Analyzing GW231109_235456 in the ET era and incorporating neutron star physics into future GW inference

arXiv:2510.22290 & arXiv:2511.22987

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

Utrecht University

Nikhef

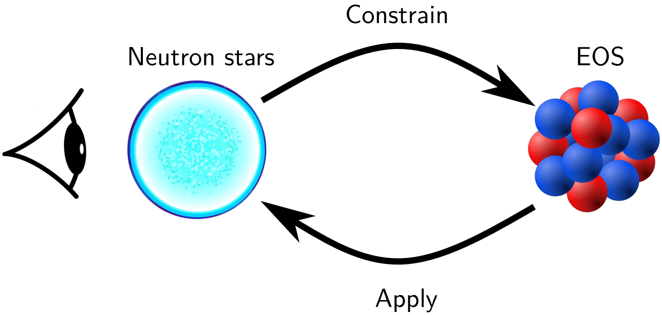
Table of Contents

Structure of this talk

Data analysis of neutron stars forms a **loop**:

1. Constraining the EOS with neutron star observations
2. Applying EOS knowledge in neutron star data analysis (e.g., GW)

How can we efficiently perform this loop?



Contents

GWTC-4.0 and GW231109_235456

- GWTC-4.0 released recently [1]:
  - Over 200 gravitational wave events analyzed in total

GWTC-4.0 and GW231109_235456

- GWTC-4.0 released recently [1]:
  - Over 200 gravitational wave events analyzed in total

- **No confident binary neutron star detections**

GWTC-4.0 and GW231109_235456

- GWTC-4.0 released recently [1]:
  - Over 200 gravitational wave events analyzed in total

- **No confident binary neutron star detections**

- However: sub-threshold candidate **GW231109_235456** identified [2]
  - SNR ~ 9.7 (distance: ~ 165 Mpc)
  - Fainter, but mass closer to GW170817 than GW190425

GWTC-4.0 and GW231109_235456

- GWTC-4.0 released recently [1]:
  - Over 200 gravitational wave events analyzed in total

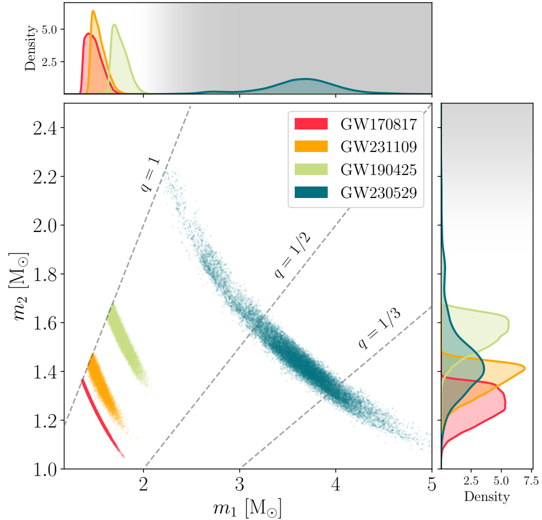
- **No confident binary neutron star detections**

- However: sub-threshold candidate **GW231109_235456** identified [2]
  - SNR ~ 9.7 (distance: ~ 165 Mpc)
  - Fainter, but mass closer to GW170817 than GW190425

What can we learn about the EOS from such a merger?

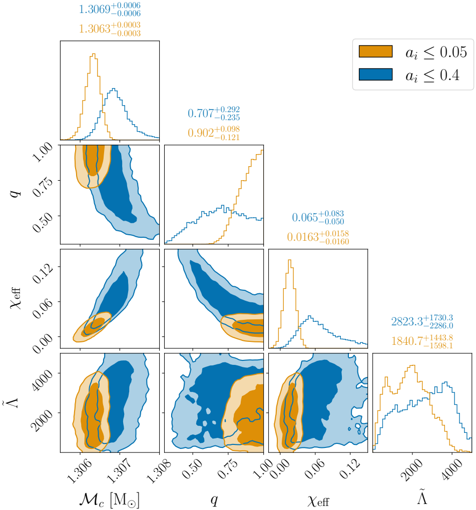
GW231109_235456: component masses

Component masses compared to other low-mass GW events [3–5]



Parameter estimation on GW231109_235456

- `IMRPhenomXP_NRTidalv3`
- Standard priors for m_i, $\Lambda_i \leq 5000$, spins below 0.05 or 0.4

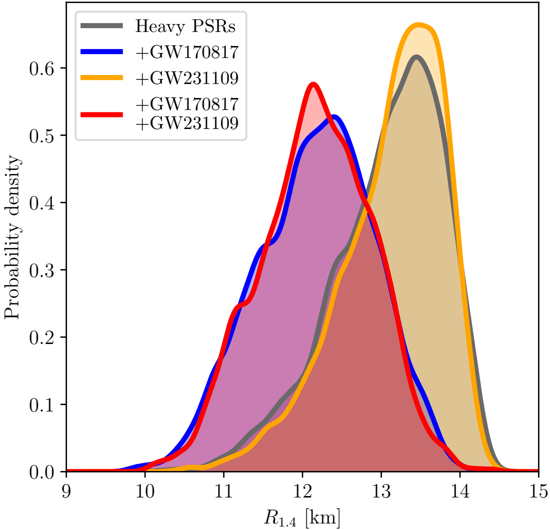


Constraining EOS from GW231109_235456

Put information on jester here

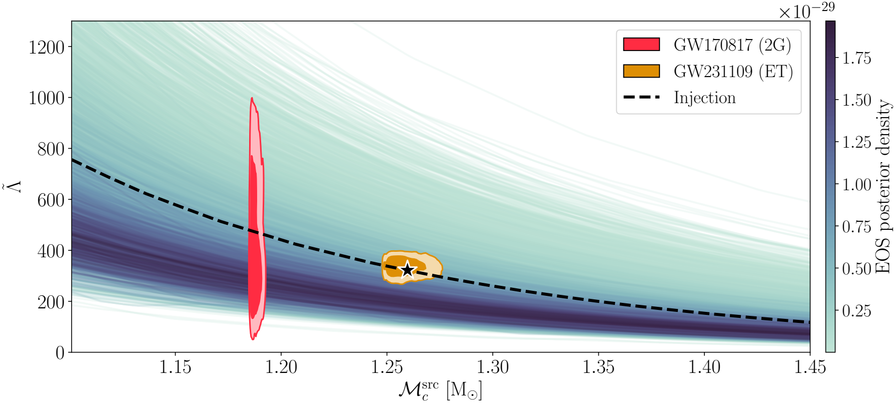
Constraining EOS from GW231109_235456

Constraints on radius of 1.4 $M_\odot$ neutron star ($R_{1.4}$):



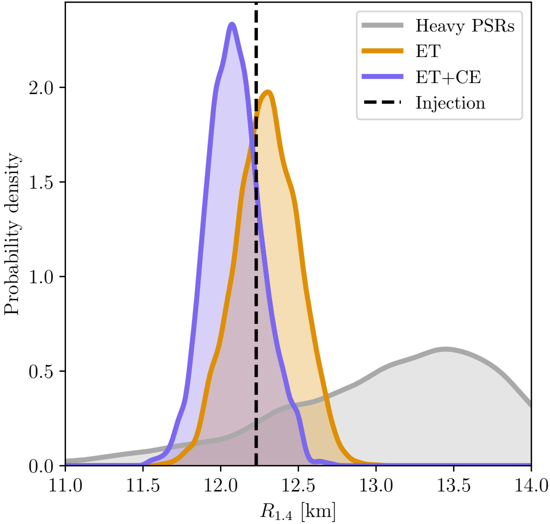
Projection: Einstein Telescope & Cosmic Explorer

- Simulate GW231109-like event with third-generation detectors
- Einstein Telescope: SNR $\sim$ 134, with Cosmic Explorer: SNR $\sim$ 294
- Recovery improved



Projection: radius constraints

Recover radius with accuracy of 300-400 meters (ET+CE vs ET)



Conclusion (part 1)

- GW231109_235456: sub-threshold BNS candidate from O4a
- SNR matters for EOS inference
  - Current detectors: poor constraints
  - ET and CE: precise radius measurements ($\sim$ 300-400 m)
- JESTER can handle individual high SNR signals: efficiently go from NS observations to EOS constraints

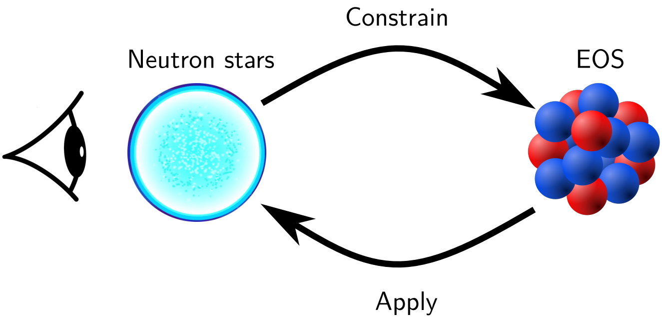
Contents

Structure of this talk

Data analysis of neutron stars forms a **loop**:

1. Constraining the EOS with neutron star observations
2. Applying EOS knowledge in neutron star data analysis (e.g., GW)

How can we efficiently perform this loop?



Neural priors: motivation

- Bayesian inference depends on choice of priors:

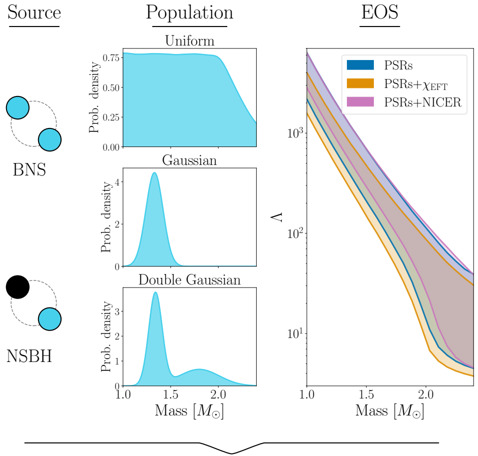
$$\mathcal{P}(\theta_{\mathrm{GW}}|d) \propto \frac{\mathcal{L}(d|\theta_{\mathrm{GW}})\pi(\theta_{\mathrm{GW}})}{\mathcal{Z}}$$

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

Neural priors

Flexible way to encode NS physics into GW inference

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



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

NS population models

Three fiducial population models for NS masses:

1. **Uniform** [6–8]:
   - Only use EOS constraints for maximum mass (M_{TOV})
   - NS mass $\sim U[1\,\mathrm{M}_\odot, M_{\mathrm{TOV}}]$

2. **Gaussian** [9]:
   - NS mass $\sim \mathcal{N}(1.33\,\mathrm{M}_\odot, (0.09\,\mathrm{M}_\odot)^2)$

3. **Double Gaussian** [10, 11]:
   - Weighted mixture of two Gaussians
   - $0.65 \times \mathcal{N}(1.34\,\mathrm{M}_\odot, (0.07\,\mathrm{M}_\odot)^2) + 0.35 \times \mathcal{N}(1.80\,\mathrm{M}_\odot, (0.21\,\mathrm{M}_\odot)^2)$

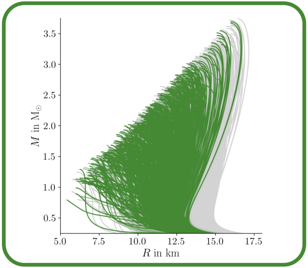
For NSBH systems:

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

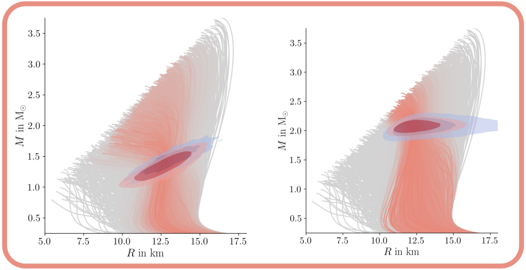
EOS constraints

- We use three EOS constraints [12]:
  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 samples obtained with JESTER [13]

Chiral EFT



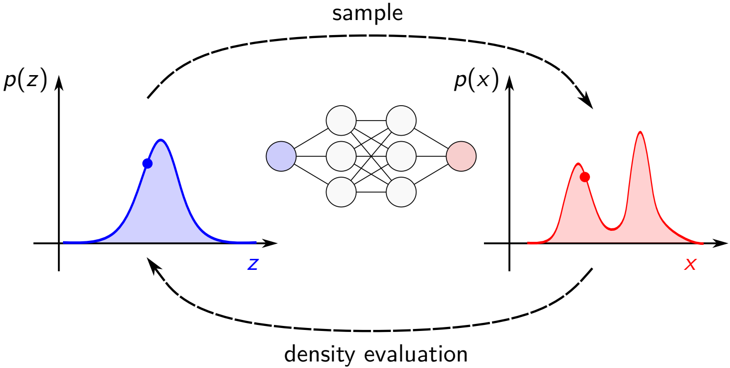
NICER



Normalizing flows

Normalizing flows [14, 15]

- Neural density estimators: trainable bijections
- Often used in PE, e.g., DINGO [16, 17], NESSAI [18, 19]
- Generate samples, evaluate density: can be used as priors [20]



Construction of neural priors

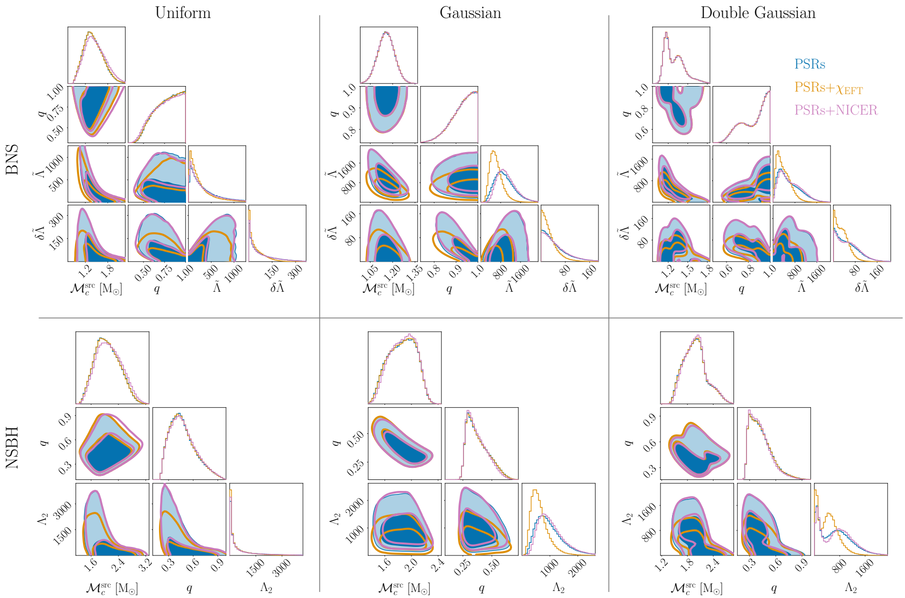
Steps to generate training data:

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: $\Lambda_1 = 0$)

Implementation:

- Created with GLASFLOW [21, 22]
- `CouplingNSF` architecture (neural spline flows [23])
- Use as a `JointPrior` in BILBY (`NFPrior`)
  - Sample & logpdf: evaluate NF
  - Rescale: unit hypercube $\rightarrow$ multivariate Gaussian $\xrightarrow{\text{NF}}$ data space

All neural priors



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)

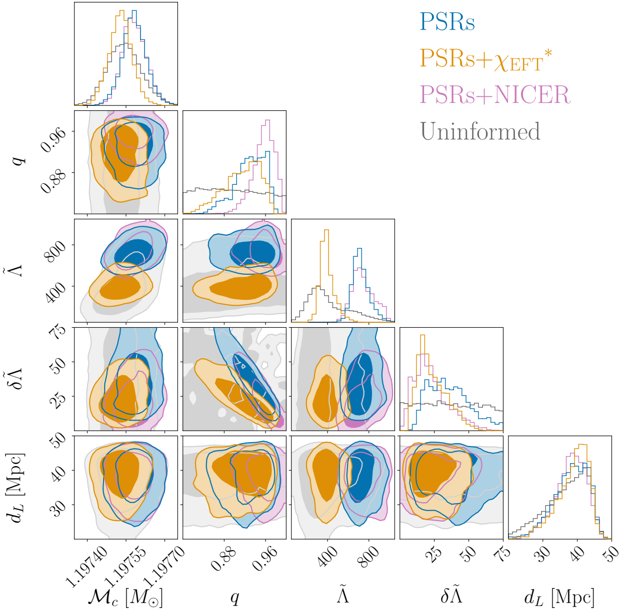
$\log_{10}(\mathcal{B}_1^2)$	Interpretation	Color
$[0, \frac{1}{2}]$	Barely worth mentioning	
$[\frac{1}{2}, 1]$	Substantial	
$[1, \frac{3}{2}]$	Strong	
$[\frac{3}{2}, 2]$	Very strong	
> 2	Decisive	

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 pop.)



GW170817: Discussion

Source classification:

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

Parameter constraints:

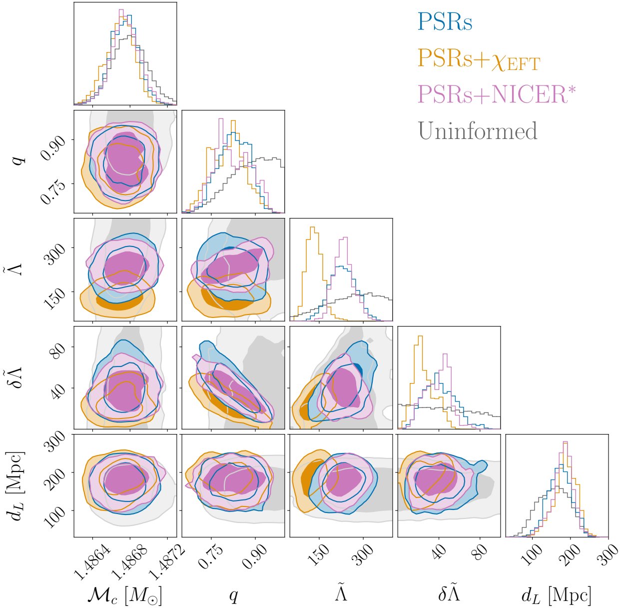
- More equal mass ratio: $q \geq 0.9$
- Constrained tidal deformability $\tilde{\Lambda}$
- Higher luminosity distance compared to agnostic prior
- Matches multimessenger analyses of GW170817 [24–28]

GW190425: Source classification

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

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

GW190425: Parameter constraints (Uniform pop.)



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:

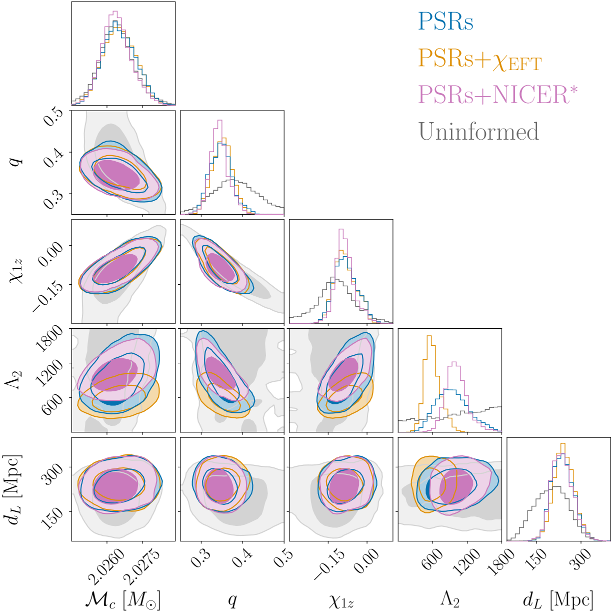
- Less equal masses: $q \leq 0.9$
- $\tilde{\Lambda} \approx 200$ (more prior-dominated due to lower SNR)
- Higher luminosity distance: 182^{+41}_{-49} Mpc vs. 157^{+64}_{-65} Mpc (90% credibility)

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 pop.)



GW230529: Discussion

Source classification:

- Decisive evidence for NSBH over BNS (agrees with LVK [5])
- 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)
- Less tidal information: `NRTidalv3` tapers at (90% credibility)
  - 641^{+318}_{-158} Hz (agnostic priors)
  - 858^{+113}_{-108} Hz (neural prior, reference model)

Conclusion (part 2)

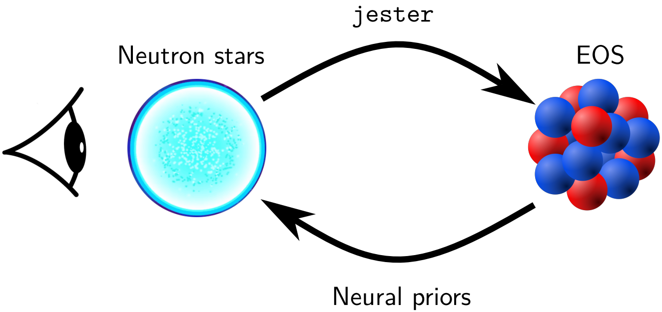
- Flexible way to encode non-trivial prior information
- Two highlights:
    1. Bayesian model selection
    2. Informed parameter constraints
- Implemented in BILBY
- Data-driven approach: easy to extend/generalize

Contents

Conclusion

Methods for closing the neutron star data analysis loop:

1. JESTER: from nuclear physics and multimessenger astronomy to EOS constraints
2. Neural priors: incorporate NS physics into GW inference



References I

[1] A. G. Abac et al. "GWTC-4.0: Updating the Gravitational-Wave Transient Catalog with Observations from the First Part of the Fourth LIGO-Virgo-KAGRA Observing Run". In: (Aug. 2025). arXiv: 2508.18082 [gr-qc].

[2] Wanting Niu et al. "GW231109_235456: A Sub-threshold Binary Neutron Star Merger in the LIGO-Virgo-KAGRA O4a Observing Run?" In: (Sept. 2025). arXiv: 2509.09741 [astro-ph.HE].

[3] B. P. Abbott et al. "GW170817: Observation of Gravitational Waves from a Binary Neutron Star Inspiral". In: *Phys. Rev. Lett.* 119.16 (2017), p. 161101. DOI: 10.1103/PhysRevLett.119.161101. arXiv: 1710.05832 [gr-qc].

[4] B. P. Abbott et al. "GW190425: Observation of a Compact Binary Coalescence with Total Mass $\sim 3.4 M_\odot$". In: *Astrophys. J. Lett.* 892.1 (2020), p. L3. DOI: 10.3847/2041-8213/ab75f5. arXiv: 2001.01761 [astro-ph.HE].

[5] 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].

[6] 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].

References II

[7] 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].

[8] 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].

[9] 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].

[10] 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].

[11] 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].

References III

[12] 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].

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

[14] 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].

[15] 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].

[16] Maximilian Dax et al. “Real-Time Gravitational Wave Science with Neural Posterior Estimation”. In: *Phys. Rev. Lett.* 127.24 (2021), p. 241103. DOI: 10.1103/PhysRevLett.127.241103. arXiv: 2106.12594 [gr-qc].

[17] Maximilian Dax et al. “Neural Importance Sampling for Rapid and Reliable Gravitational-Wave Inference”. In: *Phys. Rev. Lett.* 130.17 (2023), p. 171403. DOI: 10.1103/PhysRevLett.130.171403. arXiv: 2210.05686 [gr-qc].

References IV

[18] Michael J. Williams, John Veitch, and Chris Messenger. "Nested sampling with normalizing flows for gravitational-wave inference". In: *Phys. Rev. D* 103.10 (2021), p. 103006. DOI: 10.1103/PhysRevD.103.103006. arXiv: 2102.11056 [gr-qc].

[19] Michael J. Williams, John Veitch, and Chris Messenger. "Importance nested sampling with normalising flows". In: *Mach. Learn. Sci. Tech.* 4.3 (2023), p. 035011. DOI: 10.1088/2632-2153/acd5aa. arXiv: 2302.08526 [astro-ph.IM].

[20] 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].

[21] Michael J. Williams et al. *uofgravity/glasflow: v0.4.1*. Oct. 2024. DOI: 10.5281/zenodo.13914483. URL: https://doi.org/10.5281/zenodo.13914483.

[22] Conor Durkan et al. *nflows: normalizing flows in PyTorch*. Version v0.14. Nov. 2020. DOI: 10.5281/zenodo.4296287. URL: https://doi.org/10.5281/zenodo.4296287.

[23] Conor Durkan et al. "Neural Spline Flows". In: June 2019. arXiv: 1906.04032 [stat.ML].

[24] 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].

References V

[25] 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].

[26] 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].

[27] 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].

[28] 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].

Posterior distributions for ET/ET+CE injections