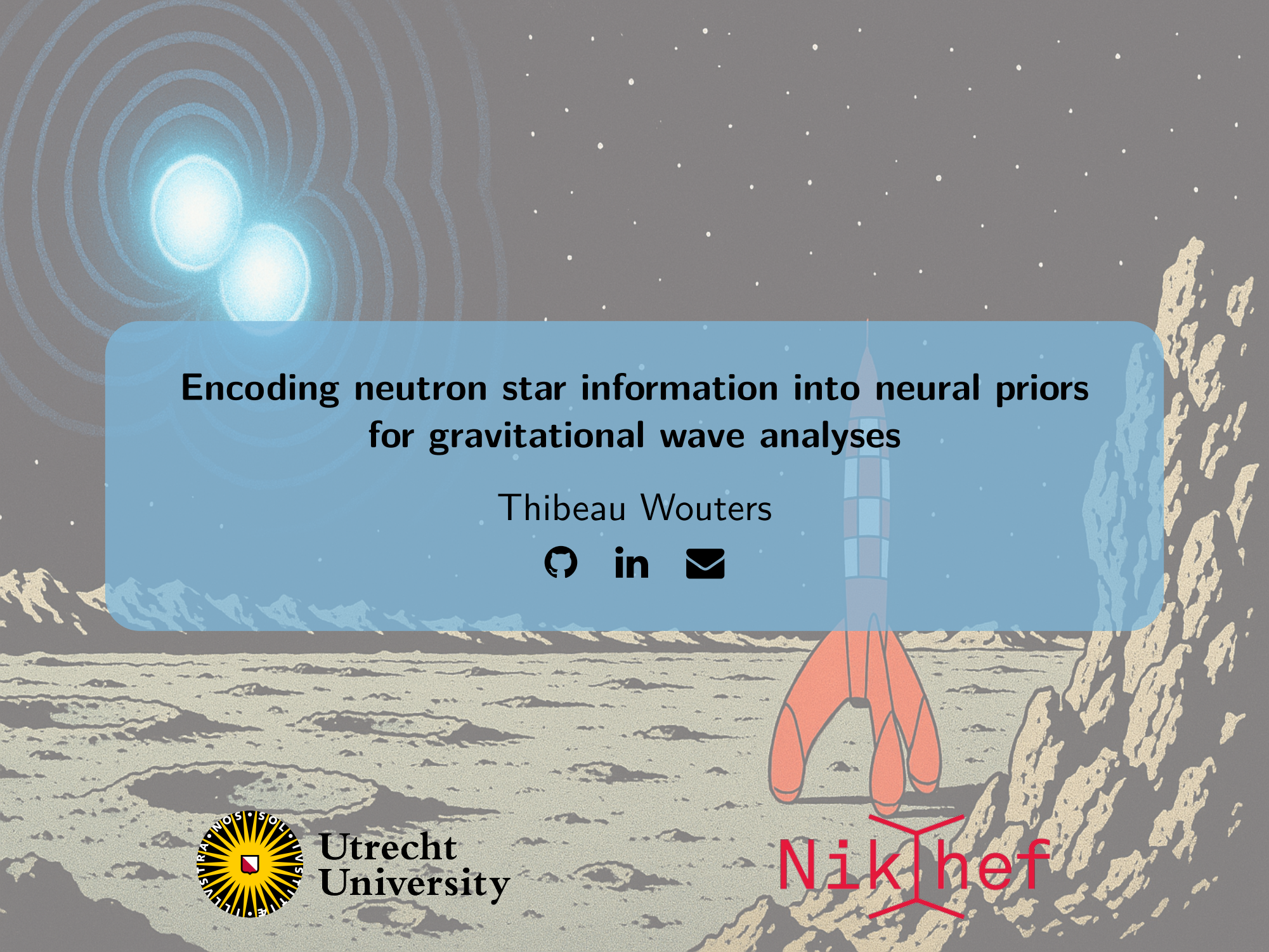

Encoding neutron star information into neural priors for gravitational wave analyses

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Key idea

- GW parameter estimation: Bayesian inference

$$\mathcal{P}(\theta_{\rm GW}|d) \propto \mathcal{L}(d|\theta_{\rm GW})\pi(\theta_{\rm GW})$$

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

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

Key idea

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Neural priors

Flexible way to encode information into priors

Key idea

1. Get predictions for GW parameters (populations, physics,...)
   - Can be an expensive/complicated model
2. Gives a dataset of samples

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   - Generative machine learning model
   - Normalized
   - Generate samples, evaluate density
   - Accurate in high dimensions
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Case study

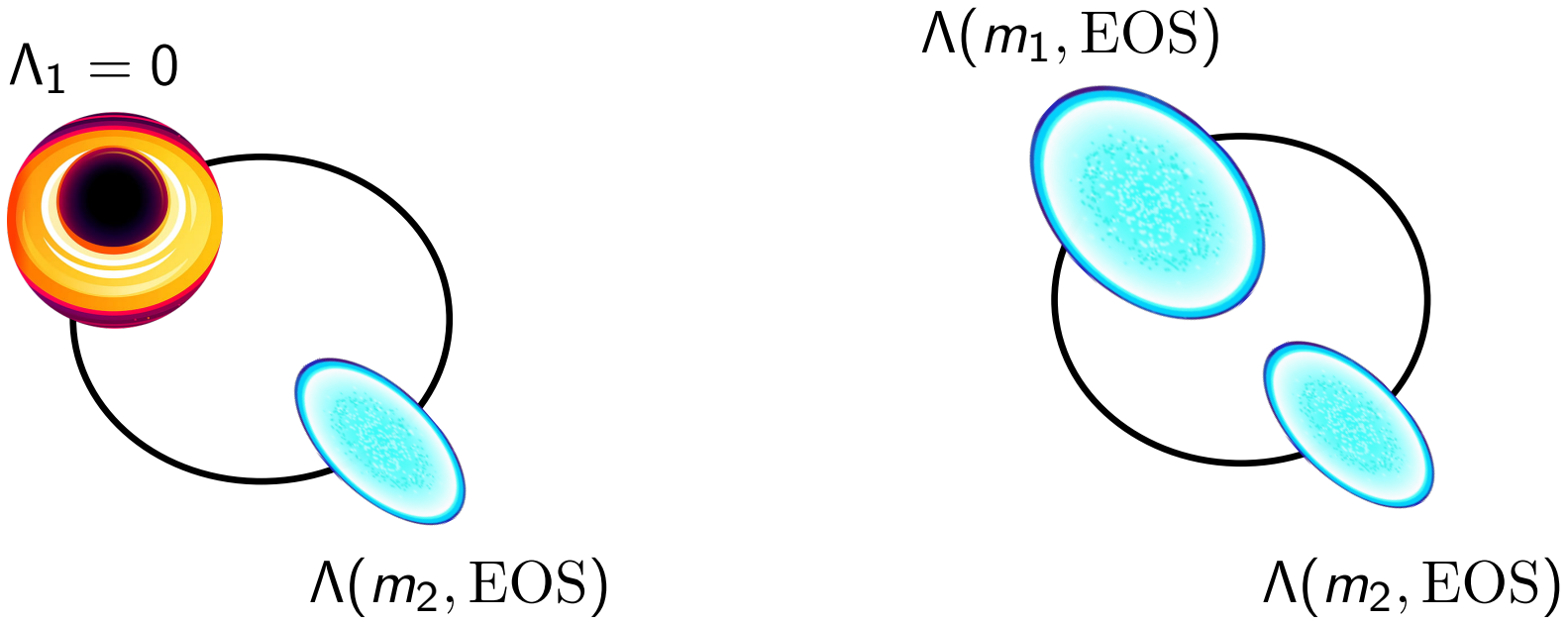
Apply this to neutron stars

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

Contents

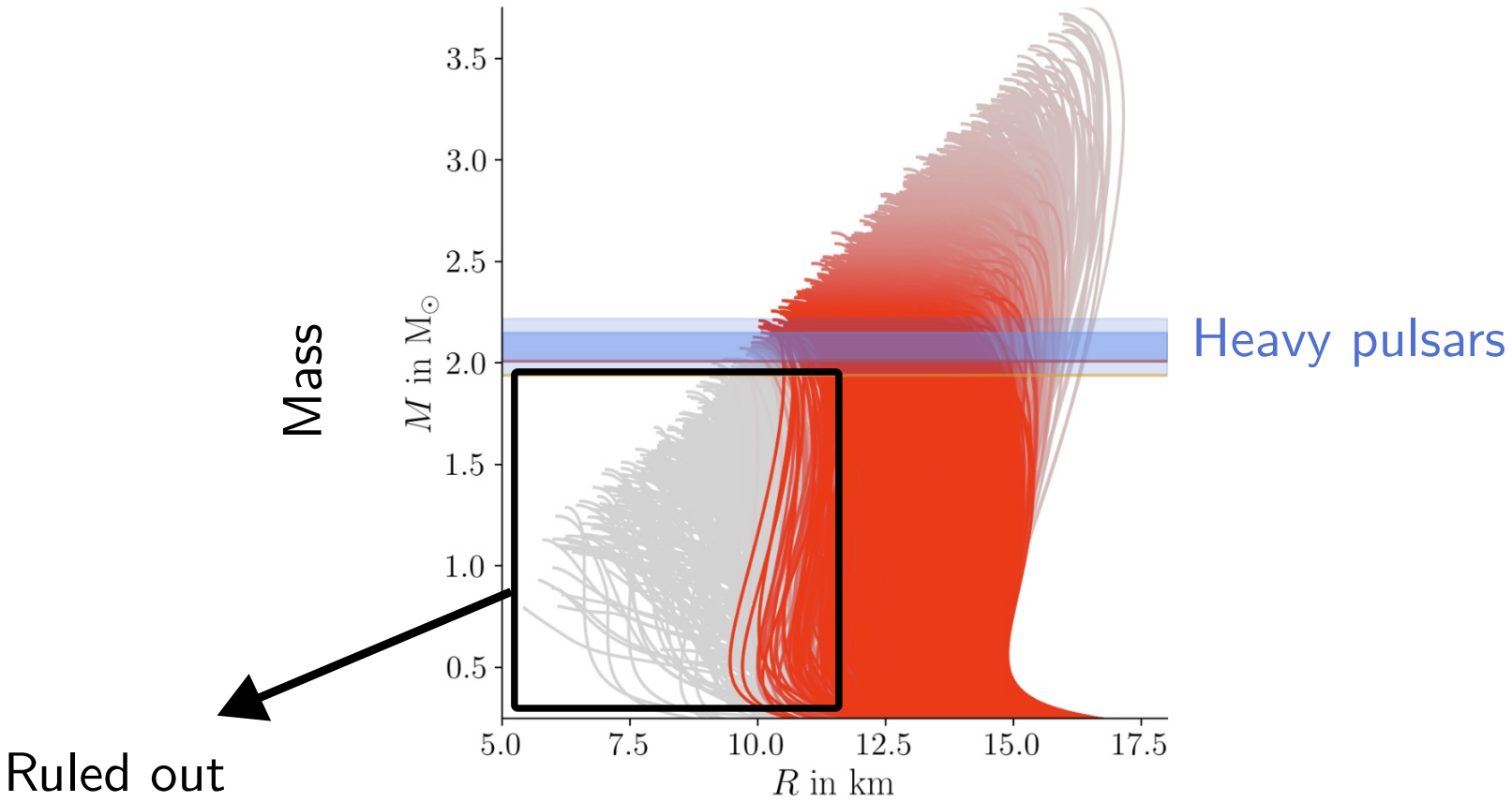
Tidal deformability

- Neutron stars are tidally deformed in a binary
- Quantified by tidal deformability Λ
- Depends on equation of state (EOS): allow for non-trivial prior information



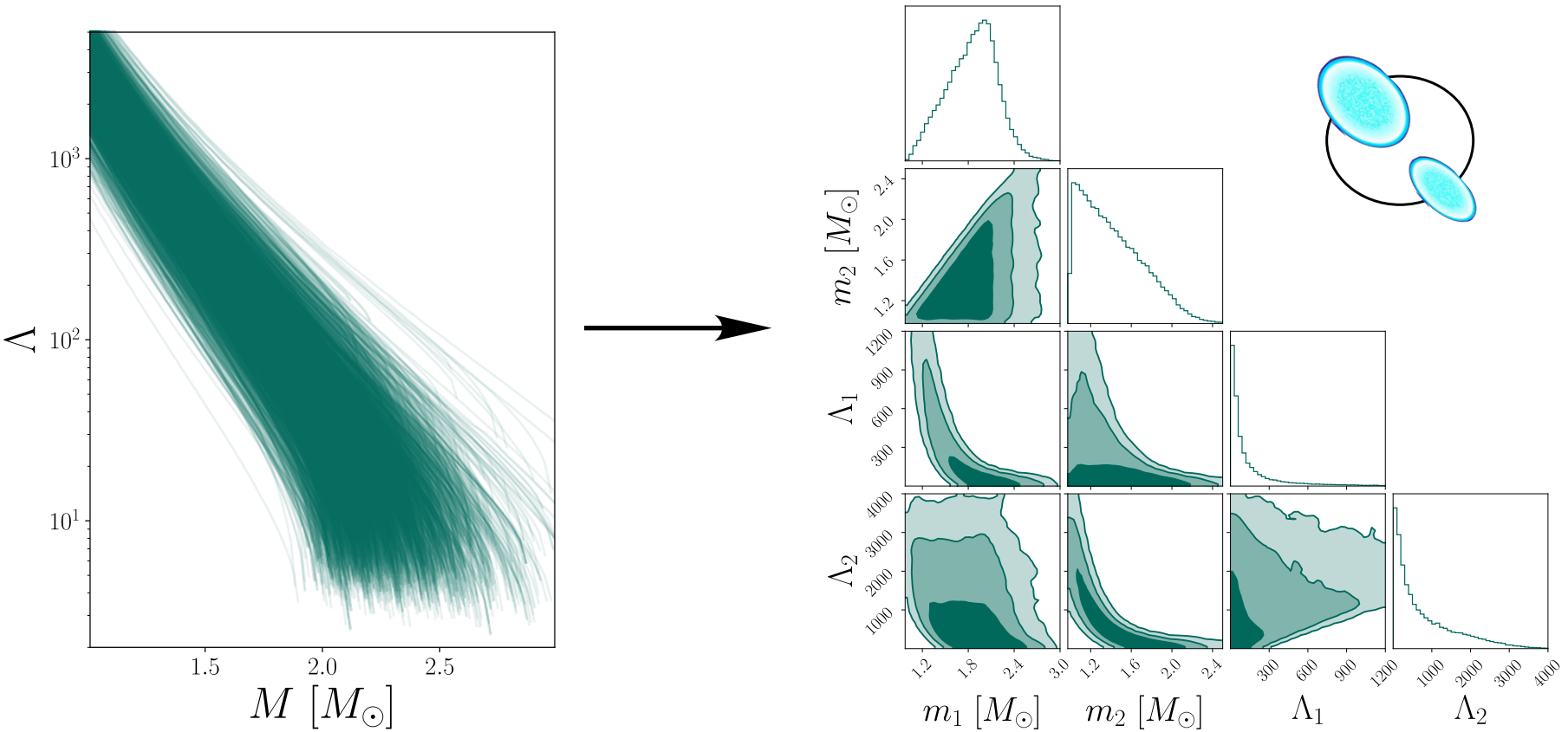
Tidal deformability constraints

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



Neural priors for neutron stars

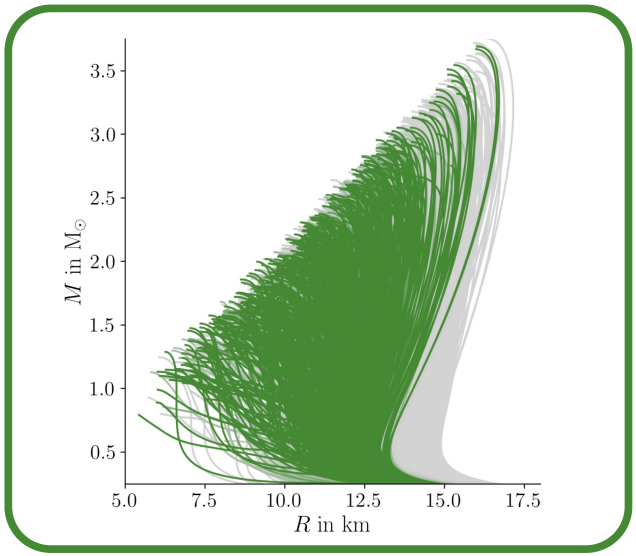
- Example: uniform population & $M_{\max} > 2.0 M_\odot$
- Emulate with normalizing flow: **neural prior**
- Can combine any population & EOS constraints



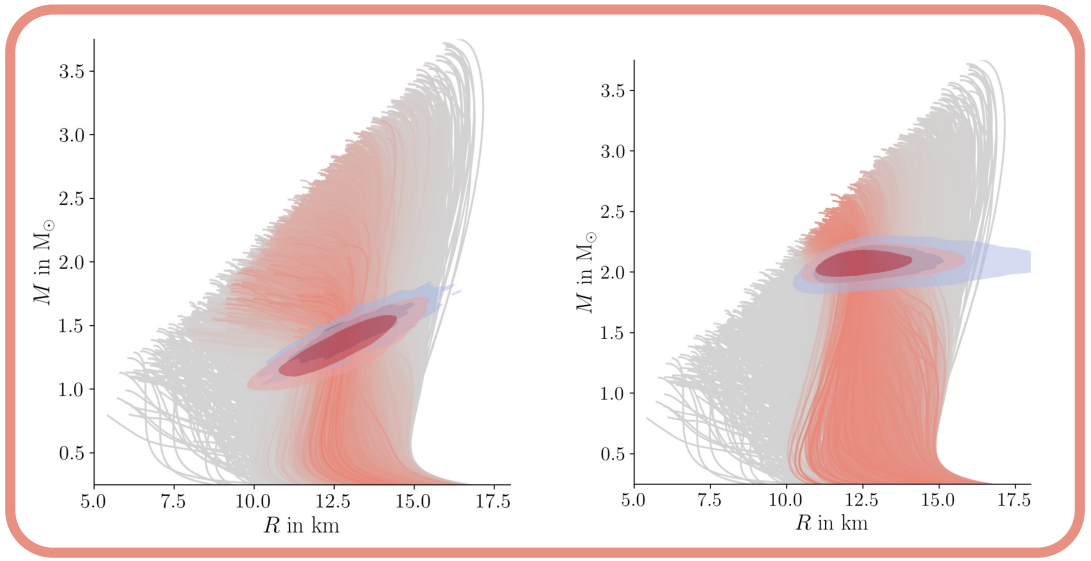
Tidal deformability constraints

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

Chiral EFT

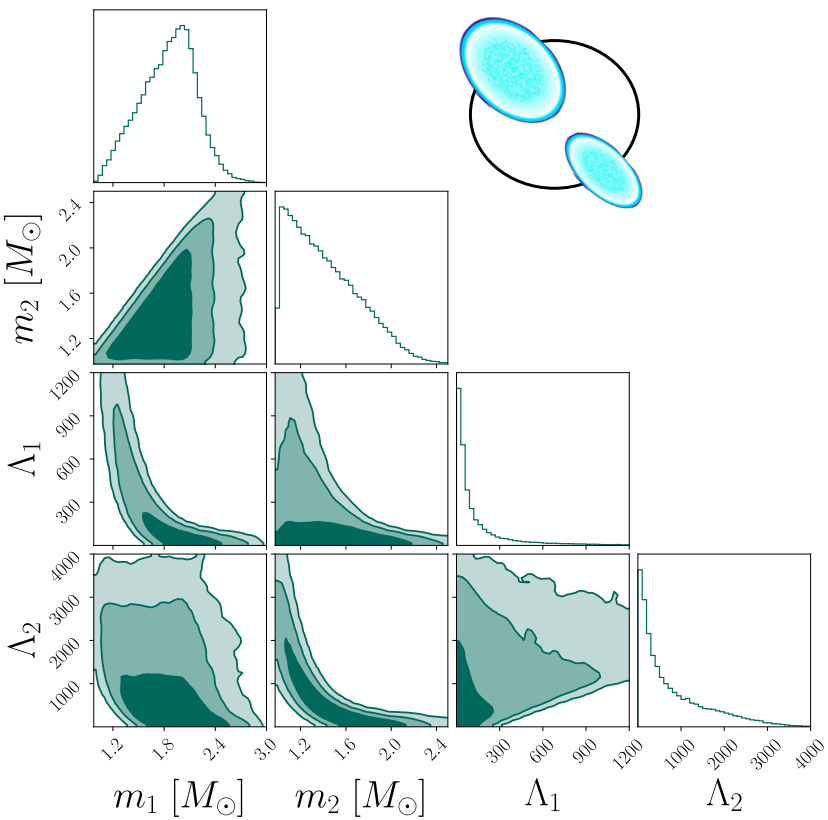


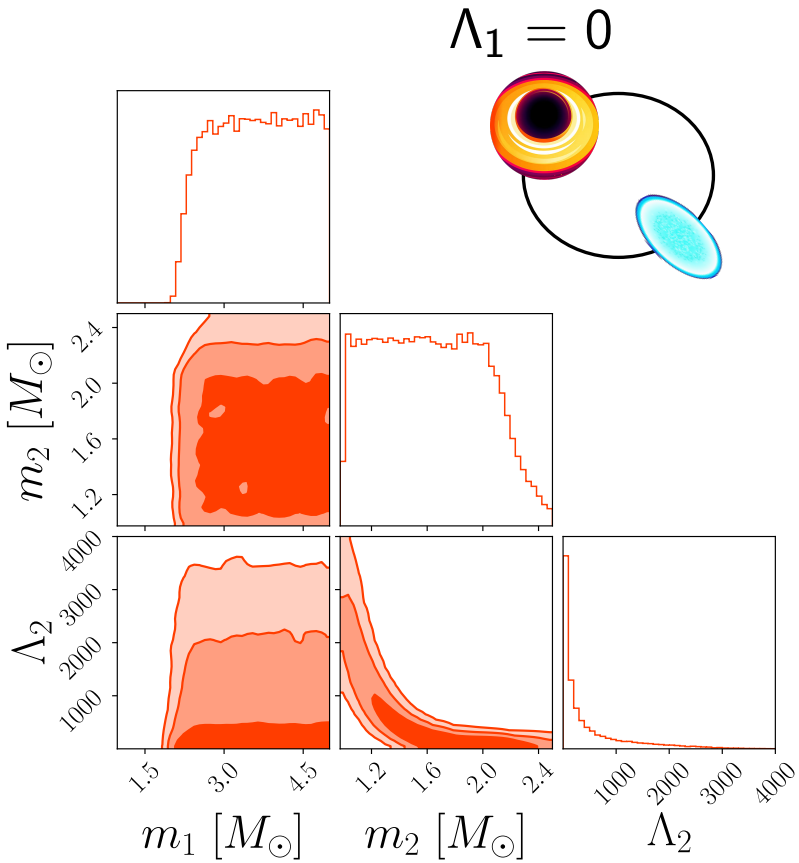
NICER



Source classification

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





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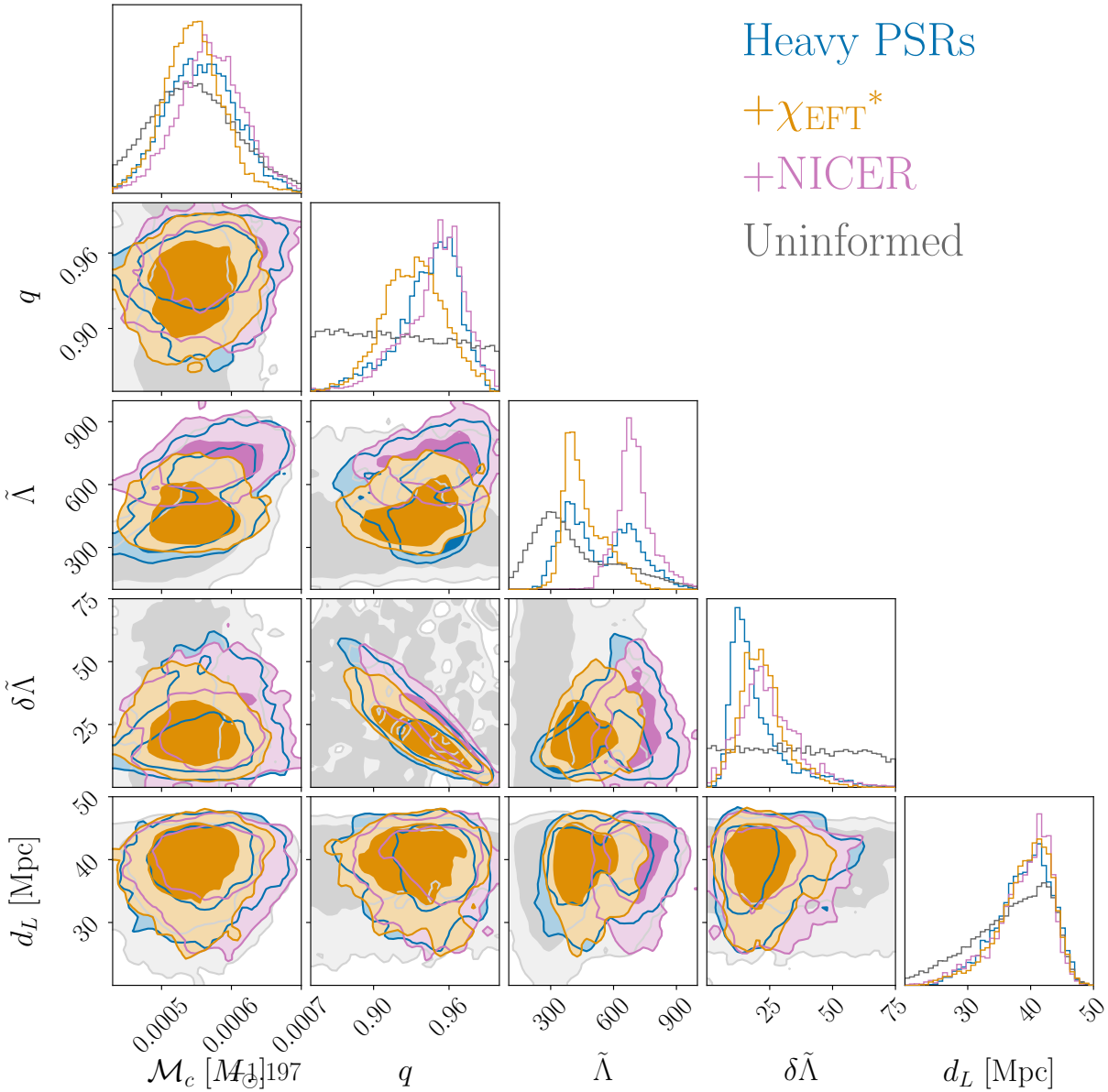
GW170817, Gaussian population



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Conclusion

- Parameter estimation often uses agnostic priors
- **Neural priors**: flexible way to encode prior information
- Proof of concept: neutron stars
  - Bayesian source classification
  - Informed parameter constraints
- **Case study in mind? Let's talk!**
  - More neutron star physics (temperature, ...)?
  - Boson stars?
  - Cosmology?
  - Populations?


Thanks for listening!

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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

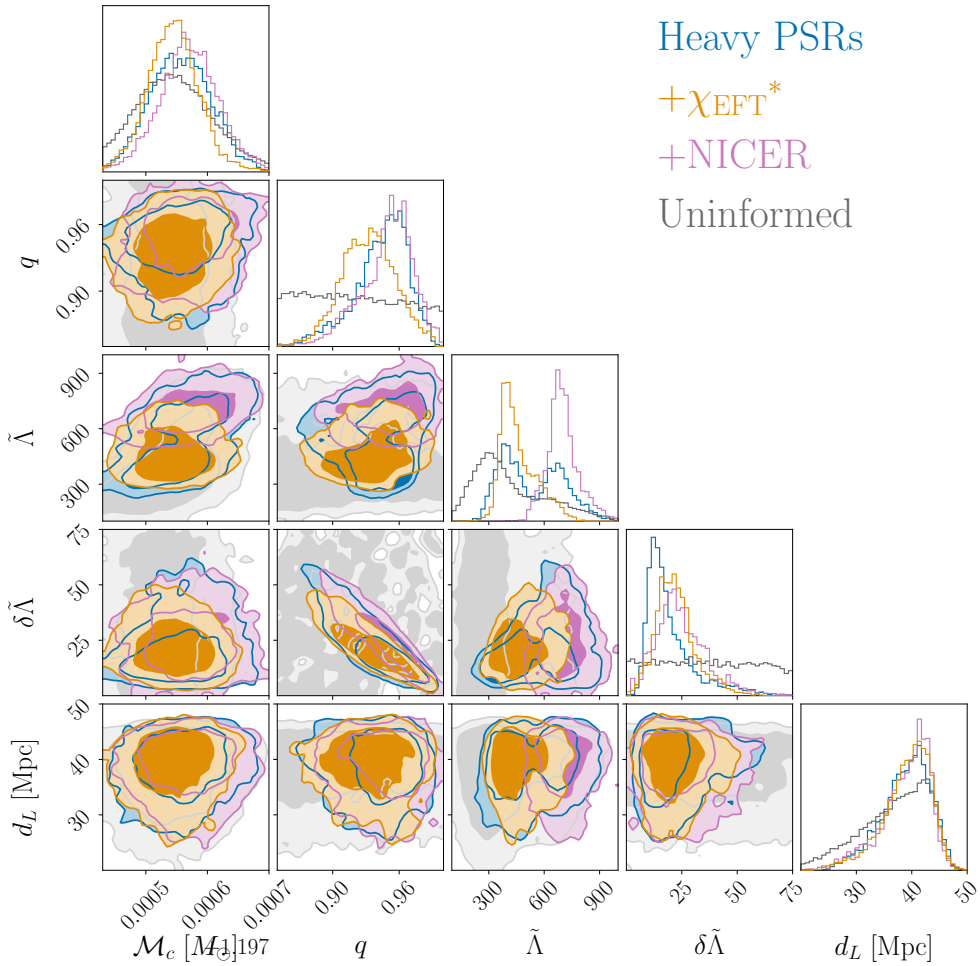
Showing $\log_{10}$ Bayes factors: negative = less preferred

- 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

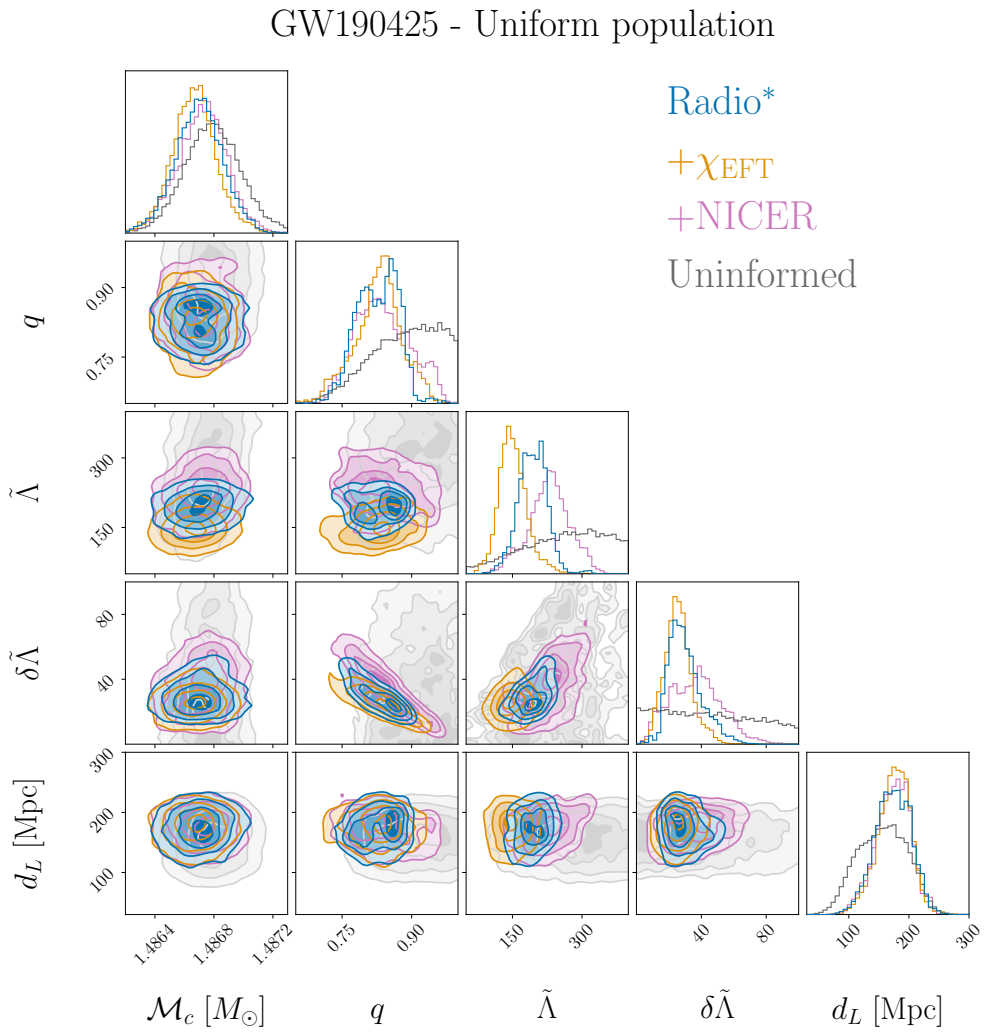
Showing $\log_{10}$ Bayes factors: negative = less preferred

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

Source	Population	EOS Constraints	GW190425
BNS	Uniform	Radio	**ref.**
		$+\chi_{\mathrm{EFT}}$	−0.09
		+NICER	−0.11
	Gaussian	Radio	−8.51
		$+\chi_{\mathrm{EFT}}$	−6.57
		+NICER	−4.42
	Double Gaussian	Radio	−0.76
		$+\chi_{\mathrm{EFT}}$	−0.56
		+NICER	−0.89
NSBH	Uniform	Radio	−1.10
		$+\chi_{\mathrm{EFT}}$	−1.10
		+NICER	−1.19
	Gaussian	Radio	−0.82
		$+\chi_{\mathrm{EFT}}$	−1.01
		+NICER	−0.98
	Double Gaussian	Radio	−1.65
		$+\chi_{\mathrm{EFT}}$	−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 $\rightarrow$ χ_{1z} more constrained
- Higher distances