Encoding neutron star information into neural priors for gravitational wave analyses

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Key idea

- GW parameter estimation:

$$\mathcal{P}(\theta_{\mathrm{GW}}|d) \propto \mathcal{L}(d|\theta_{\mathrm{GW}})\pi(\theta_{\mathrm{GW}})$$
$$\text{posterior} \propto \text{likelihood} \times \text{prior}$$

- By default, we choose agnostic prior (e.g., uniform)

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$$\text{posterior} \propto \text{likelihood} \times \text{prior}$$

- By default, we choose agnostic prior (e.g., uniform)

- What if we ***do*** have non-trivial prior information? E.g. population, independent observations,...

Neural priors

Flexible way to incorporate any prior information into GW parameter estimation.

Key idea

1. Get predictions for GW parameters (populations, physics,...)
2. Gives a dataset of samples

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   - Generative machine learning model
   - Normalized
   - Generate samples, evaluate density
   - Accurate in high dimensions
4. `NFPrior` in BILBY: easy to use in GW parameter estimation

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Case study

Apply this to information from neutron stars

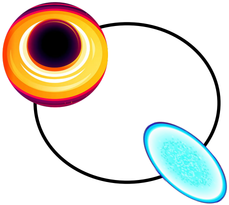
(Do you have a use case? Let's talk!)

Contents

Tidal deformability

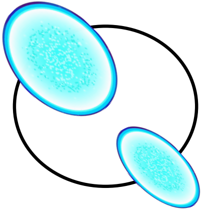
- Neutron stars are tidally deformed in a binary
- Quantified by tidal deformability Λ
- Depends on equation of state (EOS)
- Neutron stars: $\Lambda = \Lambda(m, \mathrm{EOS})$, black holes: $\Lambda = 0$

$\Lambda_1 = 0$



$\Lambda(m_2, \mathrm{EOS})$

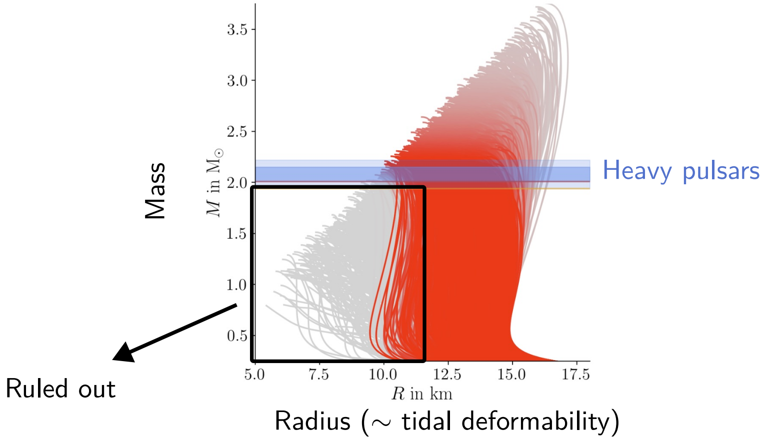
$\Lambda(m_1, \mathrm{EOS})$



$\Lambda(m_2, \mathrm{EOS})$

Tidal deformability

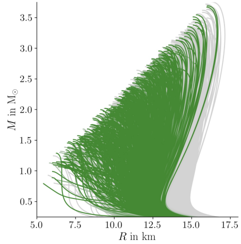
- **Heavy pulsars**: must support $2\,M_\odot$ neutron stars



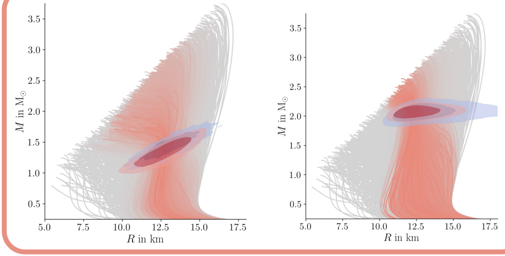
Tidal deformability

- **Heavy pulsars**: must support 2 $M_\odot$ neutron stars
- **Chiral EFT**: nuclear theory predictions
- **NICER**: mass-radius observations of neutron stars

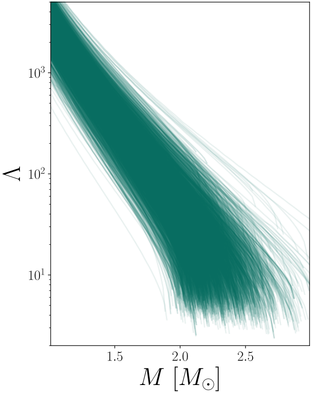
Chiral EFT

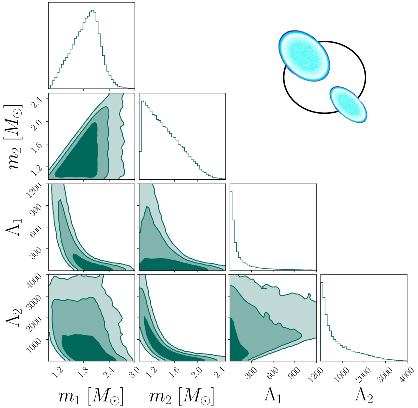


NICER



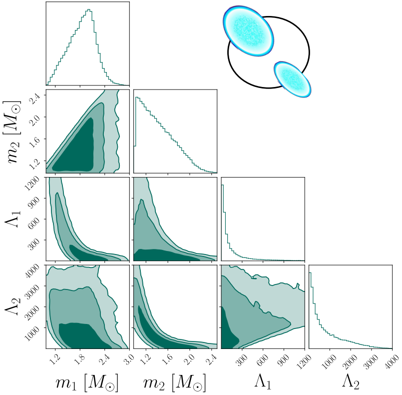
- Example: uniform population, $M_{\max} > 2.0 M_\odot$
- Generate samples: $\pi(m_1, m_2, \Lambda_1, \Lambda_2)$
- Emulate with normalizing flow: **neural prior**

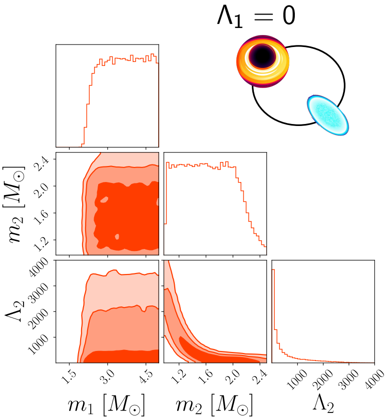




Source classification

- Also construct a **neutron star-black hole (NSBH)** prior
- Comparisons: Bayesian model selection





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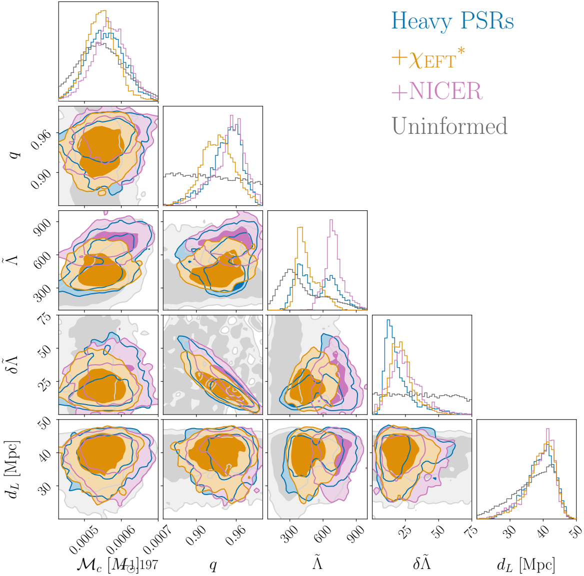
GW170817, Gaussian population



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Conclusion

- Parameter estimation often uses agnostic priors
- To incorporate non-trivial prior information, we need a way to make the distributions tractable
-

Let's talk!

Thanks for listening!

References I

[1] Kurzgesagt. *Figures taken from "Neutron Stars - The Most Extreme Things that are not Black Holes"*. Accessed on May 14, 2025. 2019. URL: https://www.youtube.com/watch?v=udFxKZRyQt4.

[2] Hergé. *Cover figure created with ChatGPT using this input figure from the comic Destination Moon*. Accessed on May 14, 2025. 2019. URL: https://www.youtube.com/watch?v=udFxKZRyQt4.

GW170817 – classification

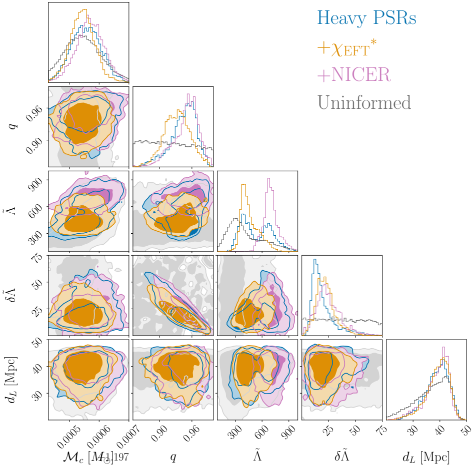
Showing $\log_{10}$ Bayes factors: negative = less preferred

- Strongly prefer BNS over NSBH
- Gaussian population, EOS inconclusive

Source	**Population**	**EOS Constraints**	**GW170817**
BNS	Uniform	Radio	-0.76
		$+\chi_{\mathrm{EFT}}$	-0.52
		+NICER	-0.86
	Gaussian	Radio	-0.14
		$+\chi_{\mathrm{EFT}}$	**ref.**
		+NICER	-0.05
	Double Gaussian	Radio	-0.43
		$+\chi_{\mathrm{EFT}}$	-0.26
		+NICER	-0.73
NSBH	Uniform	Radio	-224.11
		$+\chi_{\mathrm{EFT}}$	-224.11
		+NICER	-224.12
	Gaussian	Radio	-224.13
		$+\chi_{\mathrm{EFT}}$	-224.13
		+NICER	-224.13
	Double Gaussian	Radio	-224.12
		$+\chi_{\mathrm{EFT}}$	-224.13
		+NICER	-224.12

GW170817 – parameter constraints

- More equal mass ratio $q \geq 0.9$
- $\tilde{\Lambda}$ bimodal, resolved by extra EOS information



GW190425 – classification

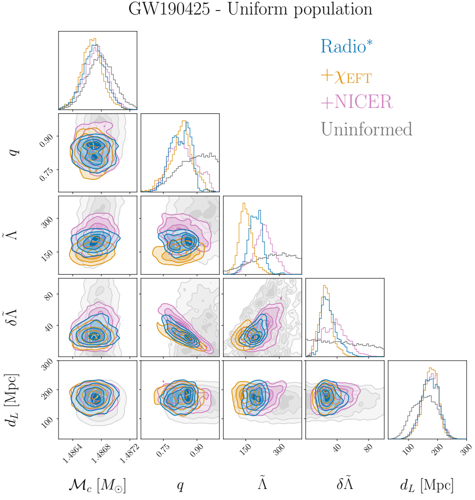
Showing $\log_{10}$ Bayes factors: negative = less preferred

- Prefer BNS over NSBH, but less conclusive
- Most consistent with uniform population

Source	Population	EOS Constraints	GW190425
BNS	Uniform	Radio	**ref.**
		$+\chi_{\rm EFT}$	-0.09
		+NICER	-0.11
	Gaussian	Radio	-8.51
		$+\chi_{\rm EFT}$	-6.57
		+NICER	-4.42
	Double Gaussian	Radio	-0.76
		$+\chi_{\rm EFT}$	-0.56
		+NICER	-0.89
NSBH	Uniform	Radio	-1.10
		$+\chi_{\rm EFT}$	-1.10
		+NICER	-1.19
	Gaussian	Radio	-0.82
		$+\chi_{\rm EFT}$	-1.01
		+NICER	-0.98
	Double Gaussian	Radio	-1.65
		$+\chi_{\rm EFT}$	-3.40
		+NICER	-2.12

GW190425 – parameter constraints

- Less equal masses ($q \leq 0.9$)
- Higher distances



GW230529 – classification

Showing $\log_{10}$ Bayes factors: negative = less preferred

- Decisive evidence for NSBH over BNS
- Weak evidence for population or EOS (low SNR)

Source	**Population**	**EOS Constraints**	**GW230529**
BNS	Uniform	Radio	−13.23
		$+\chi_{\mathrm{EFT}}$	−13.31
		+NICER	−13.23
	Gaussian	Radio	−18.90
		$+\chi_{\mathrm{EFT}}$	−18.86
		+NICER	−18.88
	Double Gaussian	Radio	−13.84
		$+\chi_{\mathrm{EFT}}$	−13.79
		+NICER	−13.98
NSBH	Uniform	Radio	−0.16
		$+\chi_{\mathrm{EFT}}$	−0.28
		+NICER	−0.42
	Gaussian	Radio	−0.28
		$+\chi_{\mathrm{EFT}}$	−0.28
		+NICER	**ref.**
	Double Gaussian	Radio	−0.18
		$+\chi_{\mathrm{EFT}}$	−0.08
		+NICER	−0.06

GW230529 – parameter constraints

- Mass ratio more constrained → χ_{1z} more constrained
- Higher distances