Incorporating neutron star physics into gravitational wave inference with neural priors

Thibeau Wouters, Peter T. H. Pang, Tim Dietrich, Chris Van Den Broeck

arXiv:2511.22987

Utrecht University

Nikhef

Table of Contents

Contents

Warm-up example: Motivation

"What is the probability that the Sun will rise tomorrow?"

Warm-up example: Motivation

"What is the probability that the Sun will rise tomorrow?"

Your prior belief (before seeing tomorrow's data) can be:

- Agnostic: $p(\text{rise}) = 0.5$, $p(\text{not rise}) = 0.5$

Warm-up example: Motivation

"What is the probability that the Sun will rise tomorrow?"

Your prior belief (before seeing tomorrow's data) can be:

- Agnostic: $p(\mathrm{rise}) = 0.5$, $p(\mathrm{not\ rise}) = 0.5$
- Informed: $p(\mathrm{rise}) \approx 1$, $p(\mathrm{not\ rise}) \approx 0$
  - Theory: celestial mechanics
  - Past observations: every day so far

Warm-up example: Motivation

"What is the probability that the Sun will rise tomorrow?"

Your prior belief (before seeing tomorrow's data) can be:

- Agnostic: $p(\mathrm{rise}) = 0.5$, $p(\mathrm{not\ rise}) = 0.5$
- Informed: $p(\mathrm{rise}) \approx 1$, $p(\mathrm{not\ rise}) \approx 0$
  - Theory: celestial mechanics
  - Past observations: every day so far

Can we do something similar for gravitational wave (GW) signals involving neutron stars (NSs)?

Bayesian inference

How does GW parameter estimation work?

Bayesian inference:

$$\mathcal{P}(\theta_{\mathrm{GW}}|d) = \frac{\mathcal{L}(d|\theta_{\mathrm{GW}})\pi(\theta_{\mathrm{GW}})}{\mathcal{Z}}$$

- Posterior $\mathcal{P}(\theta_{\mathrm{GW}}|d)$: probability of parameters θ_{GW} given data d
- Likelihood $\mathcal{L}(d|\theta_{\mathrm{GW}})$: probability of data d given parameters θ_{GW} and a waveform model
- Prior $\pi(\theta_{\mathrm{GW}})$: initial belief about parameters θ_{GW} before seeing data d

Bayesian inference

How does GW parameter estimation work?

Bayesian inference:

$$\mathcal{P}(\theta_{\mathrm{GW}}|d) = \frac{\mathcal{L}(d|\theta_{\mathrm{GW}})\pi(\theta_{\mathrm{GW}})}{\mathcal{Z}}$$

- Posterior $\mathcal{P}(\theta_{\mathrm{GW}}|d)$: probability of parameters θ_{GW} given data d
- Likelihood $\mathcal{L}(d|\theta_{\mathrm{GW}})$: probability of data d given parameters θ_{GW} and a waveform model
- Prior $\pi(\theta_{\mathrm{GW}})$: initial belief about parameters θ_{GW} before seeing data d

Our final parameter estimates are a "mixture" of prior beliefs and information from the data.

Motivation

- Bayesian inference crucially depends on priors:

$$\mathcal{P}(\theta_{\mathrm{GW}}|d) \propto \frac{\mathcal{L}(d|\theta_{\mathrm{GW}})\pi(\theta_{\mathrm{GW}})}{\mathcal{Z}}$$

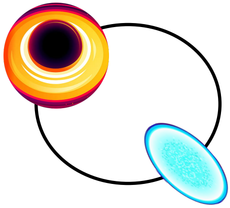
- By default, LVK uses agnostic priors, but what if we *do* have non-trivial prior information? (Theory and observations)
- Case study in this work: neutron stars (NSs) and information from
  - Population models
  - Equation of state (EOS) constraints

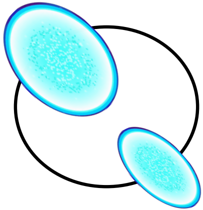
Neural priors

Flexible way to encode NS physics into GW inference

Tidal deformability

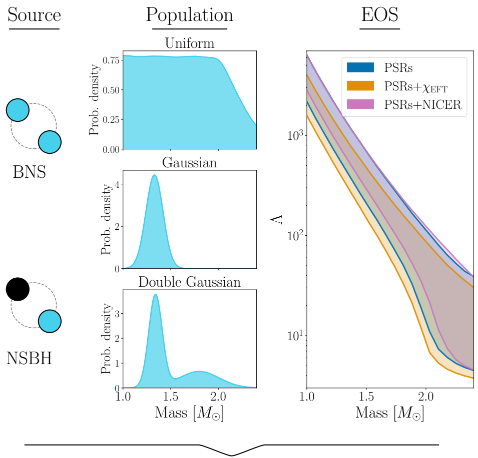
- Neutron stars are tidally deformed in a binary
- Quantified by the tidal deformability Λ
- Depends on the equation of state: $\Lambda = \Lambda(m, \mathrm{EOS})$
- Imprint in the GW phase: $\tilde{\Lambda}(m_i, \Lambda_i)$





Key idea

Train normalizing flow (NF) on samples informed by populations and EOS $\rightarrow$ **neural prior**



$$p_{\rm NF}(m_1^{\rm src}, m_2^{\rm src}, \Lambda_1, \Lambda_2 | \mathcal{H})$$

Contents

NS population models

Three fiducial population models for NS masses:

1. **Uniform** [1–3]:
   - Only use EOS constraints for maximum mass (M_{TOV})
   - NS mass $\sim U[1\,\mathrm{M}_\odot, M_{\mathrm{TOV}}]$

2. **Gaussian** [4]:
   - NS mass $\sim \mathcal{N}(1.33\,\mathrm{M}_\odot, (0.09\,\mathrm{M}_\odot)^2)$

3. **Double Gaussian** [5, 6]:
   - Weighted mixture of two Gaussians
   - $0.65 \times \mathcal{N}(1.34\,\mathrm{M}_\odot, (0.07\,\mathrm{M}_\odot)^2) + 0.35 \times \mathcal{N}(1.80\,\mathrm{M}_\odot, (0.21\,\mathrm{M}_\odot)^2)$

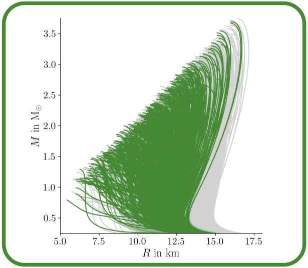
For neutron star-black hole (NSBH) systems:

- BH mass m_1^{src}: from $[M_{\mathrm{TOV}}, 5\,\mathrm{M}_\odot]$
- NS mass m_2^{src}: above models

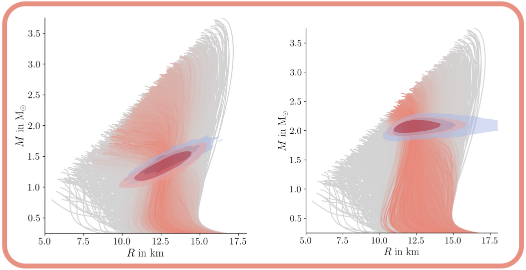
Equation of state constraints

- We use three equation of state constraints [7]:
  1. **Heavy pulsars**: must support $2\,M_\odot$ NSs
  2. **Chiral EFT** (χ_{EFT}): nuclear theory predictions (softer EOS)
  3. **NICER**: mass-radius observations of NSs (stiffer EOS)
- Posterior EOS samples obtained with JESTER [8]

Chiral EFT



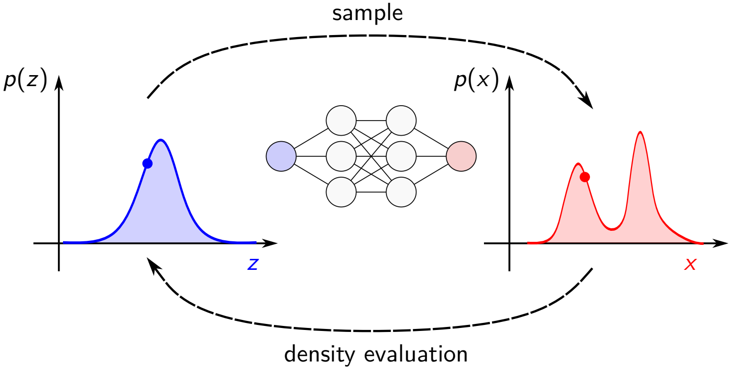
NICER



Normalizing flows

Normalizing flows [9, 10]

- Neural density estimators: trained on samples (predictions)
- Generate samples and evaluate density
- Can be used as priors in nested sampling! [11]



Construction of neural priors

Steps to generate training data:

1. Draw EOS posterior curve: determines M_{TOV}, $\Lambda(m)$
2. Draw masses from population model
3. Compute $\Lambda_i = \Lambda(m_i)$ for NSs (NSBH: $\Lambda_1 = 0$)

Construction of neural priors

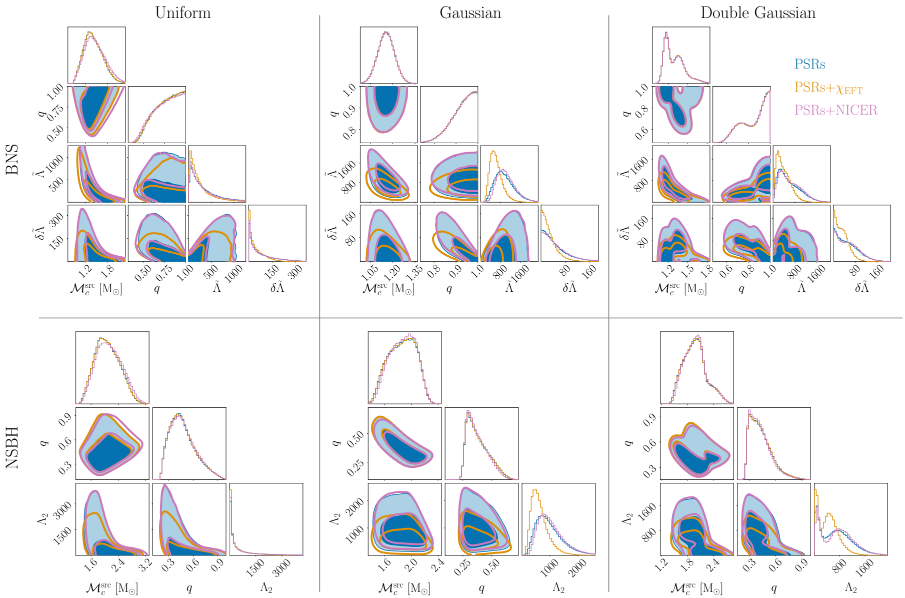
Steps to generate training data:

1. Draw EOS posterior curve: determines M_{TOV}, $\Lambda(m)$
2. Draw masses from population model
3. Compute $\Lambda_i = \Lambda(m_i)$ for NSs (NSBH: $\Lambda_1 = 0$)

Training:

- Repeat procedure N_{training} times to get training set
- Train normalizing flow to approximate density

All neural priors



Contents

Setup

Analyze GW170817, GW190425, GW230529 with:

- 4096 live points, multibanding likelihood
- `IMRPhenomXP_NRTidalv3`
- Neural priors for m_i, Λ_i (standard priors for other parameters)

Two contributions:

1. Narrower constraints with neural priors
2. Model selection with Bayes factors

Jeffreys' scale for Bayes factors ($\log_{10}$ scale)

$\log_{10}(\mathcal{B}_1^2)$	Interpretation	Color
$[0, \frac{1}{2}]$	Barely worth mentioning	
$[\frac{1}{2}, 1]$	Substantial	
$[1, \frac{3}{2}]$	Strong	
$[\frac{3}{2}, 2]$	Very strong	
> 2	Decisive	

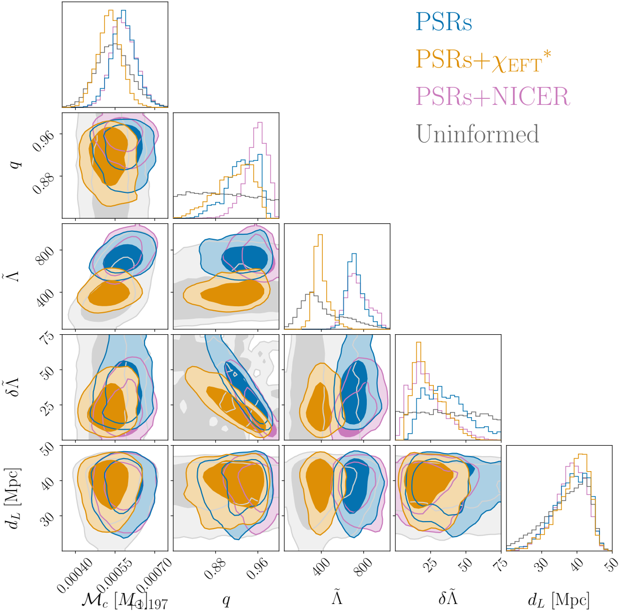
Contents

GW170817: Source classification

Showing $\log_{10}$ Bayes factors relative to model with highest evidence

Source	Population	EOS	GW170817
BNS	Uniform	PSRs	-1.83
		PSRs+χ_{EFT}	-0.80
		PSRs+NICER	-1.58
	Gaussian	PSRs	-0.68
		PSRs+χ_{EFT}	**ref.**
		PSRs+NICER	-0.76
	Double Gaussian	PSRs	-1.36
		PSRs+χ_{EFT}	-0.59
		PSRs+NICER	-0.92
NSBH	Uniform	PSRs	-224.65
		PSRs+χ_{EFT}	-224.66
		PSRs+NICER	-224.66
	Gaussian	PSRs	-224.67
		PSRs+χ_{EFT}	-224.66
		PSRs+NICER	-224.66
	Double Gaussian	PSRs	-224.67
		PSRs+χ_{EFT}	-224.68
		PSRs+NICER	-224.67

GW170817: Parameter constraints (Gaussian)



GW170817: Discussion

Source classification:

- Decisive evidence for BNS over NSBH
- Prefer Gaussian population model
- Slight preference for softer EOS (PSRs+χ_{EFT})

Parameter constraints:

- More equal mass ratio: $q \geq 0.9$
- Constrained tidal deformability $\tilde{\Lambda}$
- Higher luminosity distance compared to agnostic prior
- Matches multimessenger analyses of GW170817 [12–16]

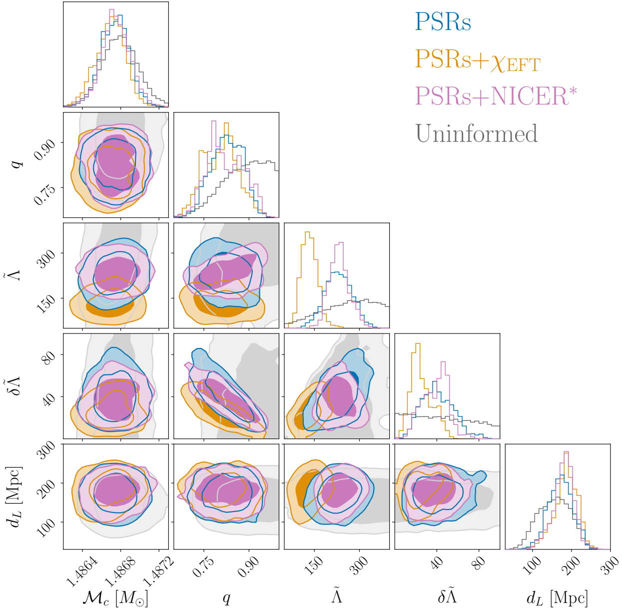
Contents

GW190425: Source classification

Showing $\log_{10}$ Bayes factors relative to best model

Source	Population	EOS	GW190425
BNS	Uniform	PSRs	-0.07
		PSRs+$\chi_{\rm EFT}$	-0.11
		PSRs+NICER	**ref.**
	Gaussian	PSRs	-6.89
		PSRs+$\chi_{\rm EFT}$	-8.47
		PSRs+NICER	-5.45
	Double Gaussian	PSRs	-0.55
		PSRs+$\chi_{\rm EFT}$	-0.79
		PSRs+NICER	-0.57
NSBH	Uniform	PSRs	-1.52
		PSRs+$\chi_{\rm EFT}$	-1.35
		PSRs+NICER	-1.63
	Gaussian	PSRs	-0.82
		PSRs+$\chi_{\rm EFT}$	-1.11
		PSRs+NICER	-1.43
	Double Gaussian	PSRs	-4.11
		PSRs+$\chi_{\rm EFT}$	-3.83
		PSRs+NICER	-24.31

GW190425: Parameter constraints (Uniform)



GW190425: Discussion

Source classification:

- Prefer BNS over NSBH (but less conclusive than GW170817)
- Most consistent with uniform population
- Masses are outliers compared to galactic binaries

Parameter constraints:

- Less equal masses: $q \leq 0.9$
- $\tilde{\Lambda} \approx 200$ (more prior-dominated due to lower SNR)
- Higher luminosity distance: 182^{+41}_{-49} Mpc vs. 157^{+64}_{-65} Mpc (90% credibility)

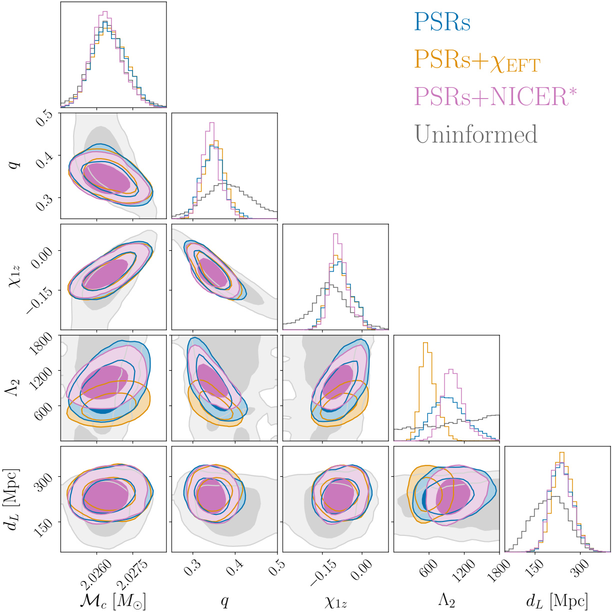
Contents

GW230529: Source classification

Showing $\log_{10}$ Bayes factors relative to best model

Source	Population	EOS	GW230529
BNS	Uniform	PSRs	-13.14
		PSRs+χ_{EFT}	-13.12
		PSRs+NICER	-12.92
	Gaussian	PSRs	-18.82
		PSRs+χ_{EFT}	-18.83
		PSRs+NICER	-18.81
	Double Gaussian	PSRs	-13.75
		PSRs+χ_{EFT}	-13.77
		PSRs+NICER	-13.71
NSBH	Uniform	PSRs	-0.08
		PSRs+χ_{EFT}	-0.02
		PSRs+NICER	-0.25
	Gaussian	PSRs	-0.05
		PSRs+χ_{EFT}	-0.20
		PSRs+NICER	**ref.**
	Double Gaussian	PSRs	-0.14
		PSRs+χ_{EFT}	-0.13
		PSRs+NICER	-0.05

GW230529: Parameter constraints (Gaussian)



GW230529: Discussion

Source classification:

- Decisive evidence for NSBH over BNS (agrees with LVK [17])
- No evidence between hypotheses (low SNR)

Parameter constraints:

- Mass ratio more constrained: $q \leq 0.4$
  - As a result, improved spin constraints (χ_{1z} closer to zero)
- Tidal deformability posteriors dominated by priors
- Luminosity distance: 235^{+59}_{-58} Mpc vs. 201^{+84}_{-97} Mpc (90% credibility)
  - Important for EM follow-up studies
- Less tidal information: `NRTidalv3` tapers at (90% credibility)
  - 641^{+318}_{-158} Hz (agnostic priors)
  - 858^{+113}_{-108} Hz (neural prior, reference model)

Contents

Conclusion

- Agnostic priors miss including valuable information
- **Neural priors**: flexible way to encode non-trivial prior information
- Case study: neutron star physics from
  - Population models
  - EOS constraints
- We consistelty recover higher luminosity distances with informed priors compared to the agnostic priors
  - Important for EM follow-up
  - Simulation studies ongoing to quantify this
- Data-driven approach: easy to extend/generalize!

Thanks for listening!

References I

[1] R. Abbott et al. "Observation of Gravitational Waves from Two Neutron Star–Black Hole Coalescences". In: *Astrophys. J. Lett.* 915.1 (2021), p. L5. DOI: 10.3847/2041-8213/ac082e. arXiv: 2106.15163 [astro-ph.HE].

[2] Philippe Landry and Jocelyn S. Read. "The Mass Distribution of Neutron Stars in Gravitational-wave Binaries". In: *Astrophys. J. Lett.* 921.2 (2021), p. L25. DOI: 10.3847/2041-8213/ac2f3e. arXiv: 2107.04559 [astro-ph.HE].

[3] Jacob Golomb et al. "Interplay of astrophysics and nuclear physics in determining the properties of neutron stars". In: *Phys. Rev. D* 111.2 (2025), p. 023029. DOI: 10.1103/PhysRevD.111.023029. arXiv: 2410.14597 [astro-ph.HE].

[4] Feryal Özel and Paulo Freire. "Masses, Radii, and the Equation of State of Neutron Stars". In: *Ann. Rev. Astron. Astrophys.* 54 (2016), pp. 401–440. DOI: 10.1146/annurev-astro-081915-023322. arXiv: 1603.02698 [astro-ph.HE].

[5] Justin Alsing, Hector O. Silva, and Emanuele Berti. "Evidence for a maximum mass cut-off in the neutron star mass distribution and constraints on the equation of state". In: *Mon. Not. Roy. Astron. Soc.* 478.1 (2018), pp. 1377–1391. DOI: 10.1093/mnras/sty1065. arXiv: 1709.07889 [astro-ph.HE].

References II

[6] Dong-Sheng Shao et al. "Maximum mass cutoff in the neutron star mass distribution and the prospect of forming supramassive objects in the double neutron star mergers". In: *Phys. Rev. D* 102.6 (2020), p. 063006. DOI: 10.1103/PhysRevD.102.063006. arXiv: 2009.04275 [astro-ph.HE].

[7] Hauke Koehn et al. "From existing and new nuclear and astrophysical constraints to stringent limits on the equation of state of neutron-rich dense matter". In: *Phys. Rev. X* 15.2 (2025), p. 021014. DOI: 10.1103/PhysRevX.15.021014. arXiv: 2402.04172 [astro-ph.HE].

[8] Thibeau Wouters et al. "Leveraging differentiable programming in the inverse problem of neutron stars". In: (Apr. 2025). arXiv: 2504.15893 [astro-ph.HE].

[9] Ivan Kobyzev, Simon J. D. Prince, and Marcus A. Brubaker. "Normalizing Flows: An Introduction and Review of Current Methods". In: *IEEE Trans. Pattern Anal. Machine Intell.* 43.11 (2021), pp. 3964–3979. DOI: 10.1109/tpami.2020.2992934. arXiv: 1908.09257 [stat.ML].

[10] George Papamakarios et al. "Normalizing Flows for Probabilistic Modeling and Inference". In: *J. Machine Learning Res.* 22.1 (2021), pp. 2617–2680. DOI: 10.5555/3546258.3546315. arXiv: 1912.02762 [stat.ML].

References III

[11] Justin Alsing and Will Handley. "Nested sampling with any prior you like". In: *Mon. Not. Roy. Astron. Soc.* 505.1 (2021), pp. L95–L99. DOI: 10.1093/mnrasl/slab057. arXiv: 2102.12478 [astro-ph.IM].

[12] David Radice and Liang Dai. "Multimessenger Parameter Estimation of GW170817". In: *Eur. Phys. J. A* 55.4 (2019), p. 50. DOI: 10.1140/epja/i2019-12716-4. arXiv: 1810.12917 [astro-ph.HE].

[13] Michael W. Coughlin et al. "Multimessenger Bayesian parameter inference of a binary neutron star merger". In: *Mon. Not. Roy. Astron. Soc.* 489.1 (2019), pp. L91–L96. DOI: 10.1093/mnrasl/slz133. arXiv: 1812.04803 [astro-ph.HE].

[14] B. P. Abbott et al. "Properties of the binary neutron star merger GW170817". In: *Phys. Rev. X* 9.1 (2019), p. 011001. DOI: 10.1103/PhysRevX.9.011001. arXiv: 1805.11579 [gr-qc].

[15] Peter T. H. Pang et al. "An updated nuclear-physics and multi-messenger astrophysics framework for binary neutron star mergers". In: *Nature Commun.* 14.1 (2023), p. 8352. DOI: 10.1038/s41467-023-43932-6. arXiv: 2205.08513 [astro-ph.HE].

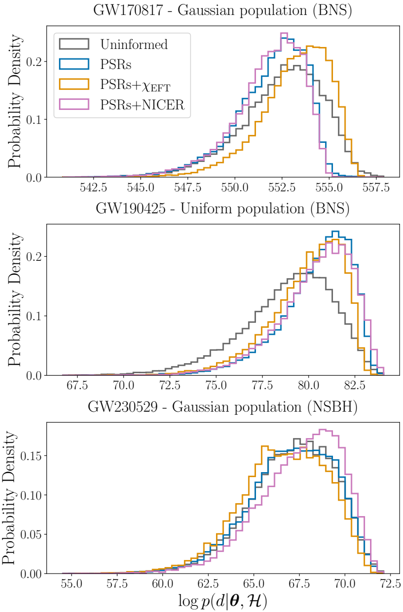
[16] Matteo Breschi et al. "Bayesian inference of multimessenger astrophysical data: Joint and coherent inference of gravitational waves and kilonovae". In: *Astron. Astrophys.* 689 (2024), A51. DOI: 10.1051/0004-6361/202449173. arXiv: 2401.03750 [astro-ph.HE].

References IV

[17] A. G. Abac et al. “Observation of Gravitational Waves from the Coalescence of a 2.5–4.5 $M_\odot$ Compact Object and a Neutron Star”. In: *Astrophys. J. Lett.* 970.2 (2024), p. L34. DOI: 10.3847/2041-8213/ad5beb. arXiv: 2404.04248 [astro-ph.HE].

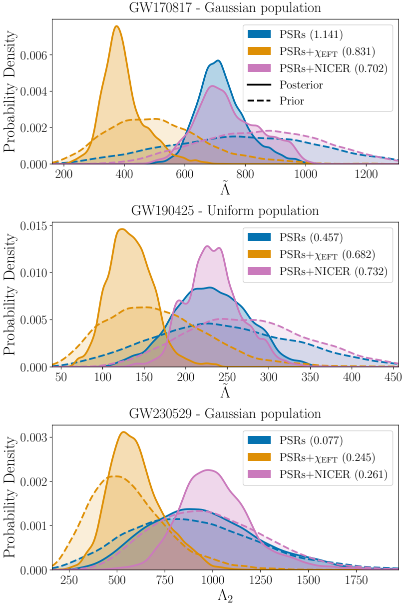
Likelihood distributions

- Likelihood distributions, obtained from final posterior samples



Information gain

- "Prior" $= \Lambda_i$ computed from EOSs conditioned on the posterior source-frame masses m_i^{src}
- "Posterior" $= \Lambda_i$ from posterior samples
- KL divergence between prior and posterior in brackets



More posteriors

Event	**Pop**	**EOS**	$m_1^{\rm src}$ $[M_\odot]$	$m_2^{\rm src}$ $[M_\odot]$	q	Λ_1	Λ_2	$\tilde{\Lambda}$	$\delta\tilde{\Lambda}$	d_L [Mpc]
GW170817 (BNS)		Uninformed	$1.47^{+0.12}_{-0.11}$	$1.26^{+0.10}_{-0.10}$	$0.86^{+0.14}_{-0.12}$	286^{+473}_{-286}	448^{+603}_{-448}	364^{+403}_{-234}	0^{+158}_{-170}	38^{+8}_{-11}
	U	PSRs	$1.51^{+0.09}_{-0.06}$	$1.23^{+0.05}_{-0.07}$	$0.81^{+0.06}_{-0.09}$	413^{+110}_{-133}	1477^{+636}_{-334}	795^{+108}_{-71}	119^{+68}_{-43}	41^{+6}_{-8}
		PSRs+$\chi_{\rm EFT}$	$1.52^{+0.08}_{-0.07}$	$1.23^{+0.06}_{-0.06}$	$0.81^{+0.08}_{-0.07}$	215^{+87}_{-111}	712^{+219}_{-175}	390^{+98}_{-93}	58^{+19}_{-25}	40^{+6}_{-8}
		PSRs+NICER	$1.57^{+0.05}_{-0.07}$	$1.19^{+0.05}_{-0.03}$	$0.75^{+0.06}_{-0.05}$	264^{+86}_{-52}	1399^{+367}_{-342}	620^{+99}_{-82}	116^{+37}_{-38}	40^{+6}_{-8}
	G	PSRs	$1.41^{+0.04}_{-0.03}$	$1.32^{+0.03}_{-0.03}$	$0.93^{+0.04}_{-0.05}$	578^{+131}_{-150}	874^{+229}_{-174}	713^{+143}_{-122}	35^{+28}_{-23}	39^{+7}_{-9}
		PSRs+$\boldsymbol{\chi}_{\rm EFT}$	$1.42^{+0.05}_{-0.04}$	$1.31^{+0.03}_{-0.04}$	$0.92^{+0.05}_{-0.06}$	298^{+130}_{-99}	495^{+173}_{-118}	385^{+141}_{-85}	21^{+19}_{-13}	40^{+6}_{-9}
		PSRs+NICER	$1.39^{+0.02}_{-0.02}$	$1.34^{+0.02}_{-0.02}$	$0.96^{+0.03}_{-0.03}$	641^{+186}_{-128}	826^{+277}_{-178}	729^{+219}_{-133}	21^{+22}_{-17}	38^{+7}_{-8}
	DG	PSRs	$1.40^{+0.03}_{-0.02}$	$1.33^{+0.02}_{-0.02}$	$0.95^{+0.02}_{-0.03}$	687^{+140}_{-156}	960^{+183}_{-231}	814^{+143}_{-185}	29^{+21}_{-13}	40^{+6}_{-7}
		PSRs+$\chi_{\rm EFT}$	$1.39^{+0.02}_{-0.02}$	$1.34^{+0.02}_{-0.02}$	$0.96^{+0.03}_{-0.03}$	382^{+148}_{-111}	507^{+153}_{-152}	444^{+136}_{-131}	11^{+12}_{-9}	39^{+7}_{-7}
		PSRs+NICER	$1.39^{+0.02}_{-0.02}$	$1.33^{+0.02}_{-0.02}$	$0.96^{+0.02}_{-0.03}$	703^{+184}_{-153}	934^{+200}_{-200}	806^{+157}_{-184}	26^{+14}_{-17}	38^{+7}_{-8}
GW190425 (BNS)		Uninformed	$1.75^{+0.13}_{-0.10}$	$1.56^{+0.10}_{-0.10}$	$0.89^{+0.11}_{-0.11}$	292^{+541}_{-292}	415^{+694}_{-415}	374^{+436}_{-333}	0^{+187}_{-173}	157^{+64}_{-65}
	U	PSRs	$1.81^{+0.10}_{-0.09}$	$1.50^{+0.07}_{-0.08}$	$0.83^{+0.08}_{-0.09}$	109^{+56}_{-57}	428^{+209}_{-200}	230^{+73}_{-71}	39^{+24}_{-23}	173^{+54}_{-47}
		PSRs+$\chi_{\rm EFT}$	$1.83^{+0.12}_{-0.10}$	$1.48^{+0.07}_{-0.10}$	$0.81^{+0.09}_{-0.09}$	58^{+40}_{-28}	259^{+174}_{-107}	132^{+44}_{-40}	23^{+21}_{-12}	187^{+48}_{-49}
		PSRs+NICER	$1.82^{+0.10}_{-0.12}$	$1.48^{+0.10}_{-0.07}$	$0.81^{+0.11}_{-0.09}$	108^{+81}_{-56}	449^{+132}_{-150}	232^{+57}_{-51}	40^{+15}_{-23}	182^{+41}_{-49}
	DG	PSRs	$1.93^{+0.08}_{-0.08}$	$1.41^{+0.05}_{-0.05}$	$0.73^{+0.06}_{-0.05}$	67^{+37}_{-38}	636^{+217}_{-206}	238^{+65}_{-61}	63^{+21}_{-21}	186^{+44}_{-44}
		PSRs+$\chi_{\rm EFT}$	$1.94^{+0.07}_{-0.06}$	$1.40^{+0.04}_{-0.05}$	$0.72^{+0.04}_{-0.05}$	51^{+23}_{-24}	408^{+125}_{-100}	156^{+37}_{-45}	37^{+10}_{-9}	190^{+41}_{-47}
		PSRs+NICER	$1.90^{+0.08}_{-0.07}$	$1.42^{+0.06}_{-0.05}$	$0.75^{+0.06}_{-0.06}$	96^{+41}_{-36}	690^{+188}_{-164}	283^{+45}_{-51}	66^{+18}_{-17}	186^{+41}_{-48}
GW230529 (NSBH)		Uninformed	$3.65^{+0.62}_{-0.85}$	$1.43^{+0.26}_{-0.24}$	$0.39^{+0.17}_{-0.13}$	–	2791^{+2113}_{-1950}	182^{+243}_{-182}	91^{+115}_{-91}	201^{+84}_{-97}
	U	PSRs	$3.73^{+0.28}_{-0.32}$	$1.38^{+0.10}_{-0.09}$	$0.37^{+0.06}_{-0.05}$	–	698^{+344}_{-303}	41^{+8}_{-8}	21^{+4}_{-4}	238^{+61}_{-63}
		PSRs+$\chi_{\rm EFT}$	$3.52^{+0.46}_{-0.45}$	$1.46^{+0.18}_{-0.14}$	$0.41^{+0.12}_{-0.08}$	–	322^{+206}_{-202}	26^{+8}_{-7}	13^{+4}_{-4}	220^{+70}_{-64}
		PSRs+NICER	$3.27^{+0.27}_{-0.57}$	$1.54^{+0.25}_{-0.12}$	$0.47^{+0.17}_{-0.08}$	–	368^{+213}_{-291}	40^{+13}_{-14}	19^{+6}_{-7}	237^{+65}_{-67}
	G	PSRs	$3.86^{+0.28}_{-0.26}$	$1.34^{+0.08}_{-0.08}$	$0.35^{+0.04}_{-0.05}$	–	933^{+497}_{-451}	46^{+14}_{-16}	23^{+7}_{-8}	236^{+59}_{-58}
		PSRs+$\chi_{\rm EFT}$	$3.83^{+0.25}_{-0.25}$	$1.35^{+0.07}_{-0.07}$	$0.35^{+0.04}_{-0.04}$	–	582^{+261}_{-198}	30^{+7}_{-8}	15^{+3}_{-4}	242^{+59}_{-57}
		PSRs+NICER	$3.89^{+0.22}_{-0.24}$	$1.33^{+0.07}_{-0.06}$	$0.34^{+0.04}_{-0.03}$	–	1000^{+321}_{-311}	49^{+9}_{-9}	25^{+4}_{-5}	235^{+59}_{-58}
	DG	PSRs	$3.78^{+0.23}_{-0.24}$	$1.36^{+0.07}_{-0.06}$	$0.36^{+0.04}_{-0.04}$	–	890^{+341}_{-333}	49^{+12}_{-13}	25^{+6}_{-7}	237^{+63}_{-64}
		PSRs+$\chi_{\rm EFT}$	$3.85^{+0.18}_{-0.21}$	$1.34^{+0.05}_{-0.06}$	$0.35^{+0.03}_{-0.03}$	–	516^{+194}_{-205}	26^{+8}_{-8}	13^{+4}_{-4}	237^{+66}_{-71}
		PSRs+NICER	$3.86^{+0.15}_{-0.16}$	$1.34^{+0.04}_{-0.04}$	$0.35^{+0.02}_{-0.02}$	–	1026^{+254}_{-306}	52^{+11}_{-13}	26^{+6}_{-6}	229^{+65}_{-68}