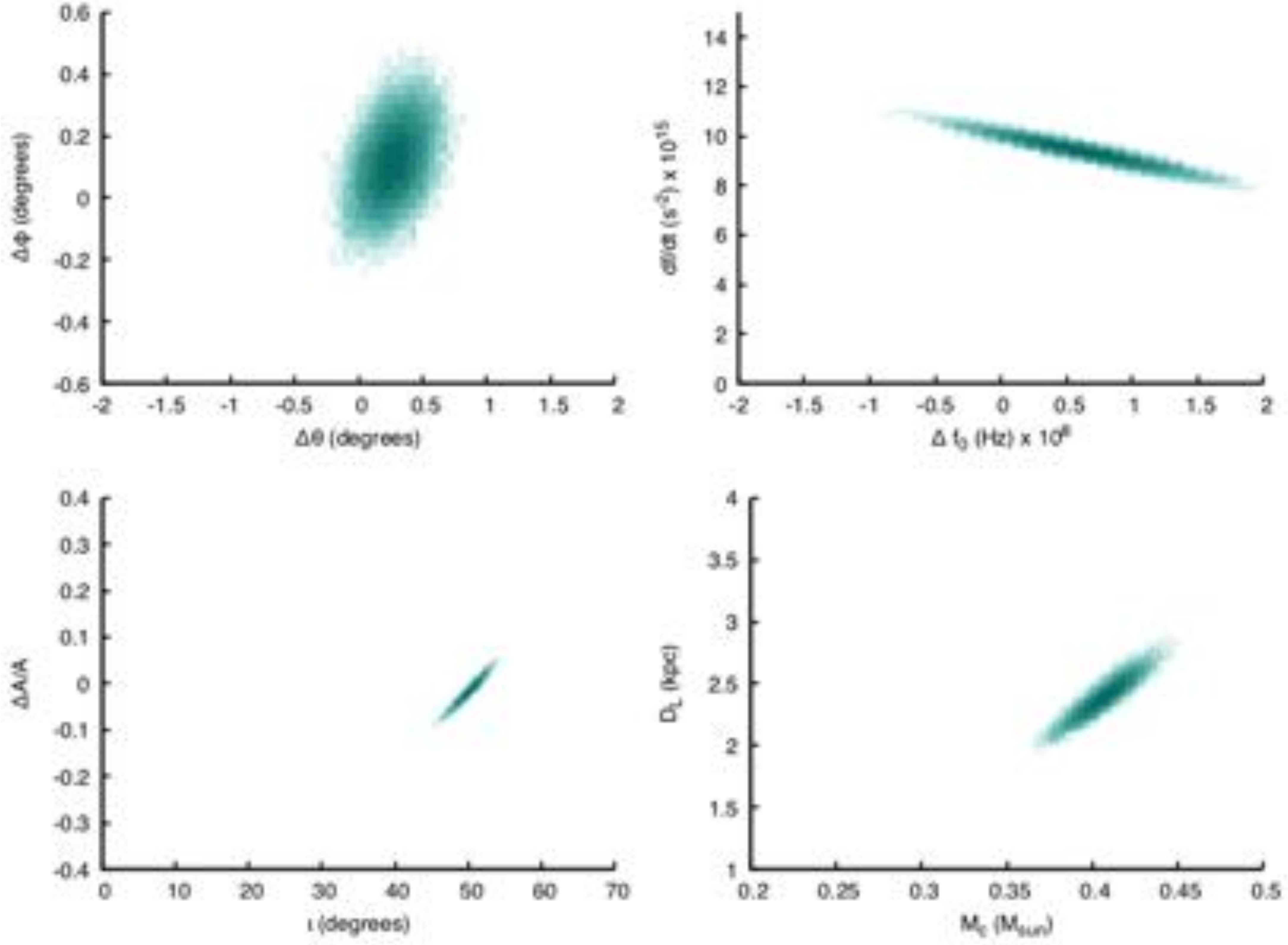
Model Everything…

Decompose data into signal and noise contributions

Output residuals with uncertainties…

…and parameter estimates





What’s new?

$$H_{\vec{x}\to\vec{y}} = \frac{p(d|\vec{y})}{p(d|\vec{x})}\frac{p(\vec{y})}{p(\vec{x})}\frac{q(\vec{x}|\vec{y})}{q(\vec{y}|\vec{x})}$$

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Improved data model

- More flexible noise model
  - Time-frequency spectral model
  - Parameterized model for confusion noise
- Accomodate gaps in data
- Efficiently incorporate new data

Smarter priors

- Hyperparameters for spatial distribution
- Informed priors on chirp mass distribution from population models
- Build priors from previous data, or EM observations

Increased sampling efficiency

- Data-driven likelihood-based proposals…
- and sampler-driven proposals from preliminary catalogs…
- …mean RJMCMC can be used for model selection

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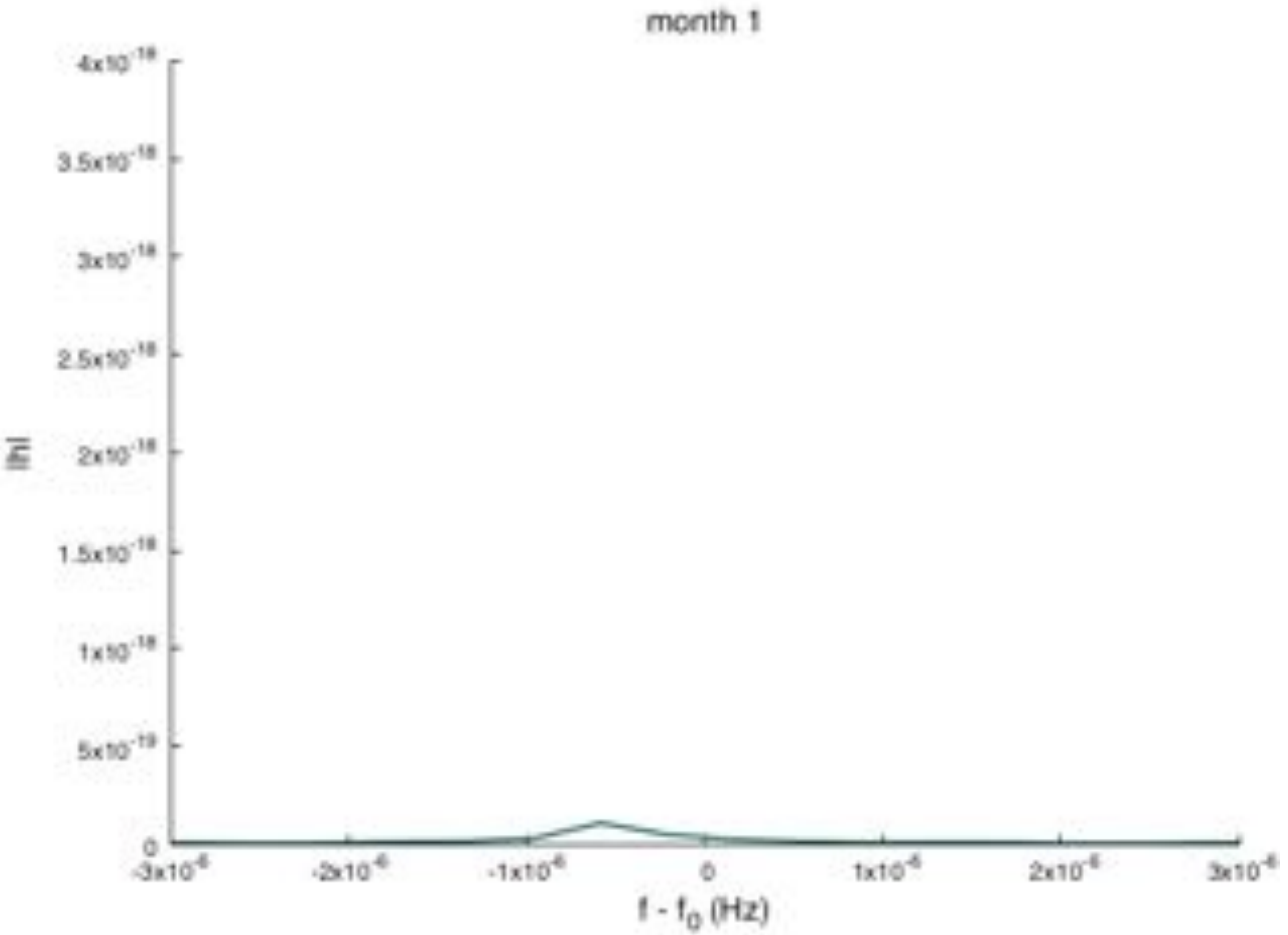

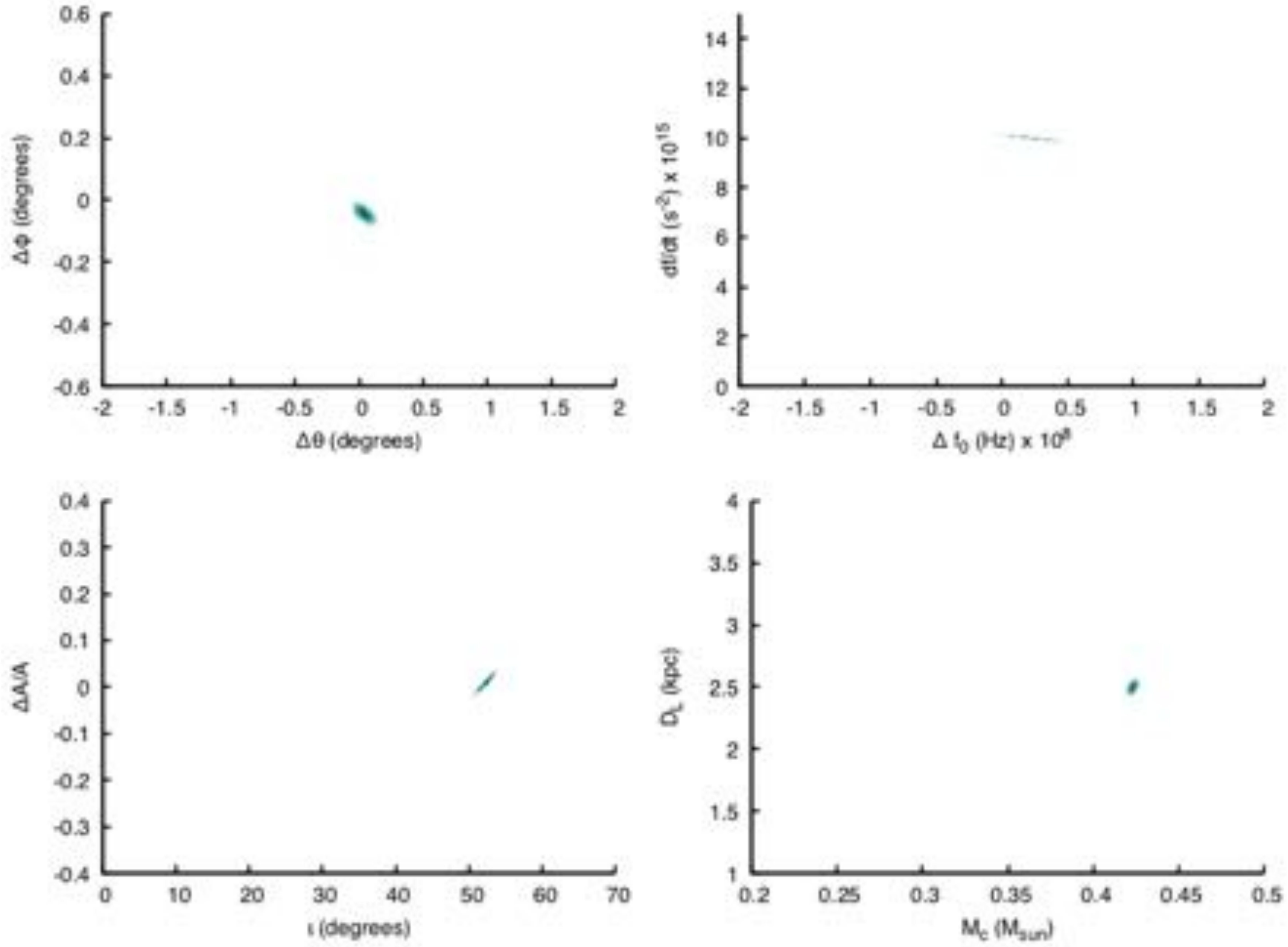

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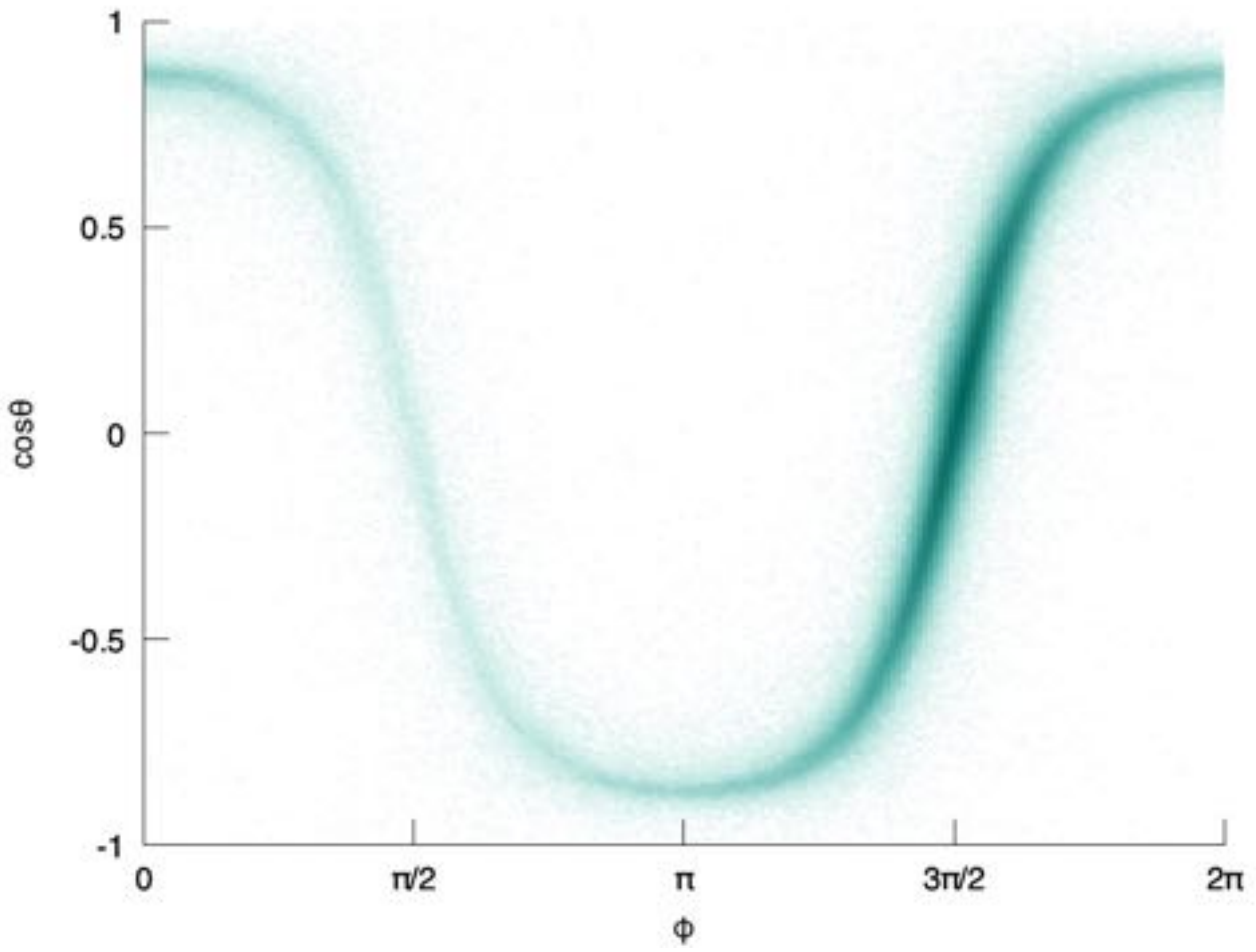

Galaxy-model prior for sky location

"Malmquist" like SNR prior

Population-based chirp mass priors?

Build priors from posteriors for low-latency updates

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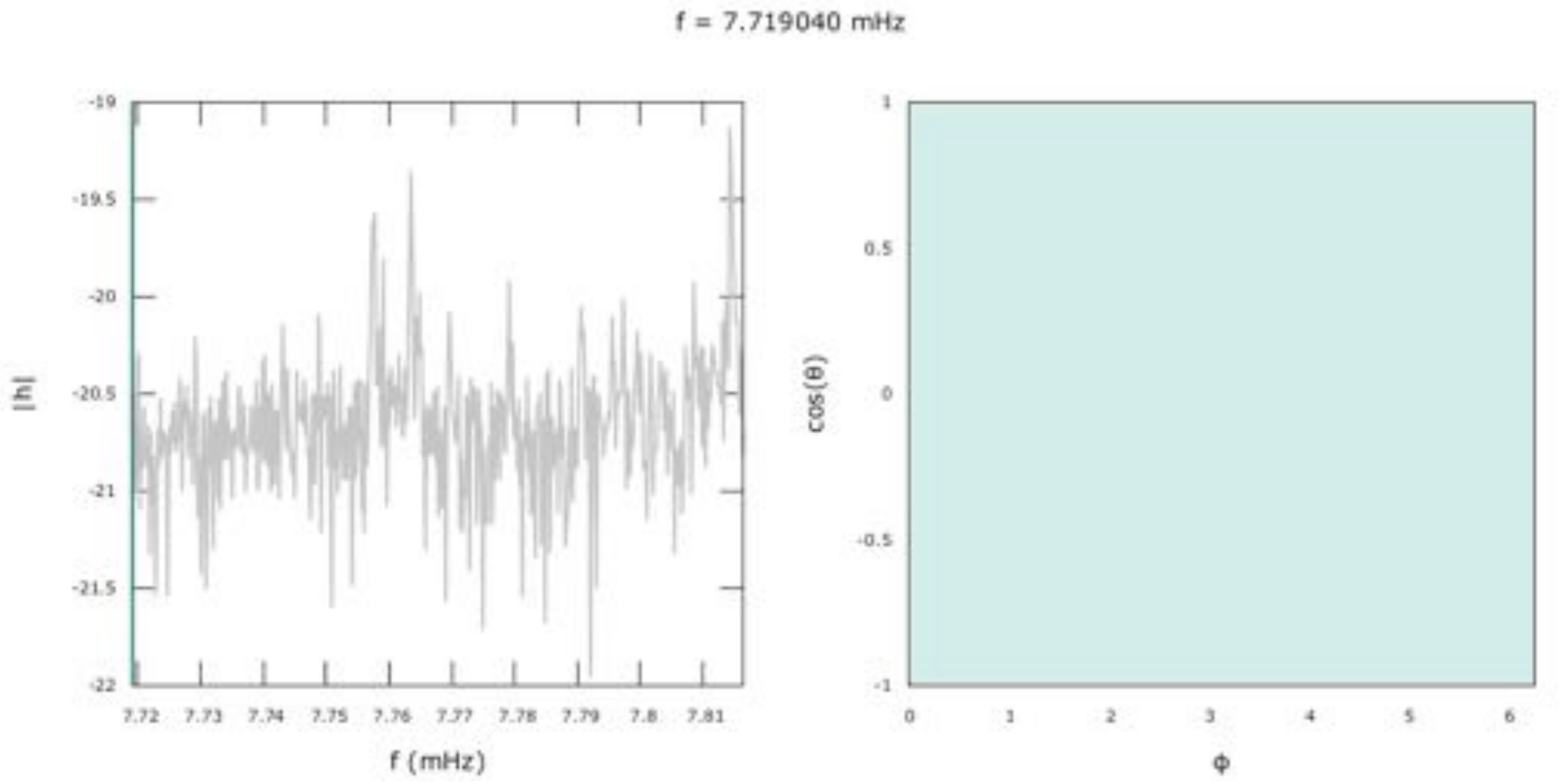
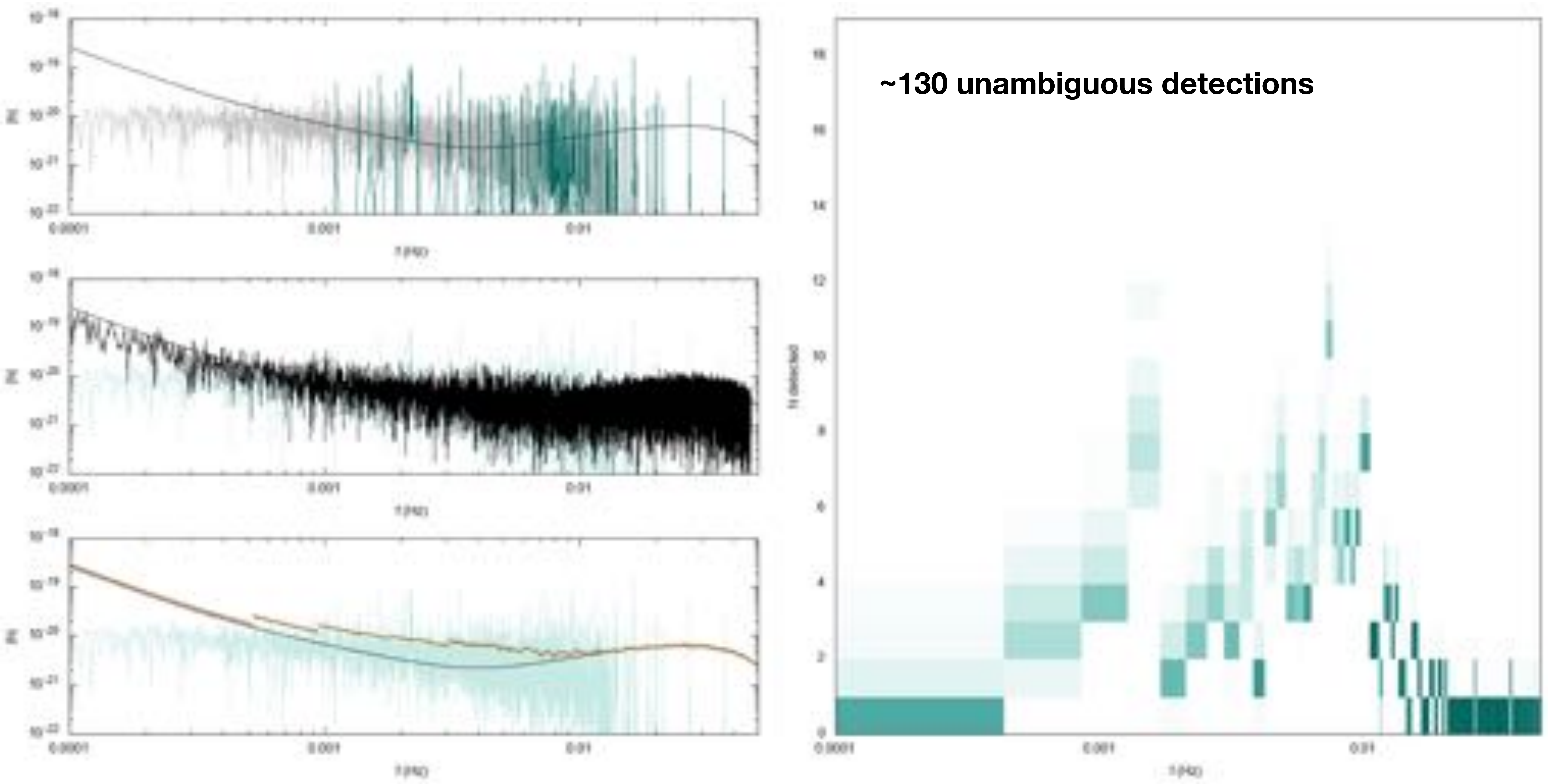
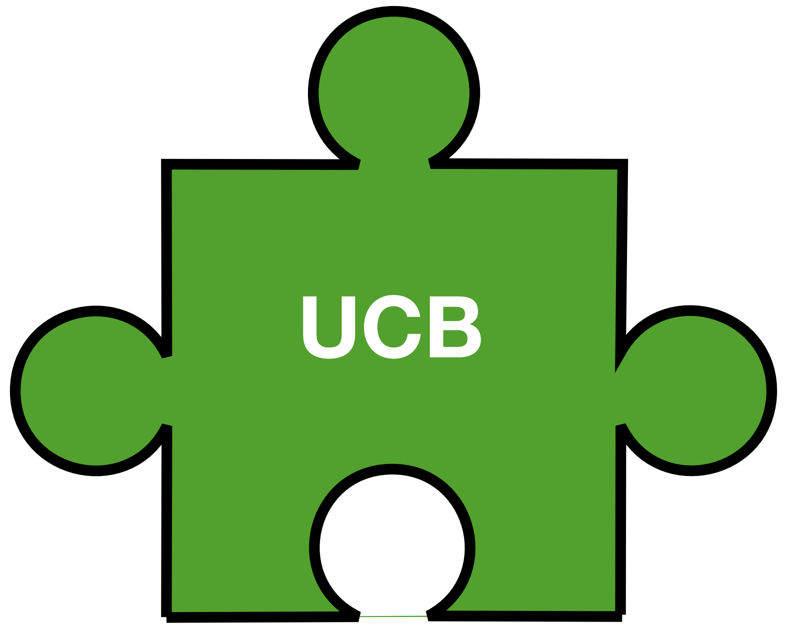


Demonstration on 1 week of data



The Big Picture



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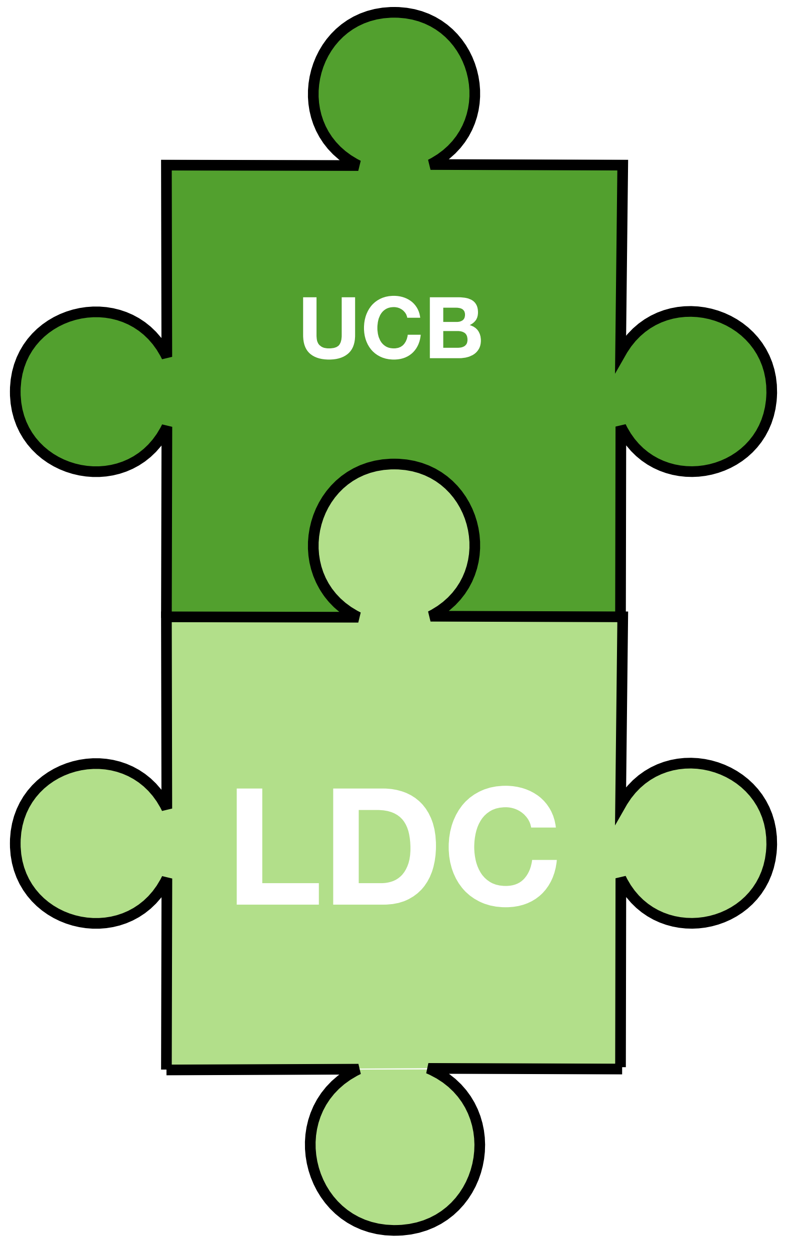

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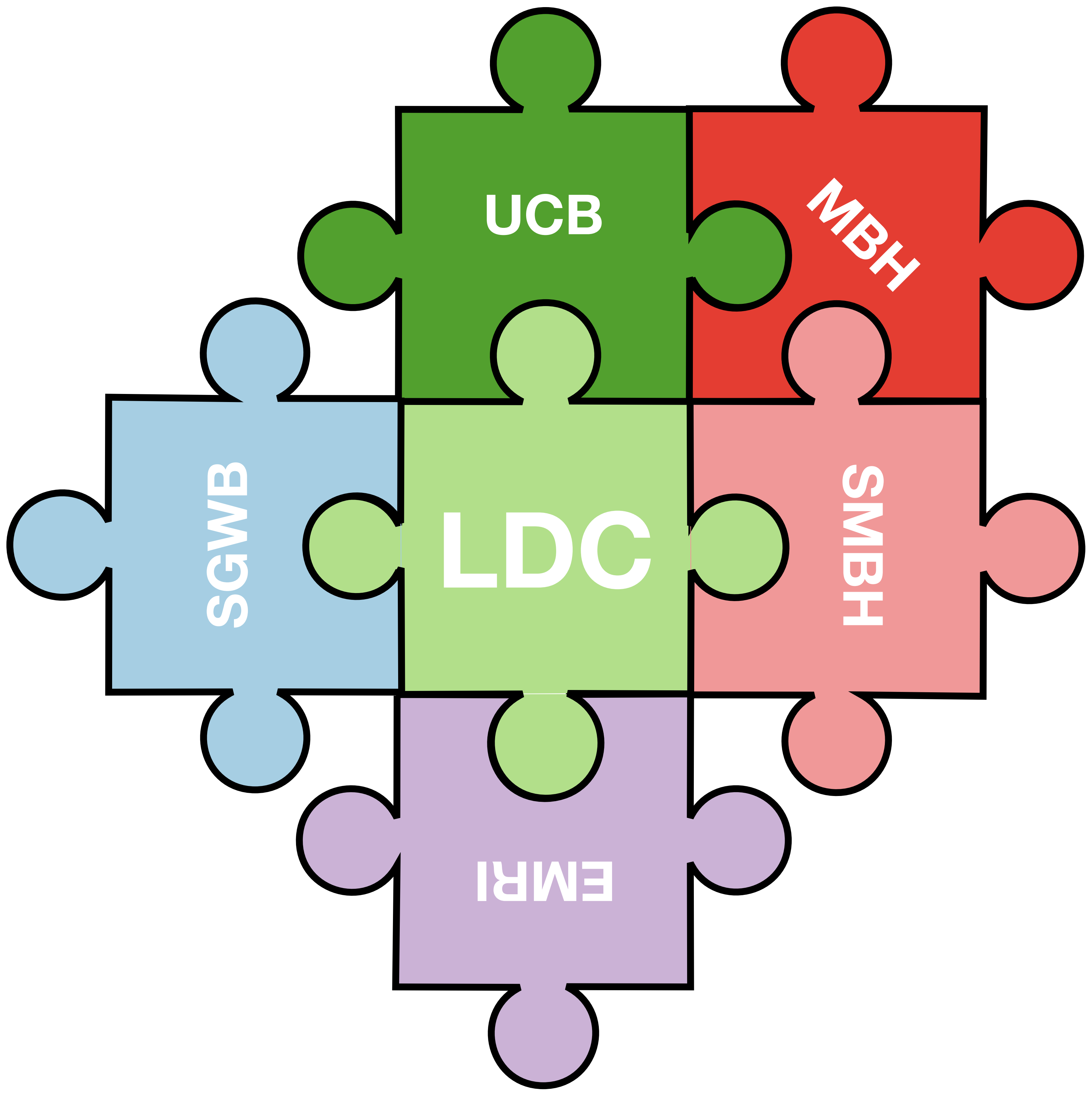

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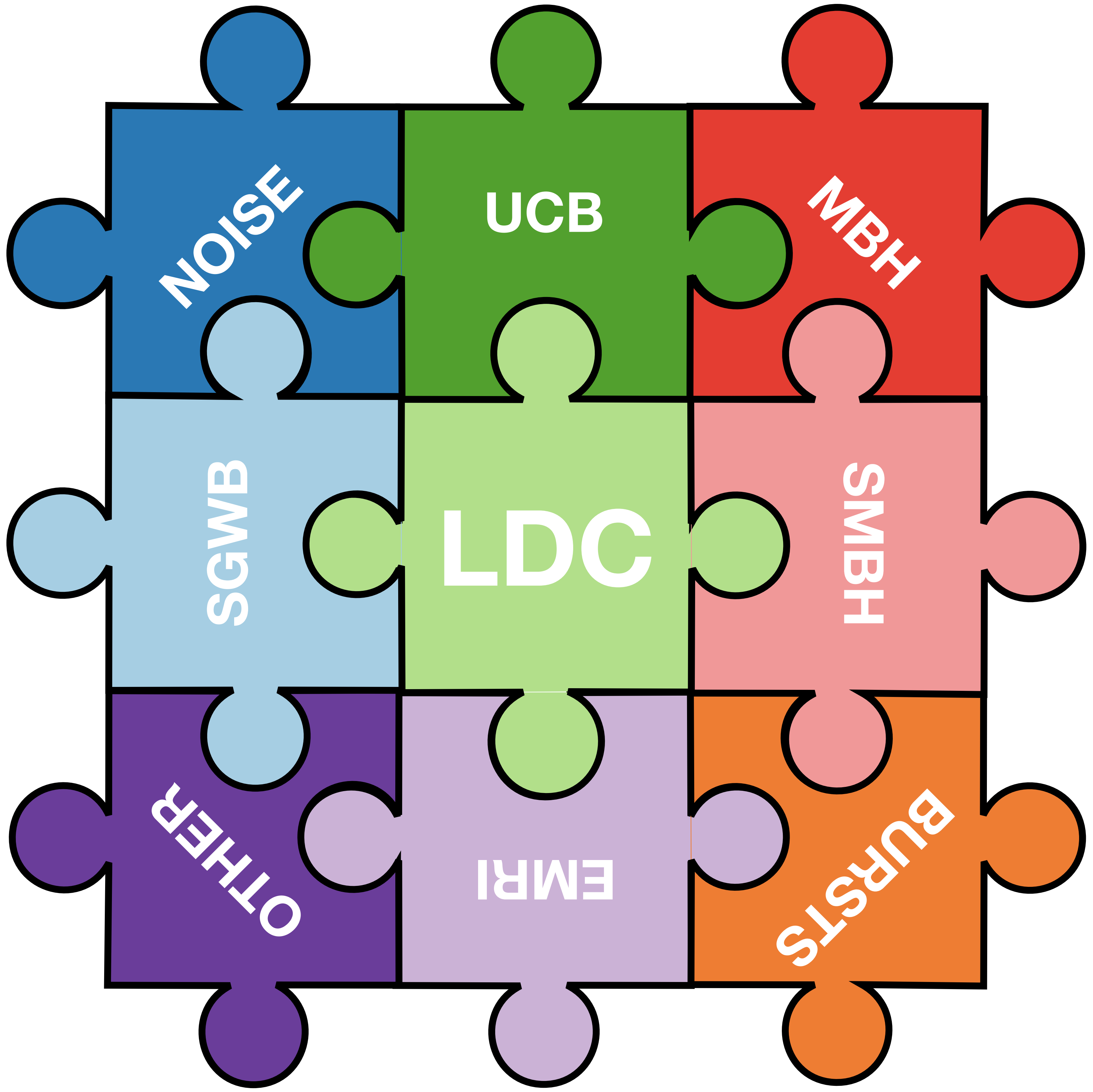

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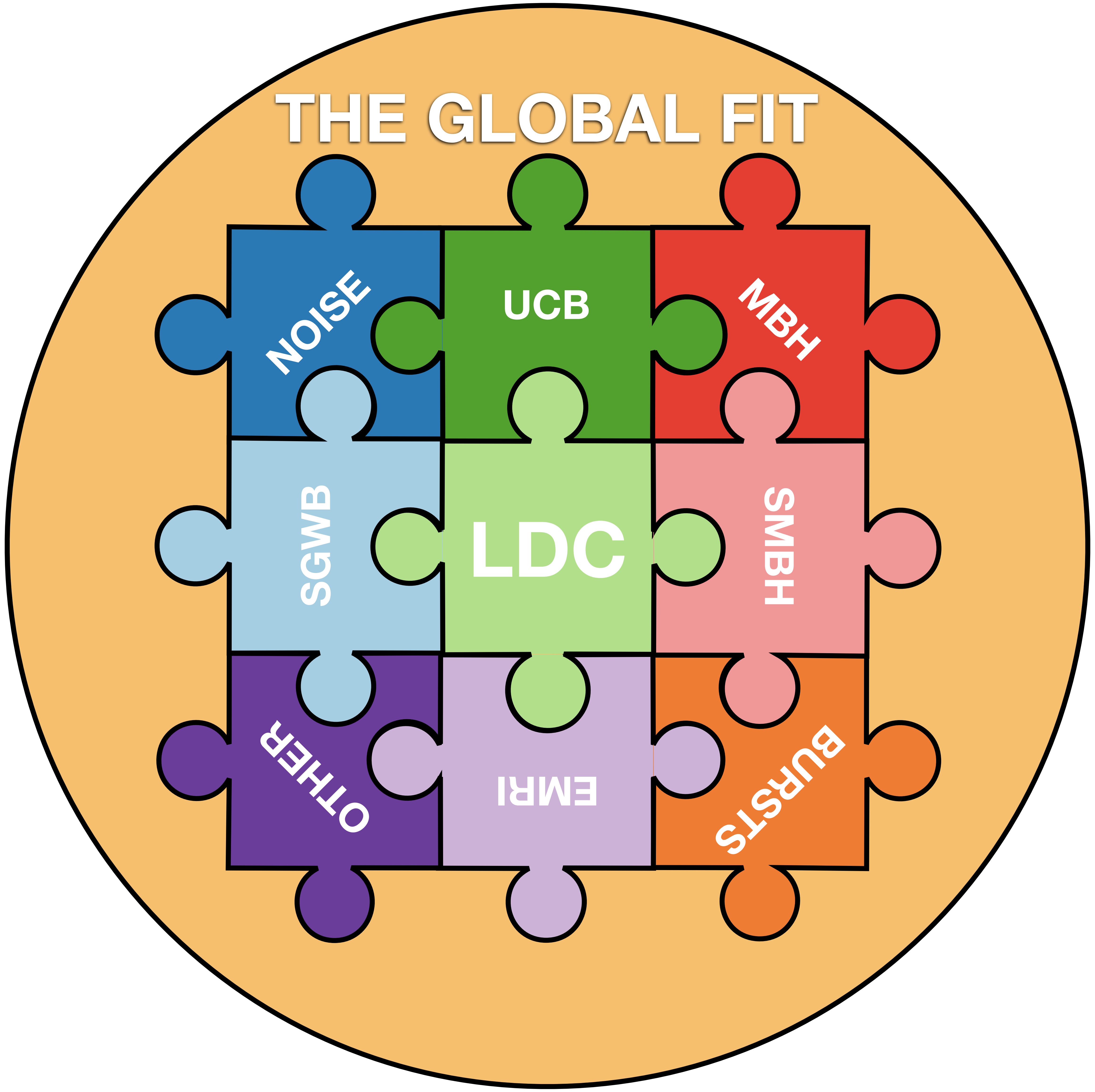

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