Gravitational Wave Astrophysics and Inference

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General Outline

- Gravitational Waves
- Bayesian Analysis & Parameter Estimation for Gravitational Waves
- Bayesian Hypothesis Testing for Gravitational Waves
- Nonlinear Tides in the Binary Neutron Star Merger Event GW170817

GW150914

GW150914

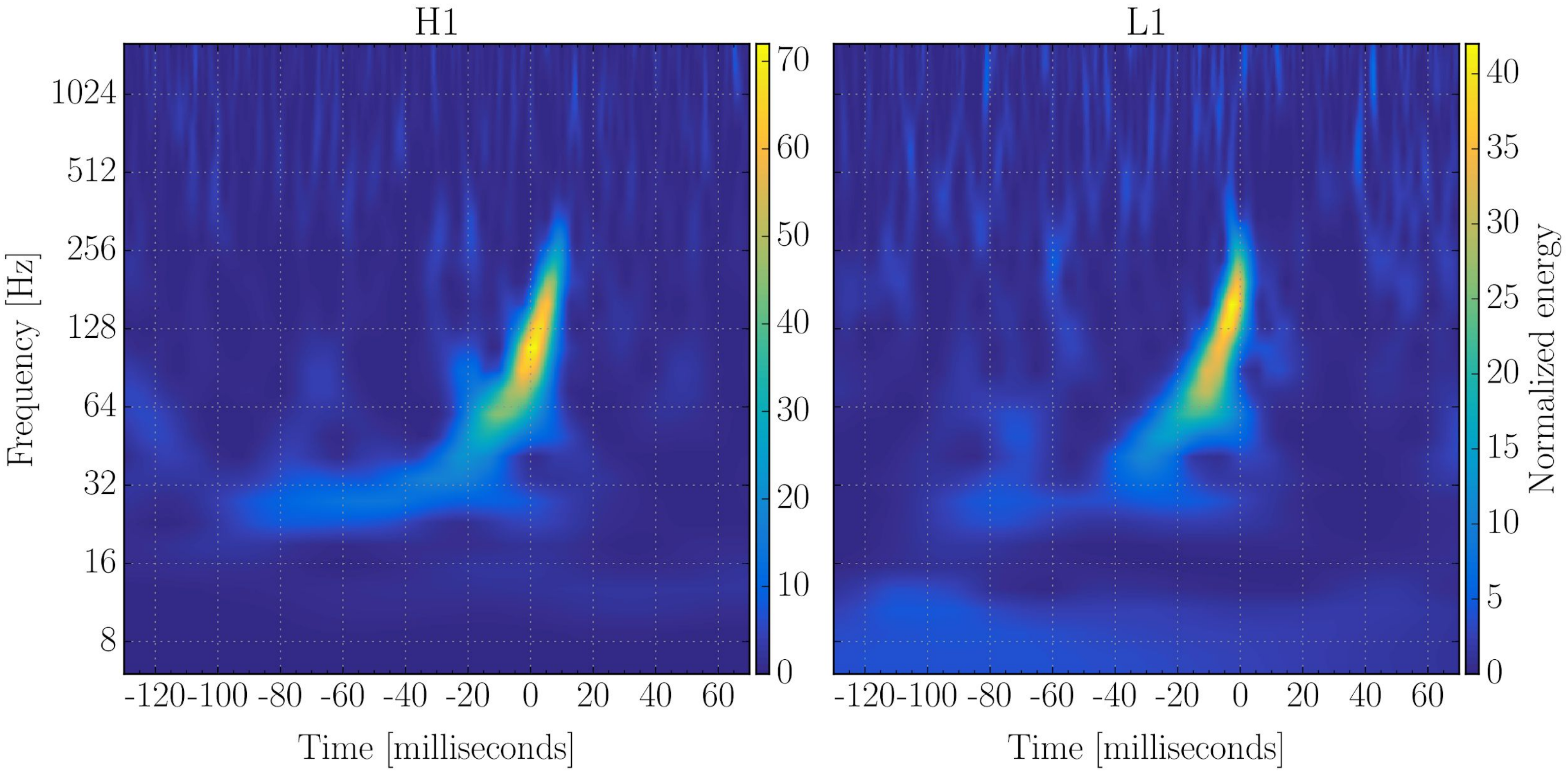
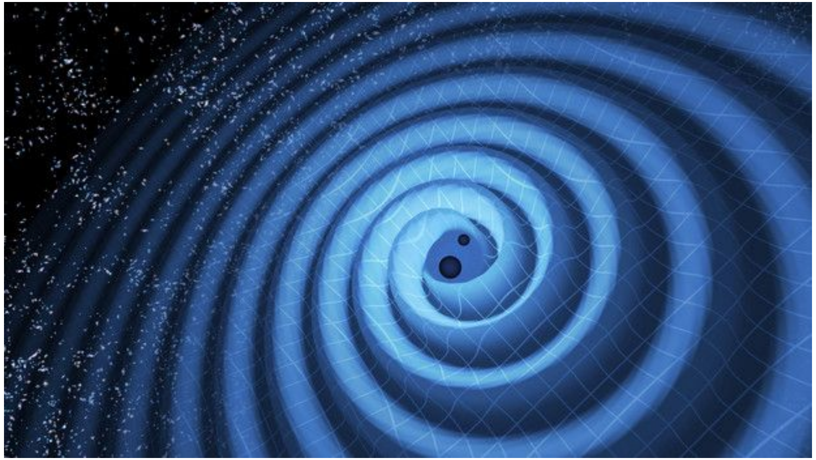


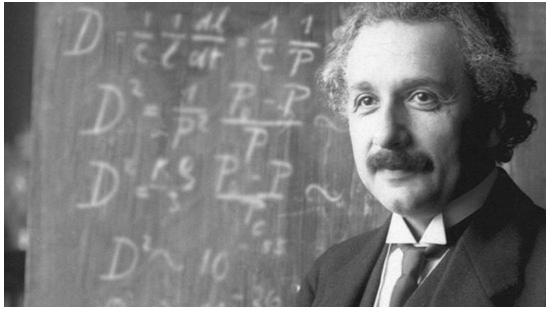
Figure 10 of “Characterization of transient noise in Advanced LIGO relevant to gravitational wave signal GW150914” (LVC et al 2016)

Gravitational Waves and General Relativity

- Einstein's theory of general relativity states, "Space tells matter how to move. Matter tells space how to curve."*

- How did LIGO and Virgo do it?





*Gravitation (1976), M.T.W.

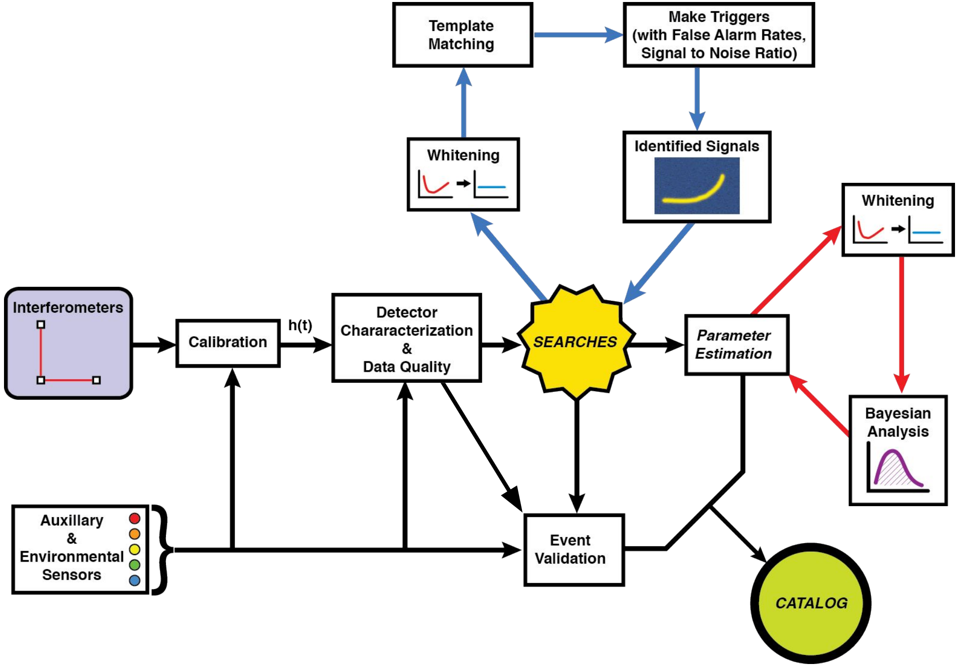
(Top) : Image credit: LIGO/T. Pyle
(Bottom) : https://curiosity.com/topics/you-can-see-a-chalkboard-covered-in-albert-einsteins-writing-at-oxford-university-curiosity/

Gravitational Wave Observatories

Image Credit: https://www.ligo.caltech.edu/news/ligo20191004

Gravitational Wave Astrophysical Analysis

- Gravitational wave astronomy is made possible by the hard work of thousands of scientists, engineers, and students.

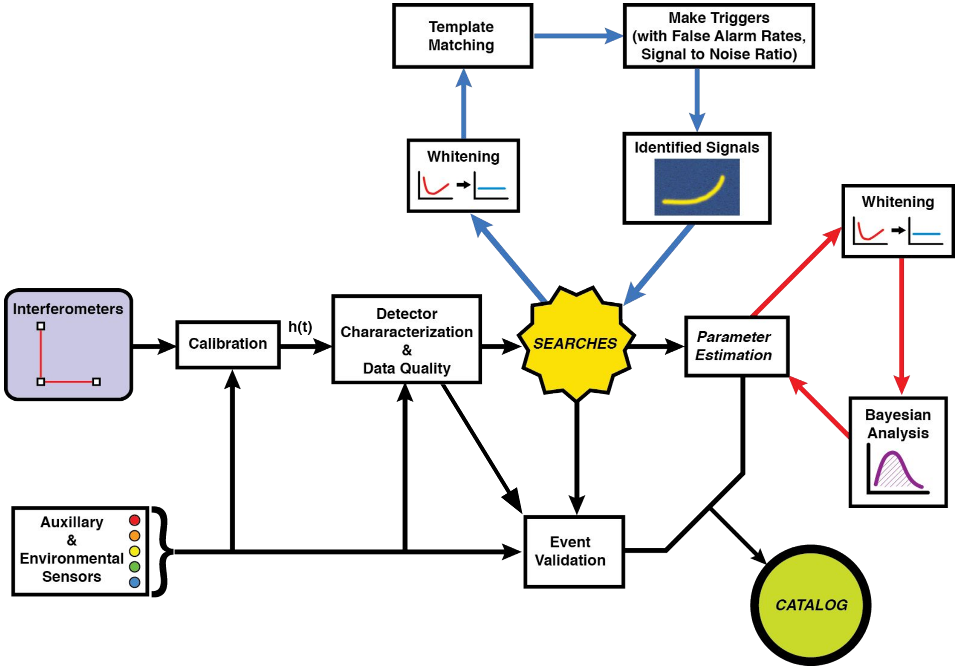


A Guide to LIGO-Virgo Detector Noise and Extraction of Transient Gravitational-wave Signals (Science Summary):

https://www.ligo.org/science/Publication-DataAnalysisGuide/index.php

Gravitational Wave Astrophysical Analysis

- Gravitational wave astronomy is made possible by the hard work of thousands of scientists, engineers, and students.
- This talk will focus on Parameter Estimation and Bayesian Analysis.



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Bayesian Parameter Estimation

- In Bayesian inference, Bayes' theorem gives the full "engine" for statistical inference.

$$\boxed{p(\vec{\theta}\,|\,\mathrm{H})\,p(\mathbf{d}\,|\,\vec{\theta},\mathrm{H})} = \boxed{p(\vec{\theta}\,|\,\mathbf{d},\mathrm{H})p(\mathbf{d}\,|\,\mathrm{H})}$$

$$\boxed{\text{Prior} \times \text{Likelihood}} = \boxed{\text{Posterior} \times \text{Evidence}}$$

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$$\boxed{\pi(\vec{\theta}\,|\,\mathrm{H})\,\mathcal{L}(\mathbf{d}\,|\,\vec{\theta},\mathrm{H})} = \boxed{\mathcal{P}(\vec{\theta}\,|\,\mathbf{d},\mathrm{H})\,\mathcal{Z}(\mathbf{d}\,|\,\mathrm{H})}$$

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$$\text{Posterior} = \frac{\text{Prior} \times \text{Likelihood}}{\text{Evidence}}$$

Parameter Estimation for Gravitational Waves

- We want to measure at quite a few parameters of the compact binaries.

Intrinsic Parameters

$$m_1, m_2, \vec{S}_1, \vec{S}_2, \Lambda_1, \Lambda_2$$

Dynamics of the source

Extrinsic Parameters

$$D_L, \alpha, \delta, \iota, \psi, \phi_c, t_c$$

Changes how we observe the system

- We have to measure 16 parameters where some of the parameters are known to be degenerate with one another.

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- Put them all together and you have a prior distribution.

$$\pi(\vec{\theta} \,|\, \mathrm{H})$$

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$$\mathcal{L}(\mathbf{d} \,|\, \vec{\theta}, \mathrm{H})$$

GW170817: Binary Neutron Star Merger

- Two important parameters to measure are combinations of the masses of the binary. Chirp Mass & Symmetric Mass Ratio.

$$\mathcal{M} = \frac{(m_1 m_2)^{3/5}}{(m_1 + m_2)^{1/5}}$$

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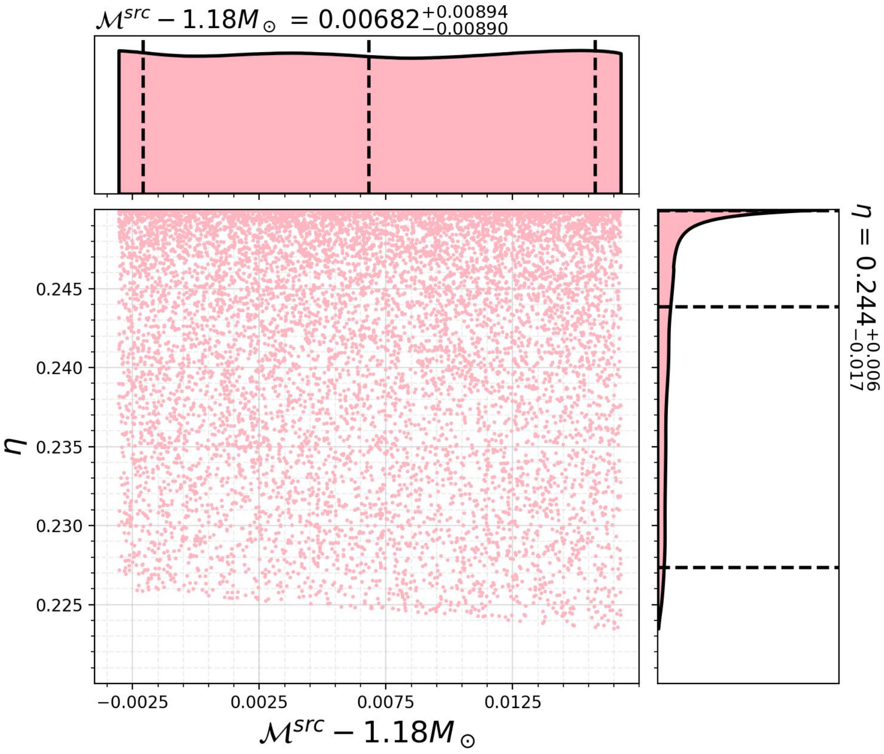

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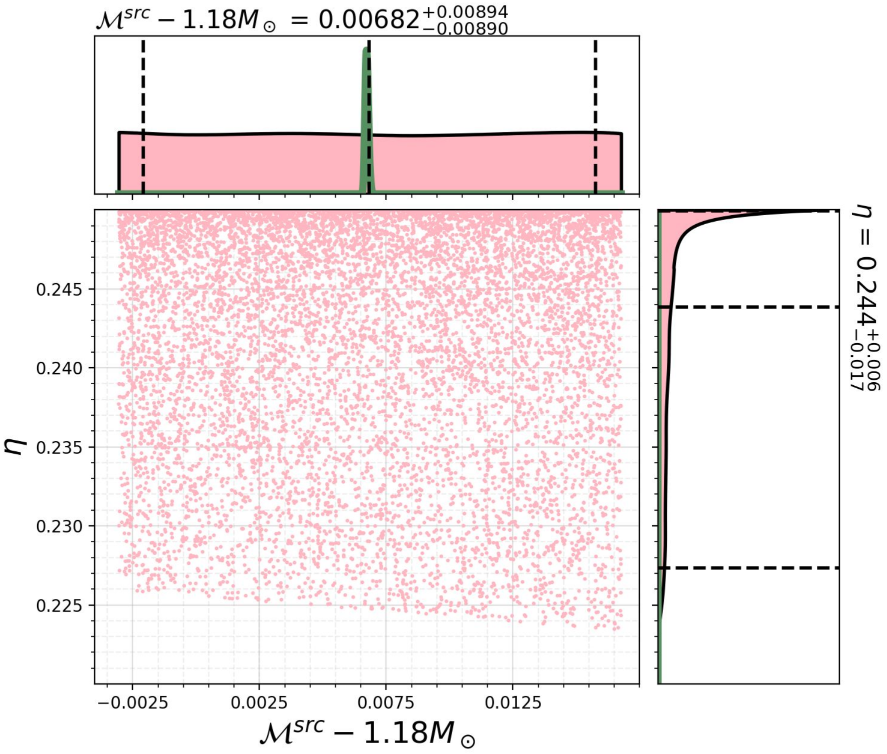

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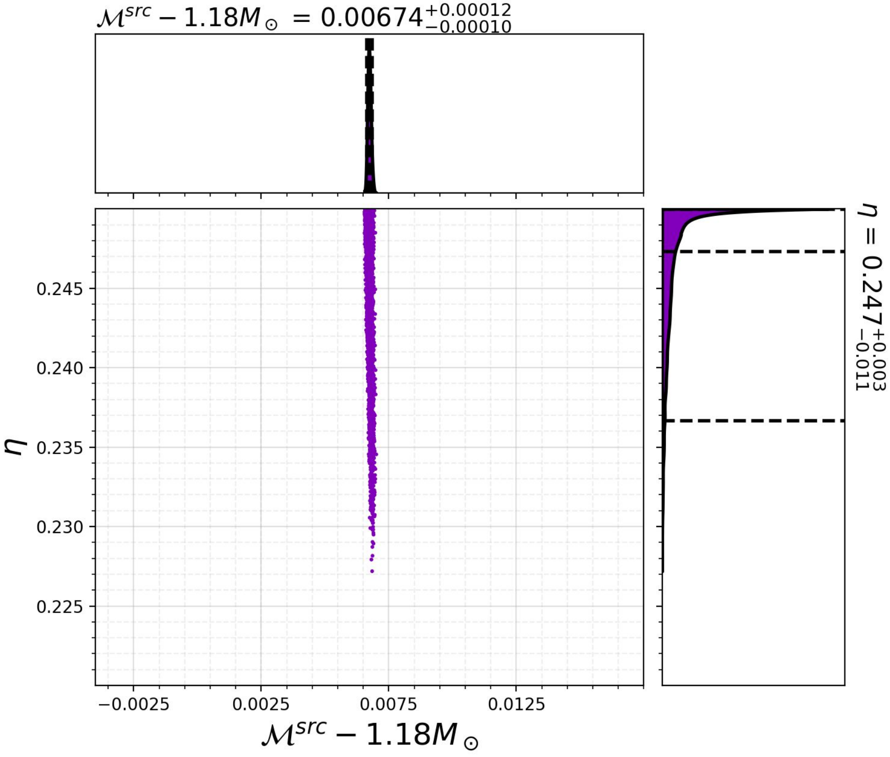

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GW170817: Two Competing Hypotheses

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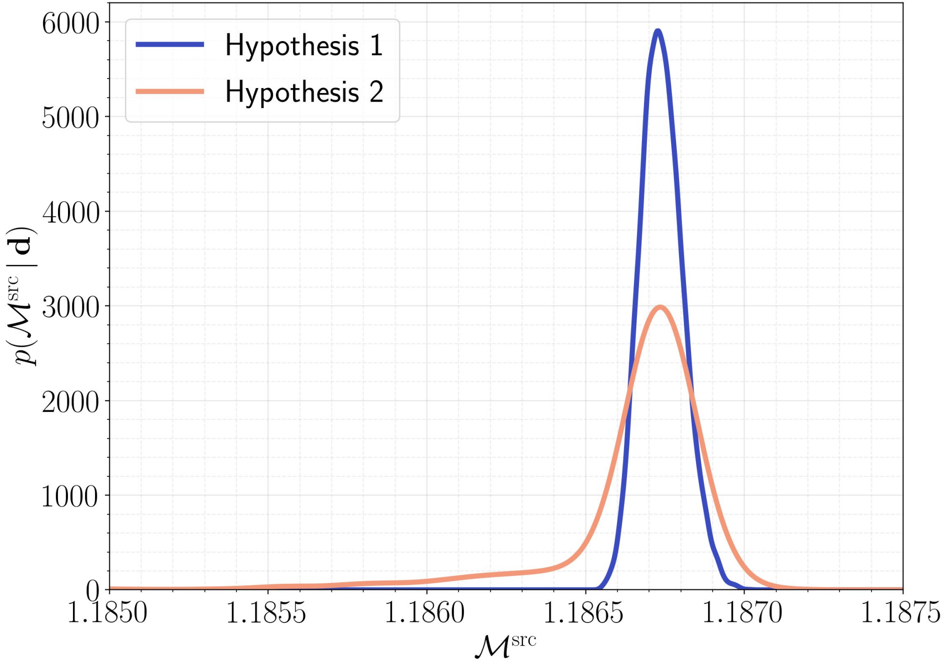

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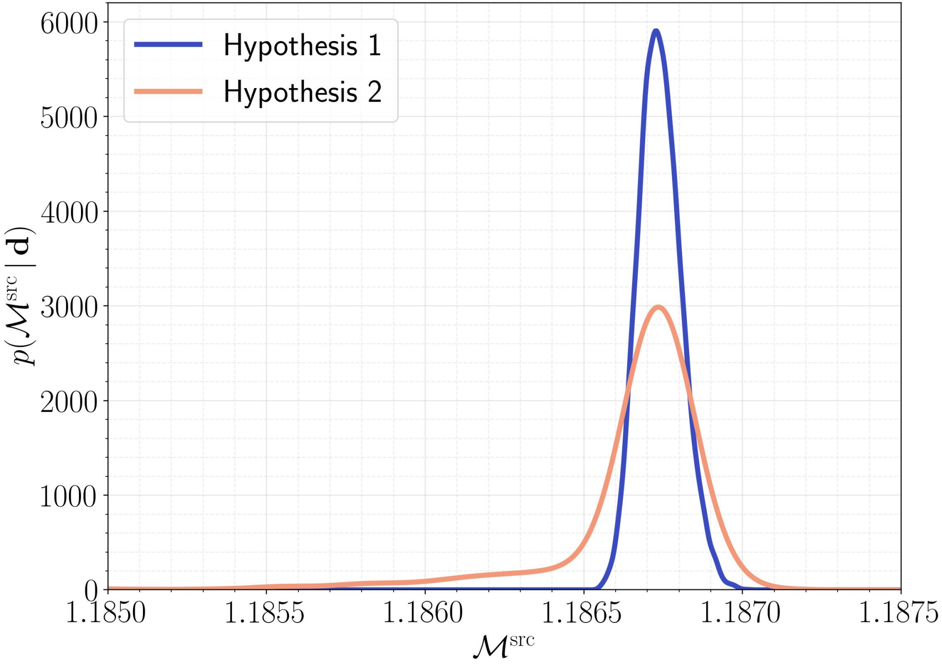

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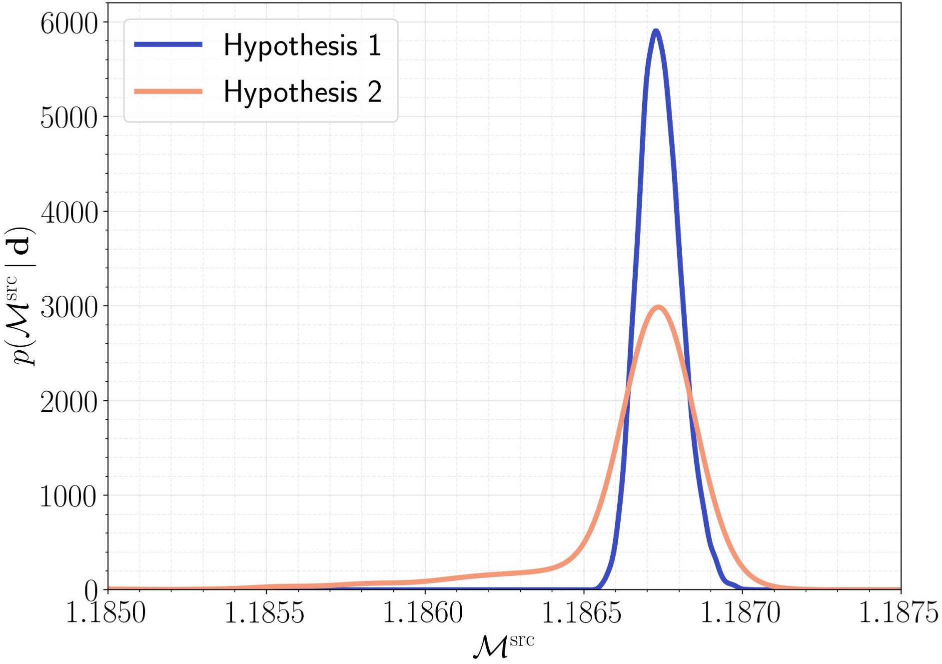
GW170817: Two Competing Hypotheses

- Parameter estimation using different prior distributions may yield different posterior distributions!
- Which posterior distribution is more credible / best supported by the data?
- Need Bayesian hypothesis testing to answer this.



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From Parameter Estimation to Hypothesis Testing

- Bayes theorem provides a method for weighing the evidence of a hypothesis.
- The evidence for a particular hypothesis is the normalizing constant for our posterior distribution. Also called marginal likelihood:

$$\mathcal{Z}(d\,|\,\mathrm{H_A}) = \int \pi(\vec{\theta}\,|\,\mathrm{H_A})\,\mathcal{L}(d\,|\,\vec{\theta},\mathrm{H_A})d\vec{\theta}$$

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- Asks the question of how well the prior distribution predicts the data.

From Parameter Estimation to Hypothesis Testing

- If we consider two hypotheses, we can construct a likelihood ratio, called the Bayes factor:

$$\mathcal{B}^{\mathrm{H_A}}_{\mathrm{H_B}} = \frac{\mathcal{Z}(d \mid \mathrm{H_A})}{\mathcal{Z}(d \mid \mathrm{H_B})}$$

GW170817: Nonlinear Tides

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- Essick et al (2016) suggests that we could miss >70% of binary neutron star mergers!

- Could offer a unique look into oscillation modes and structure of interior neutron star.

Reyes, S., Brown, D., 2018, arXiv:1808.07013 [astro-ph.HE]

GW170817: Nonlinear Tides

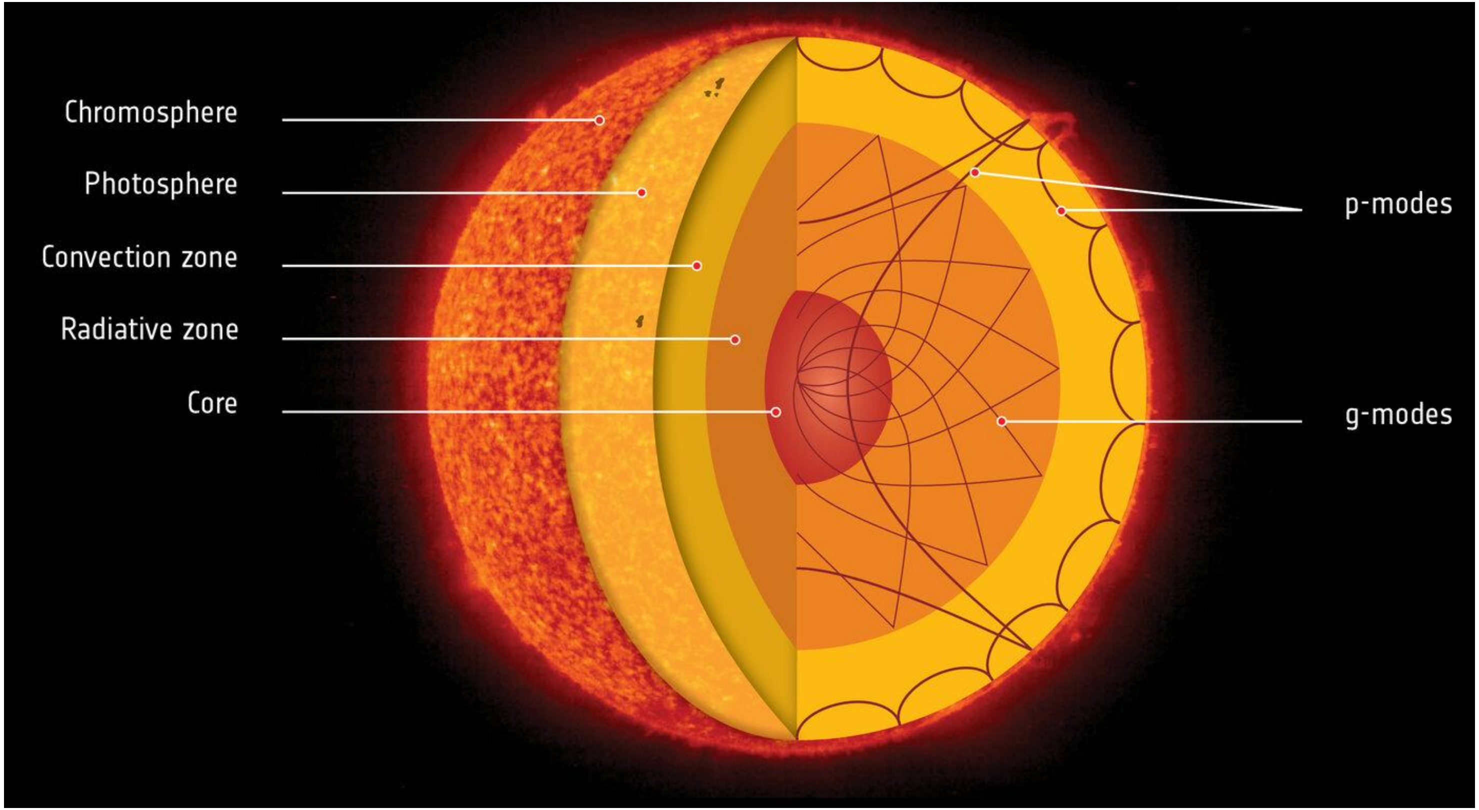

Image credit: http://www.esa.int/Science_Exploration/Space_Science/Space_Science/Gravity_waves_detected_in_Sun_s_interior_reveal_rapidly_rotating_core

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- Gravitational wave phase shift at Inner Stable Circular Orbit (ISCO):

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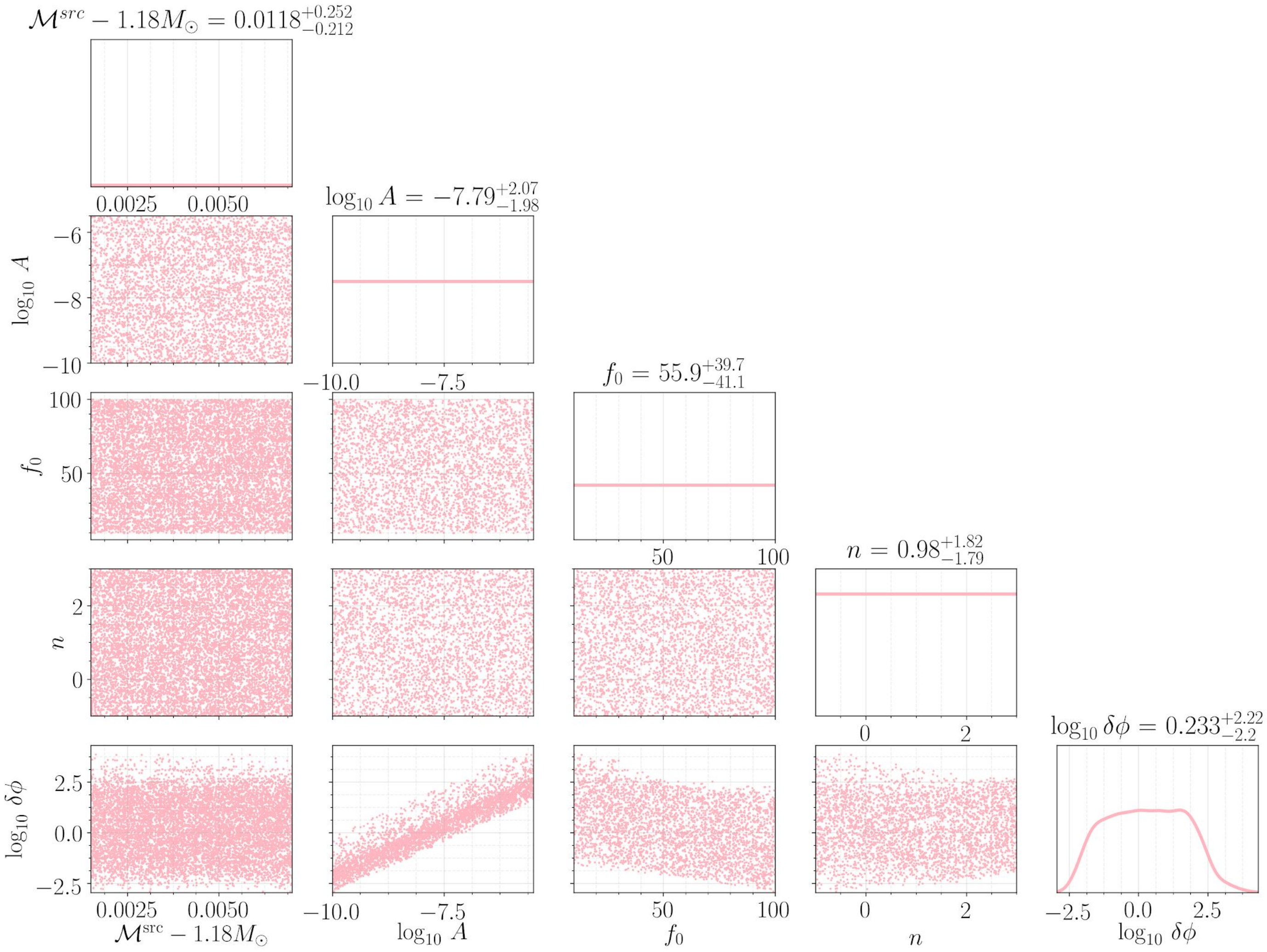
- We construct a waveform model that incorporates these new nonlinear tidal parameters.

Parameter Estimation for NL Tides in GW170817



$\mathcal{M}^{src} - 1.18M_\odot = 0.0118^{+0.252}_{-0.212}$
$\log_{10} A = -7.79^{+2.07}_{-1.98}$
$f_0 = 55.9^{+39.7}_{-41.1}$
$n = 0.98^{+1.82}_{-1.79}$
$\log_{10} \delta\phi = 0.233^{+2.22}_{-2.2}$
$\mathcal{M}^{src} - 1.18M_\odot$
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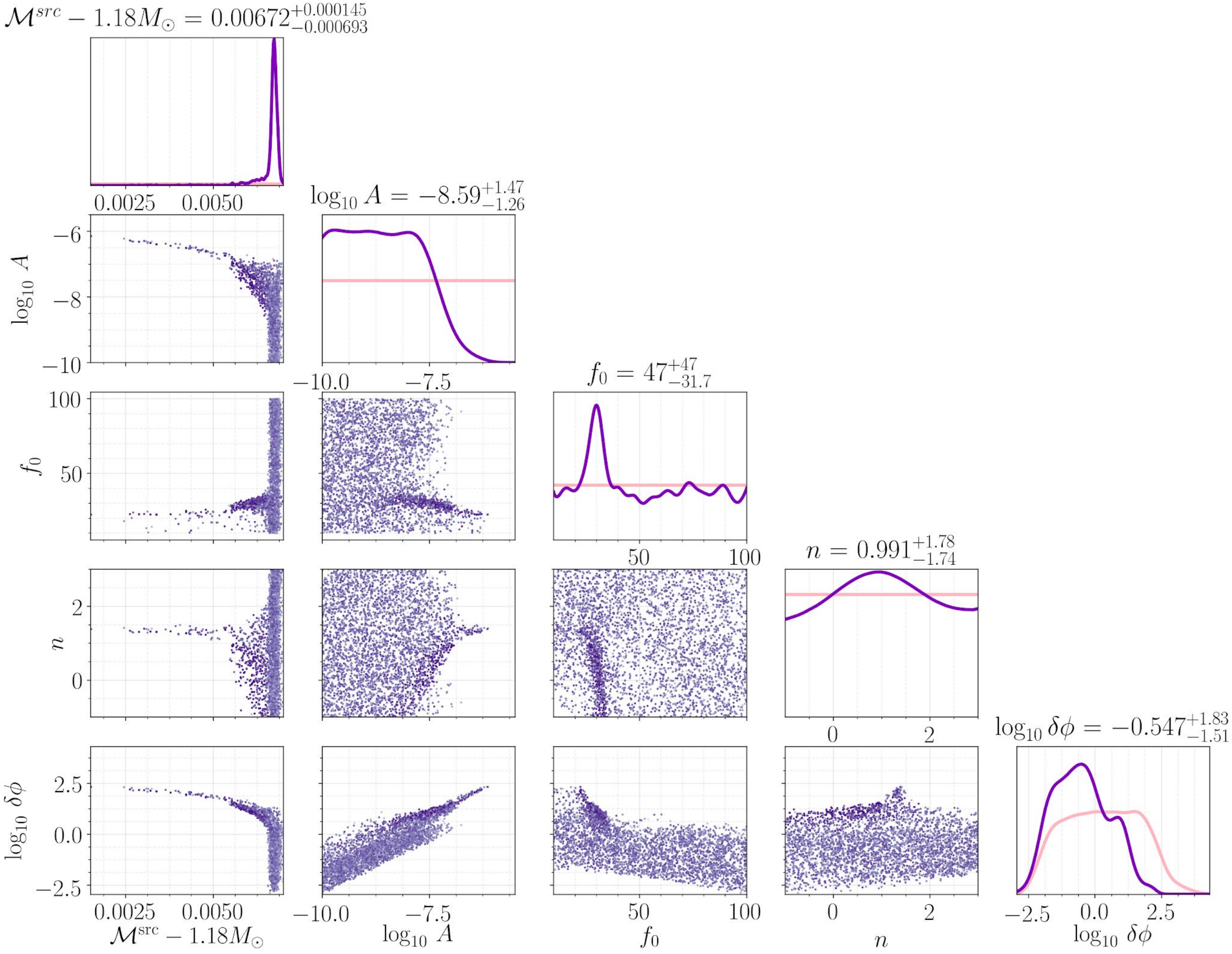
$\mathcal{M}^{src} - 1.18M_\odot = 0.00672^{+0.000145}_{-0.000693}$
$\log_{10} A = -8.59^{+1.47}_{-1.26}$
$f_0 = 47^{+47}_{-31.7}$
$n = 0.991^{+1.78}_{-1.74}$
$\log_{10}\delta\phi = -0.547^{+1.83}_{-1.51}$
$\mathcal{M}^{src} - 1.18M_\odot$
$\log_{10} A$
f_0
n
$\log_{10}\delta\phi$

Bayes Factors for Nonlinear Tides

- The Bayes Factor answers the question of how much more likely one hypothesis predicts the data vs the other hypothesis.

- Find a Bayes factor of ~ $0.7^{+0.1}_{-0.1}$, indicating a nonsignificant result.

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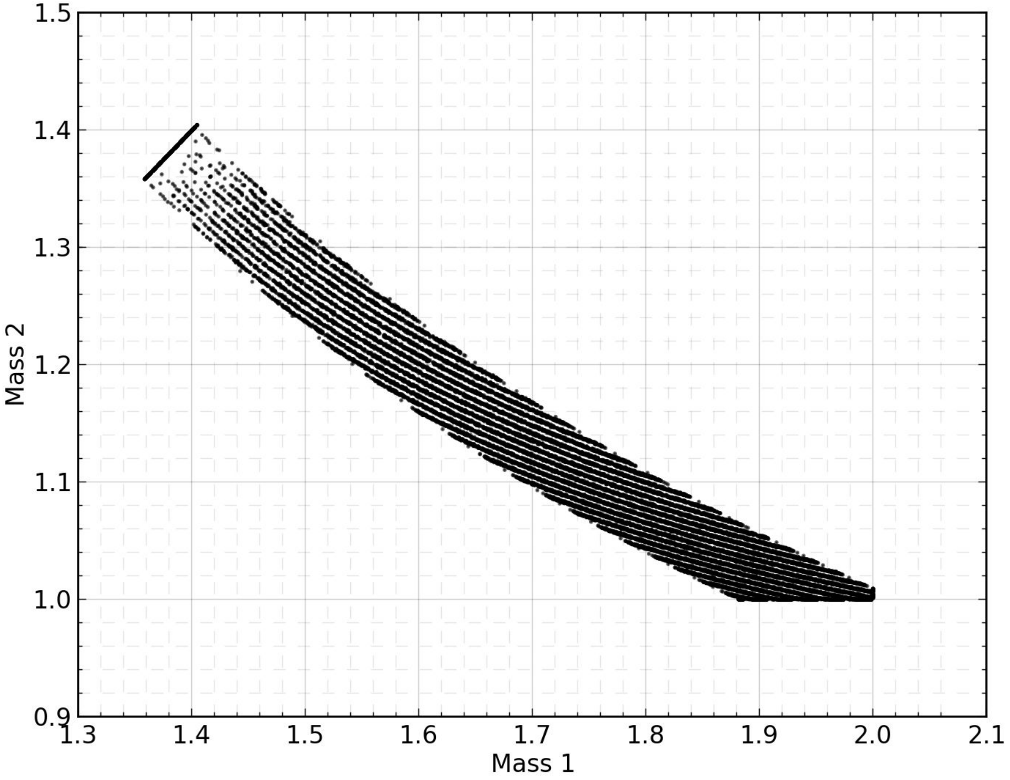
- Our prior contains broad parts of the parameter space that induce negligible change to the gravitational wave phase, possibly inflating the Bayes factor.
- Can we do better? Can we tell *measurable* nonlinear tides apart from *non-measurable* nonlinear tides.

Measurable Nonlinear Tides

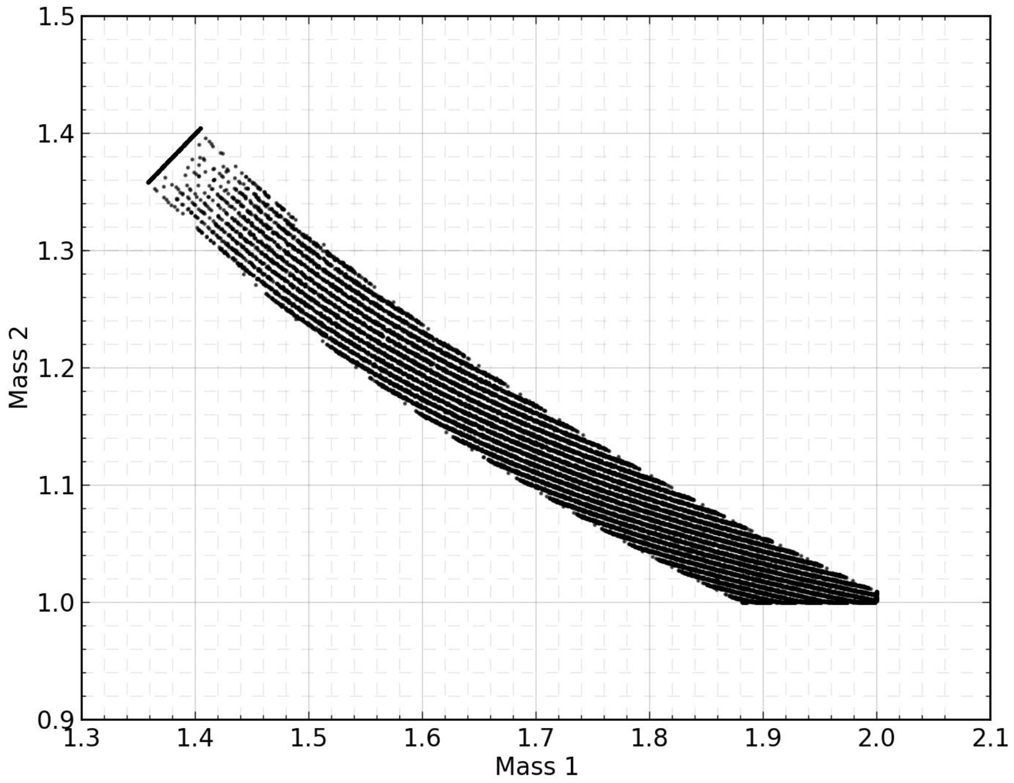
- Construct a big bank of standard-waveform gravitational wave templates.
- Filter the results of our nonlinear tidal analysis and calculate the maximal match of our parameter estimation to this bank. This is called the fitting factor.



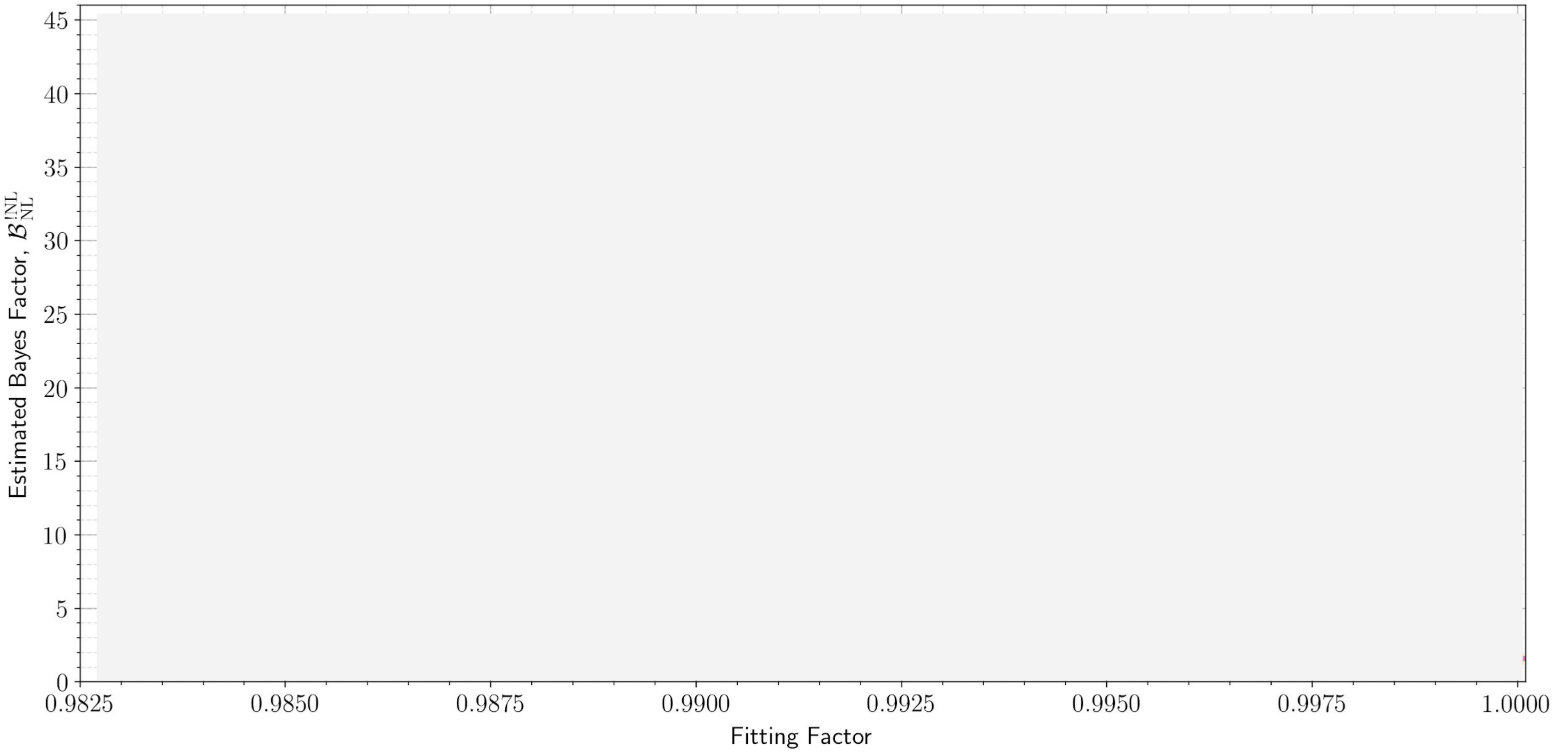
Measurable Nonlinear Tides

- Recalculate the Bayes factor as a function of the fitting factor.

- This lets us calculate the Bayes factor based on how closely the waveforms match a standard waveform.



The Bayes Factor vs Fitting Factor



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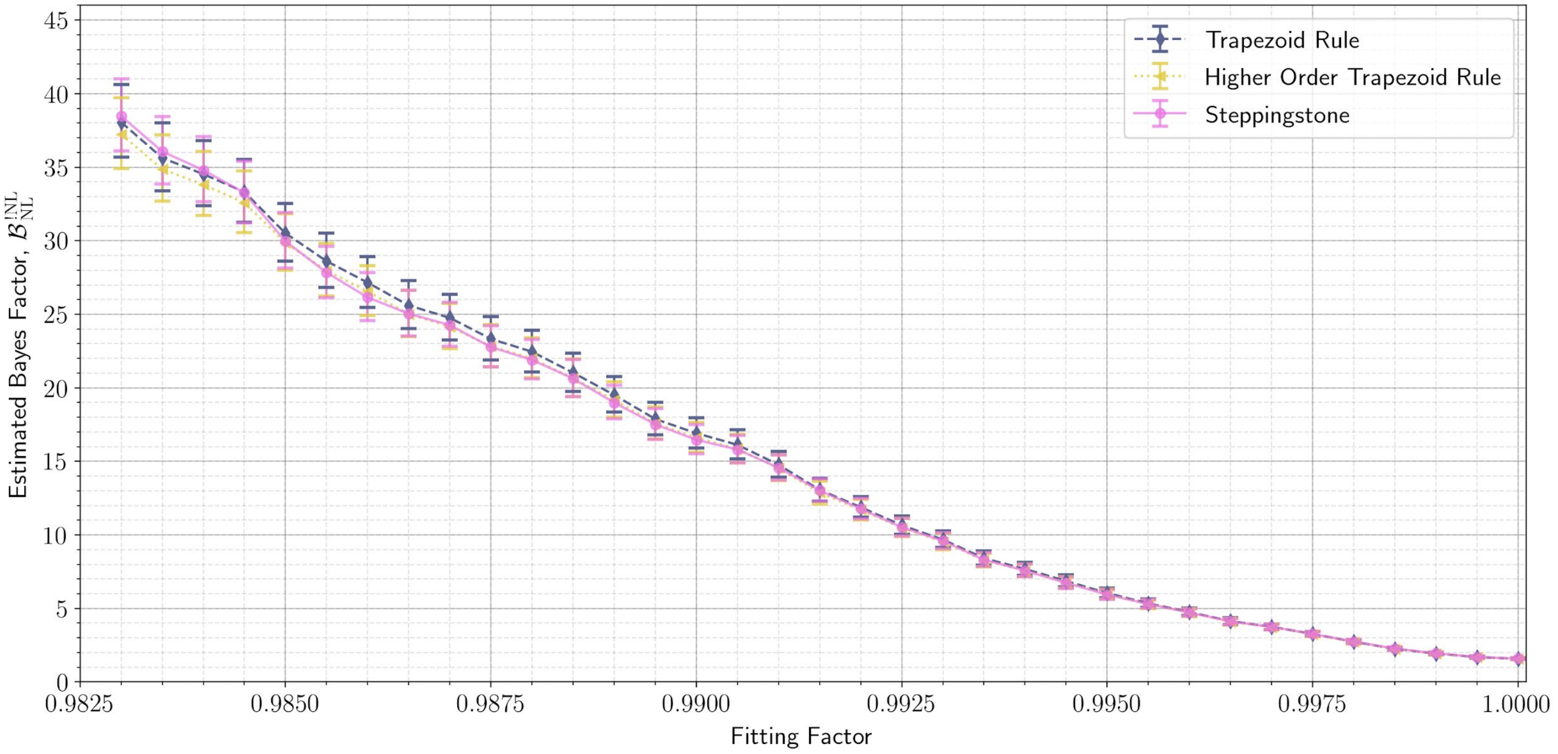

Difficulties for Future Studies in Nonlinear Tides

- GW170817 represents a signal with exceptionally large signal to noise ratio. We expect ~97 % of binary neutron star detections will have lower signal to noise ratios.

- We may have to wait for ~100's of events to get a confident hypothesis decision on nonlinear tides.

Conclusion

- With more gravitational wave events we will be able to gather enough data to constrain hypotheses and learn more about compact binaries.

- Increased sensitivity and new gravitational wave detectors will only help us gather more data.

- Nonetheless we still have to think hard about waveform systematics.

References

- De, S., Finstad, D., Lattimer, J.M., et al. 2018, Phys. Rev. Lett., 121, 091102
- Essick, R., Vitale, S., Weinberg, N. 2016, Phys. Rev., D94, 103012
- Essick, R., Weinberg, N., arxiv:1809.00264 [astro-ph.HE]
- Reyes, S., Brown, D., 2018, arXiv:1808.07013 [astro-ph.HE]
- Weinberg, N., Arras, P., Burkart, J. 2013, Astrophys. J., 769, 121
- Weinberg, N. N. 2016. The Astrophysical Journal, 819(2), 109

Acknowledgments

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- Steven Reyes is supported by National Science Foundation grant PHY1707954.

- This research made use of data provided by the Gravitational Wave Open Science Center.

- Thanks to my committee and all of the folks who helped me get this far.

Questions?

Extra Slides

Parameter Estimation for Gravitational Waves

- We know exactly how to look for gravitational waves. The matched-filter is the optimal linear filter for maximizing our signal to noise ratio in additive Gaussian noise.

$$\boxed{n(t) = d(t) - s(t)}$$

- Construct a log likelihood that assumes that after subtracting the signal from the data that we are left with Gaussian noise.

$$\ln \mathcal{L}(\mathbf{d} \,|\, \vec{\theta}, \mathrm{H}) \propto -\frac{1}{2} \Big\langle \underbrace{\tilde{d}(f) - \tilde{s}(f; \vec{\theta}), \;\; \tilde{d}(f) - \tilde{s}(f; \vec{\theta})}_{\text{Noise Weighted Inner Product}} \Big\rangle$$

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From Parameter Estimation to Hypothesis Testing

- Bayes theorem provides a method for weighing the evidence between two competing hypotheses.

- Can be thought of as the average-likelihood across the prior distribution.

$$\mathcal{Z}(d \,|\, \mathrm{H_A}) = \frac{\int \pi(\vec{\theta} \,|\, \mathrm{H_A})\, \mathcal{L}(d \,|\, \vec{\theta}, \mathrm{H_A}) d\vec{\theta}}{\int \pi(\vec{\theta} \,|\, \mathrm{H_A}) d\vec{\theta}}$$

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Bayesian Hypothesis Testing: Methodology

- Estimating the evidence is challenging.

- We could use an arithmetic mean estimator, sample from the prior distribution via Monte Carlo procedure and find the average likelihood.

- But this is too slow, has a high-variance and bias.

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- Instead we use a simulated annealing procedure where we use multiple temperatures in the stochastic sampling to slowly drag a Markov-Chain Monte Carlo sampler from the prior distribution to the posterior distribution.

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- Instead we use a simulated annealing procedure where we use multiple temperatures in the stochastic sampling to slowly drag a Markov-Chain Monte Carlo sampler from the prior distribution to the posterior distribution.

- Sounds complicated, but multi-tempered samplers do exist. Requires lots of computational power, but we can parallelize the process.

  Provides accurate estimation.

  Known as the thermodynamic integration through power-posteriors.

Thermodynamic Integration for Bayes Factors

- Ordinarily our posterior distribution is defined as:

$$\mathcal{P}(\vec{\theta}\,|\,\mathbf{d}, \mathrm{H}) \propto \pi(\vec{\theta}\,|\,\mathrm{H})\,\mathcal{L}(\mathbf{d}\,|\,\vec{\theta}, \mathrm{H})$$

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- Consider a "power-posterior" defined as:

$$\mathcal{P}_\beta(\vec{\theta}\,|\,\mathbf{d},\mathrm{H}) \propto \pi(\vec{\theta}\,|\,\mathrm{H})\,\mathcal{L}^\beta(\mathbf{d}\,|\,\vec{\theta},\mathrm{H})$$

for inverse-temperatures, β between 0 and 1.

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for inverse-temperatures, β between 0 and 1.

- When $\beta = 0$, we sample from the prior. When $\beta = 1$, we sample from the posterior. By sampling between 0 and 1, we can sample efficiently across the entire space.

Thermodynamic Integration for Bayes Factors

- Through a bit of algebra and some calculus we can solve for the log evidence for our original problem:

$$\ln \mathcal{Z}(\mathbf{d}\,|\,\mathrm{H}) = \int_0^1 \langle \ln\, \mathcal{L} \rangle_{\mathcal{P}_\beta(\vec{\theta}\,|\mathbf{d})} d\beta$$

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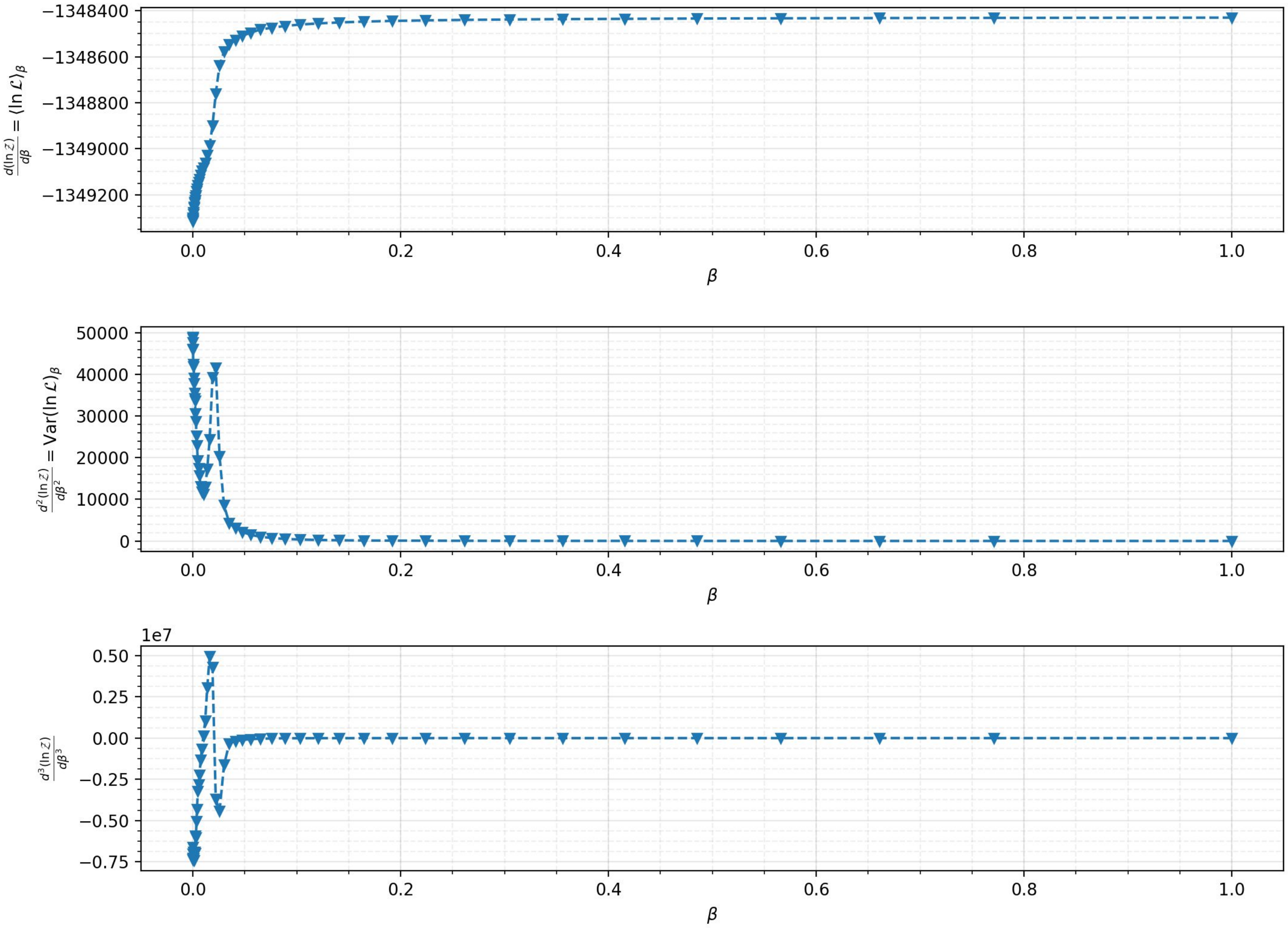
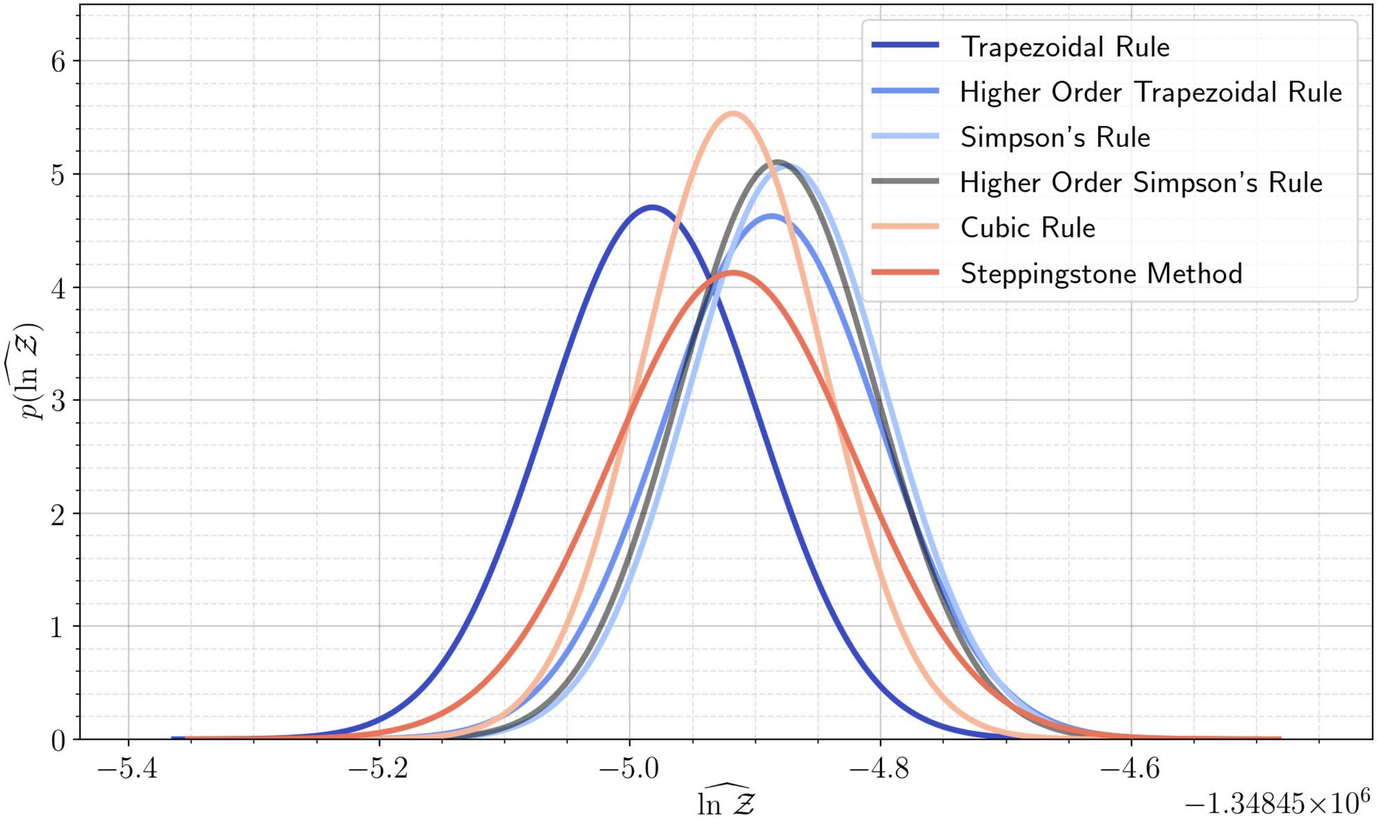
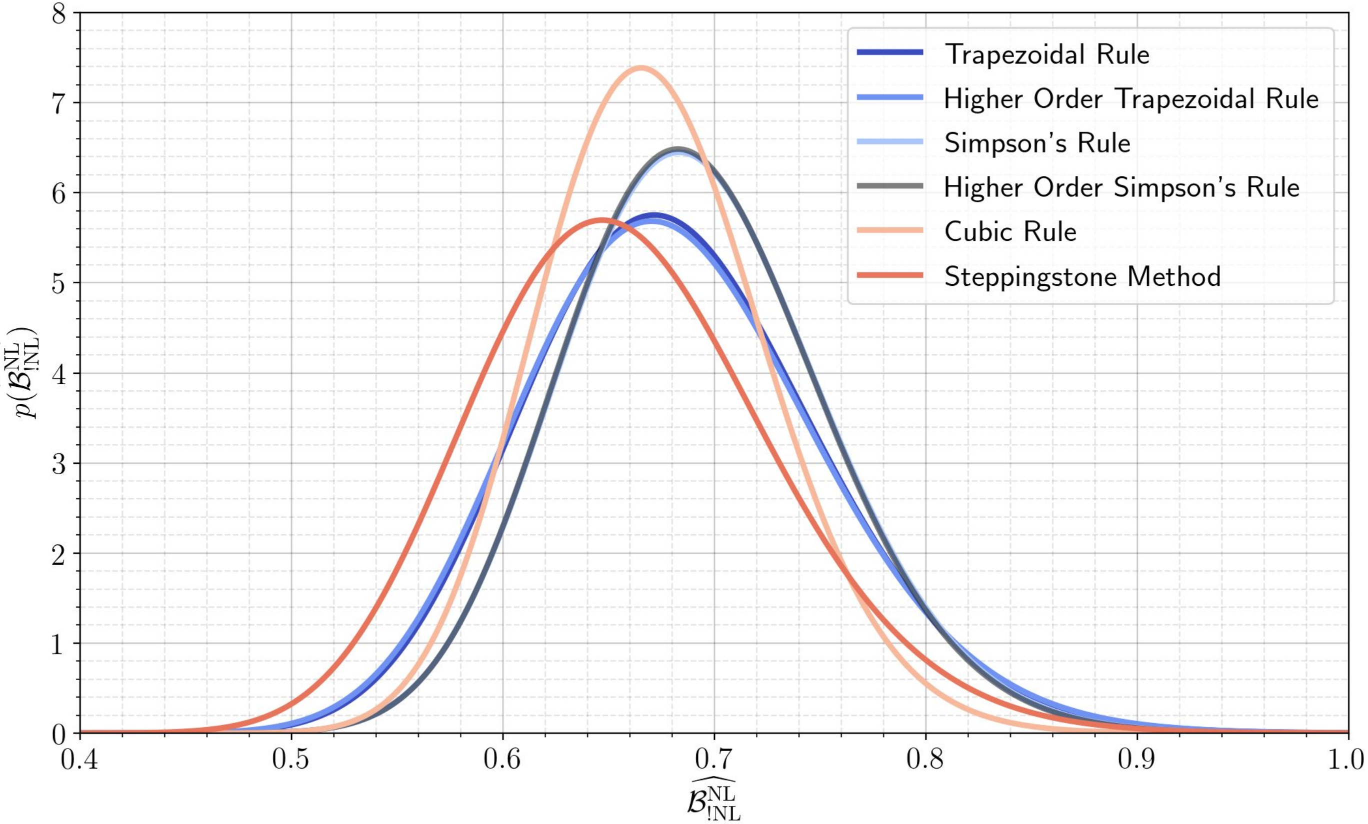
Inspecting the thermodynamic integrand


$\frac{d(\ln Z)}{d\beta} = \langle \ln \mathcal{L} \rangle_\beta$
−1348400
−1348600
−1348800
−1349000
−1349200
0.0
0.2
0.4
0.6
0.8
1.0
β
$\frac{d^2(\ln Z)}{d\beta^2} = \mathrm{Var}(\ln \mathcal{L})_\beta$
50000
40000
30000
20000
10000
0
0.0
0.2
0.4
0.6
0.8
1.0
β
1e7
$\frac{d^3(\ln Z)}{d\beta^3}$
0.50
0.25
0.00
−0.25
−0.50
−0.75
0.0
0.2
0.4
0.6
0.8
1.0
β

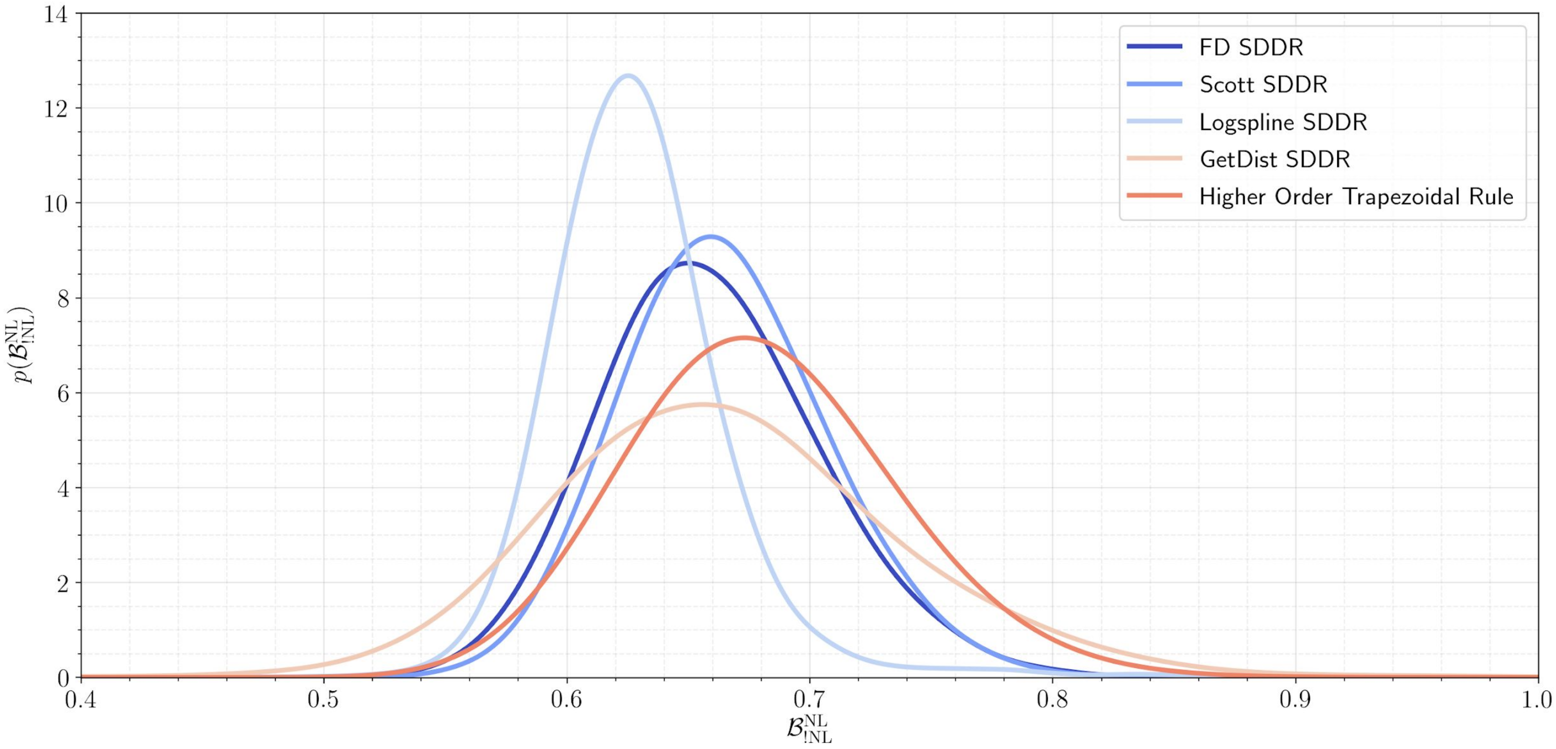
Thermodynamic Integration Evidence Estimation



Thermodynamic Integration Bayes Factors

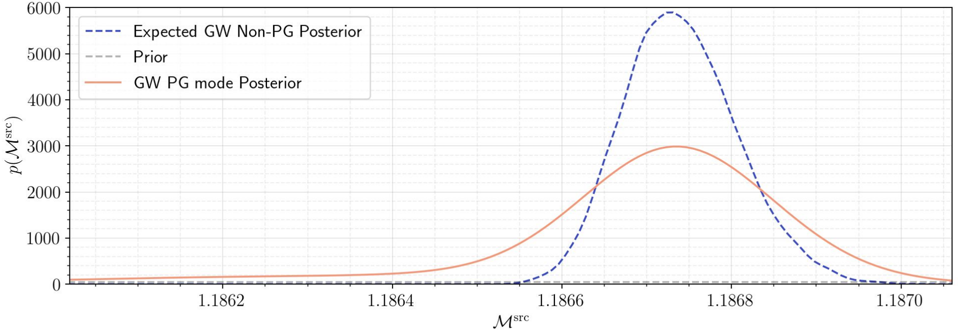


Savage Dickey Density Ratio Bayes Factors



Parameter Inference for Nonlinear Tidal Effects

- We also find a major degeneracy with the nonlinear tidal waveform that entangles it with the chirp mass!



From a chapter in my dissertation.
Data from Reyes & Brown (2018), De et al (2018)

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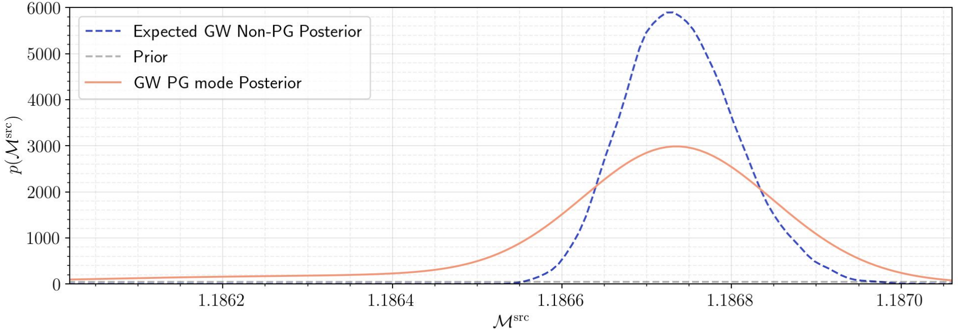

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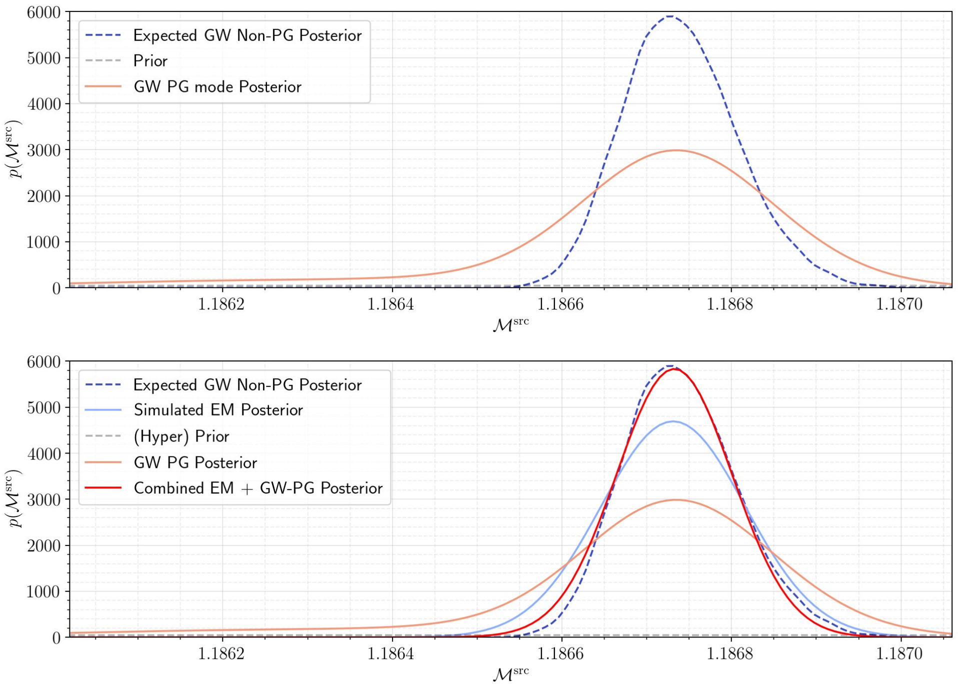

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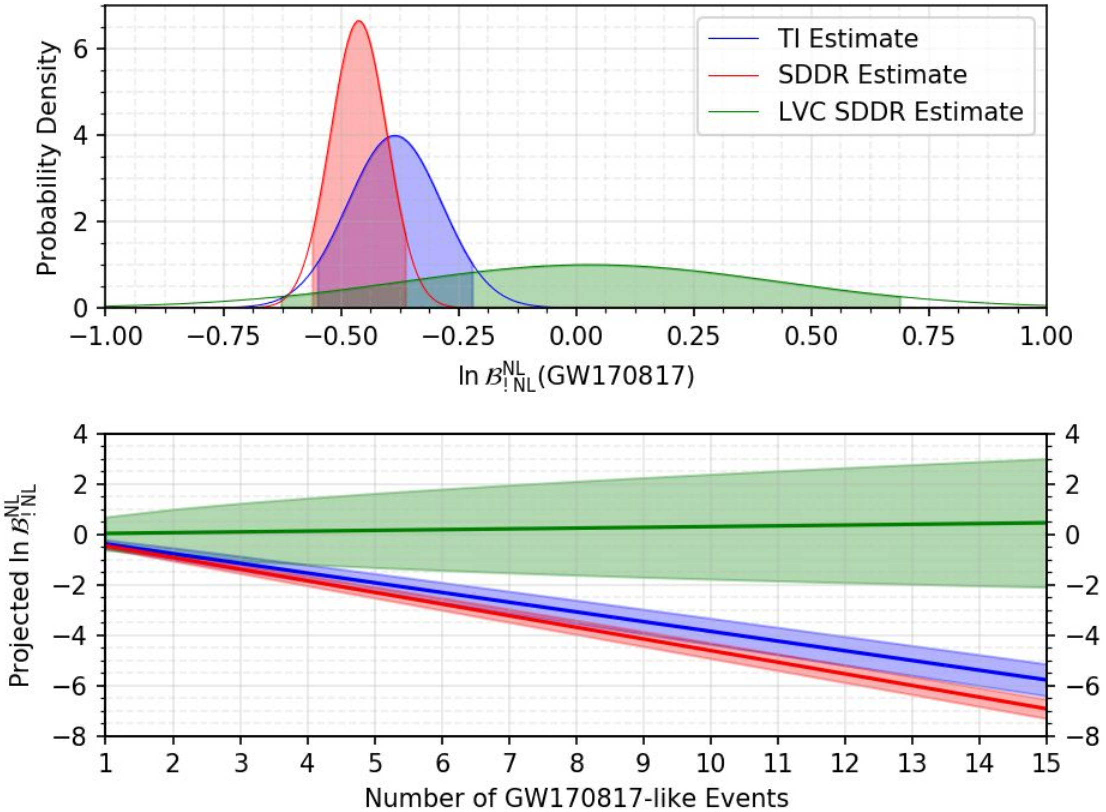
Nonlinear Tides in the Long Term



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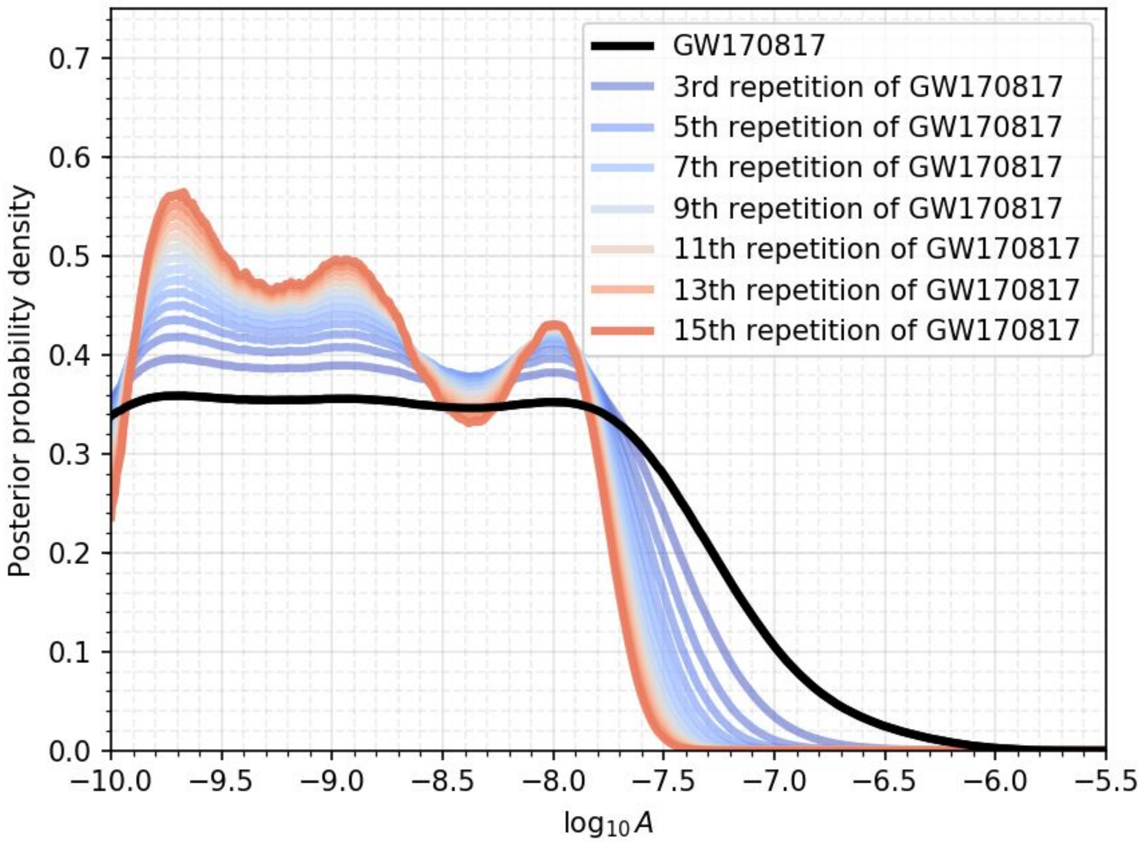
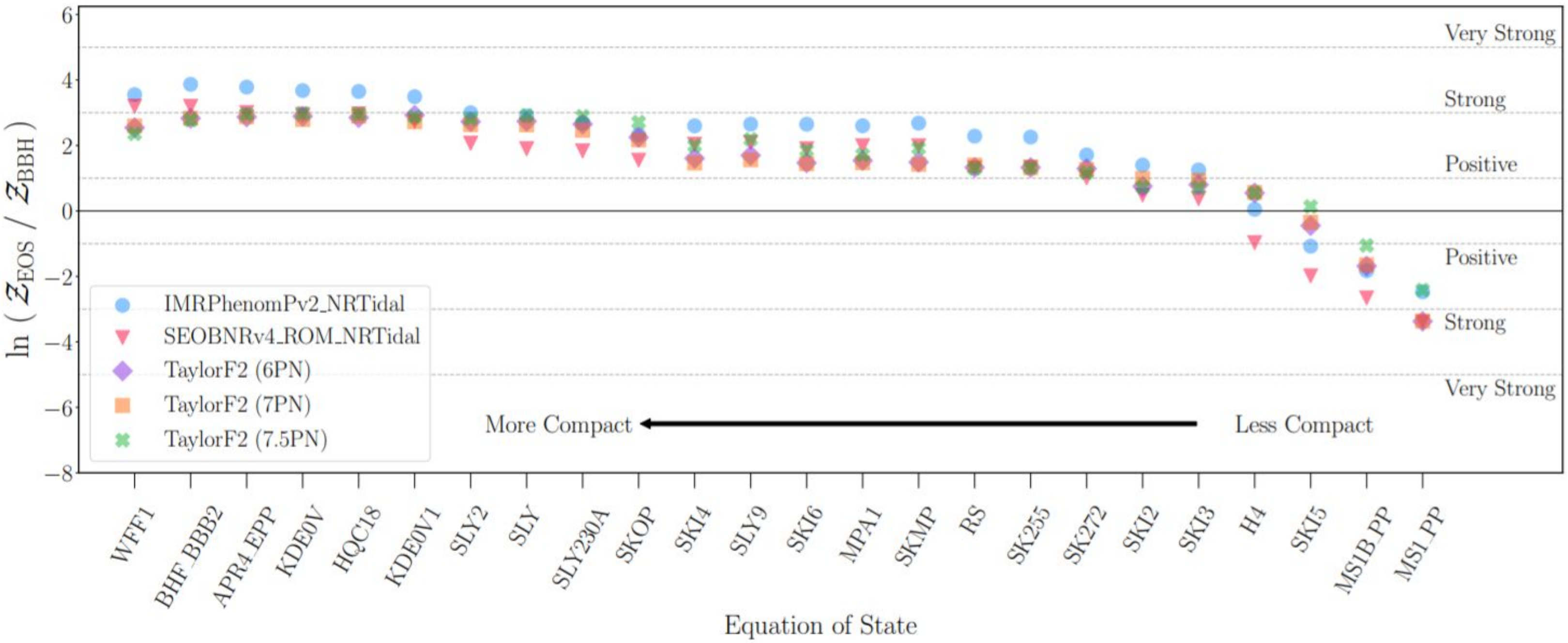


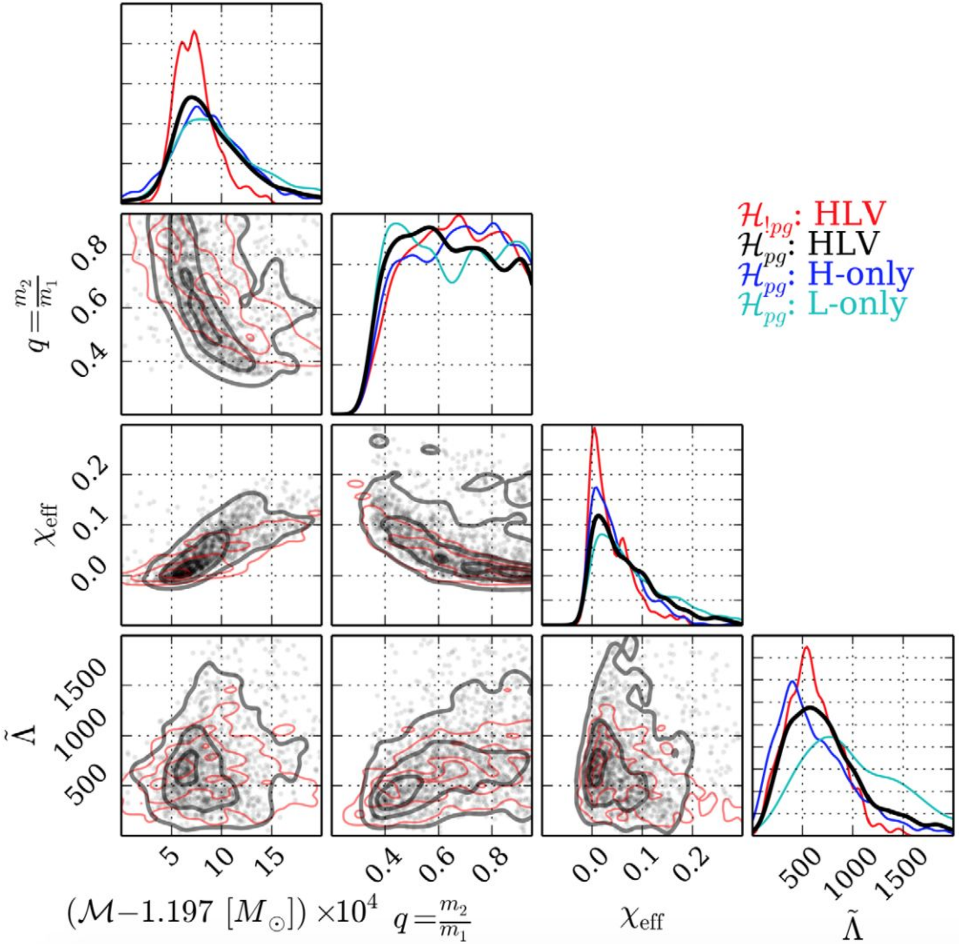
Waveform Systematics are Important

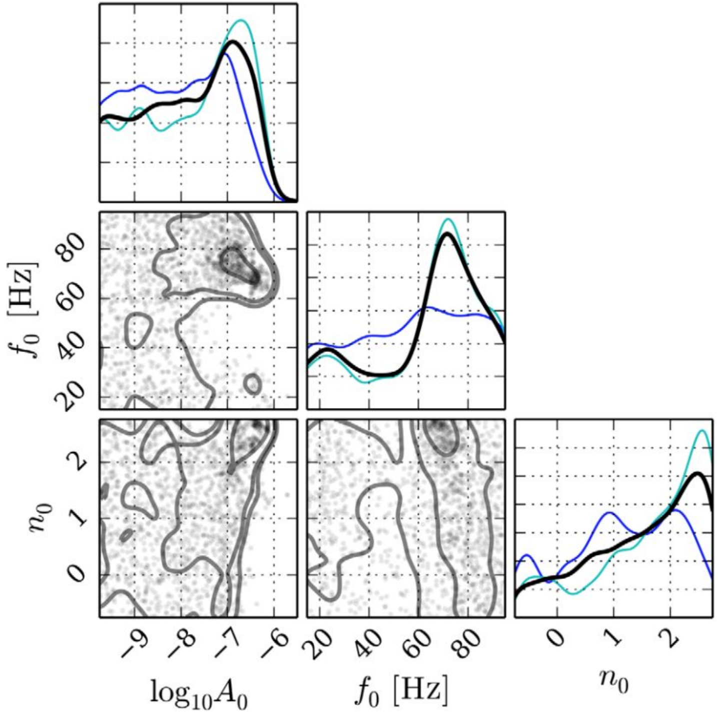


From LVC 2019 “Model comparison from LIGO-Virgo data on GW170817’s binary components and consequences for the merger remnant”

LVC PG Modes

From LVC 2019 “Constraining the p-Mode–g-Mode Tidal Instability with GW170817”





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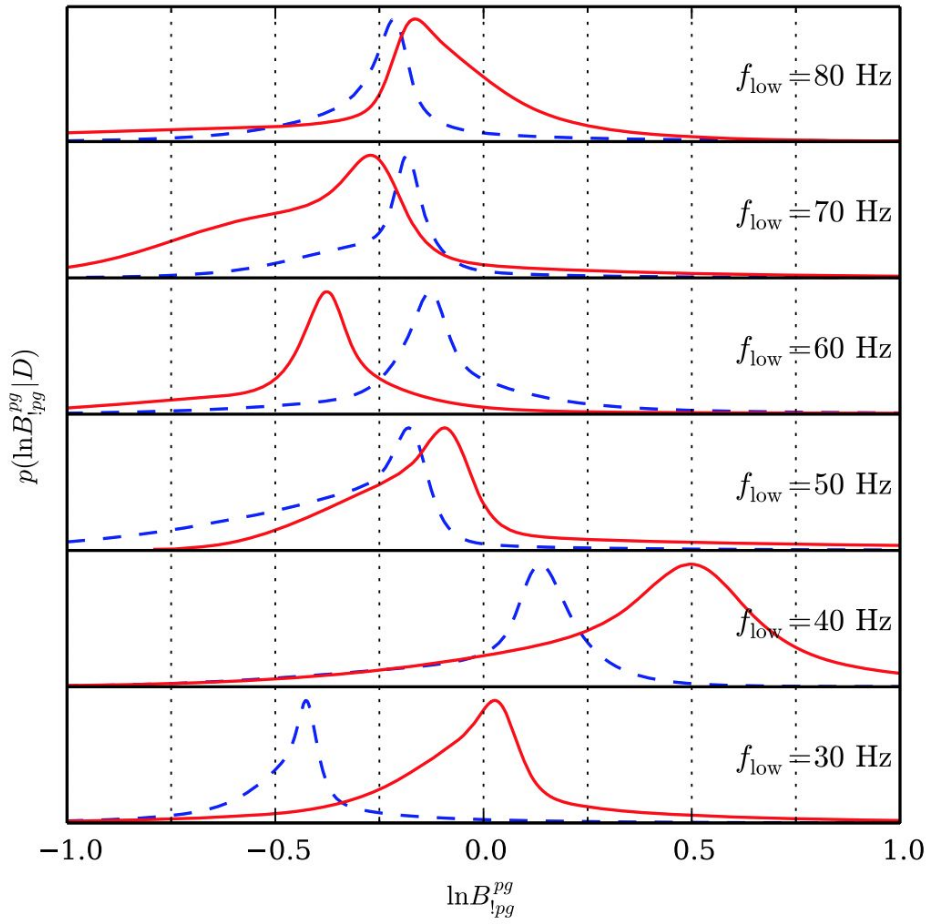

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