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

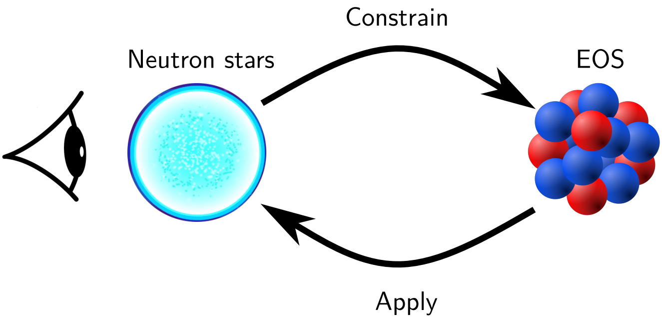
Nikhef

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?



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GWTC-4.0 and GW231109_235456

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

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  - SNR $\sim$ 9.7 (distance: $\sim$ 165 Mpc)
  - But mass closer to GW170817 than GW190425

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- **No confident binary neutron star detections**

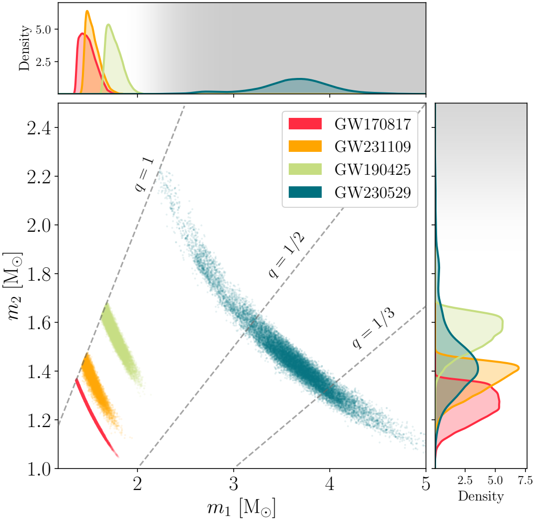
- However: sub-threshold candidate **GW231109_235456** identified [2]
  - SNR ~ 9.7 (distance: ~ 165 Mpc)
  - But mass closer to GW170817 than GW190425

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

(More on populations, remnant, EM counterpart: `arXiv:2510.22290`)

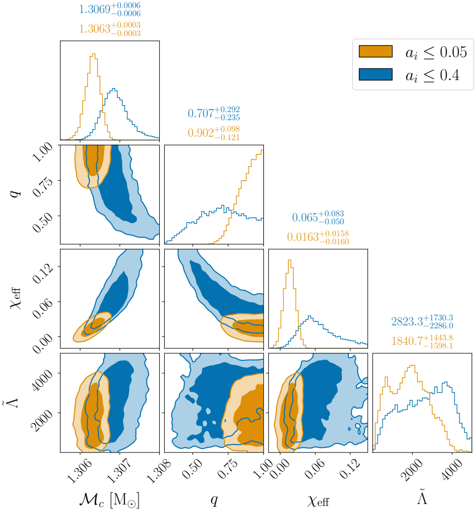
GW231109_235456: component masses

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



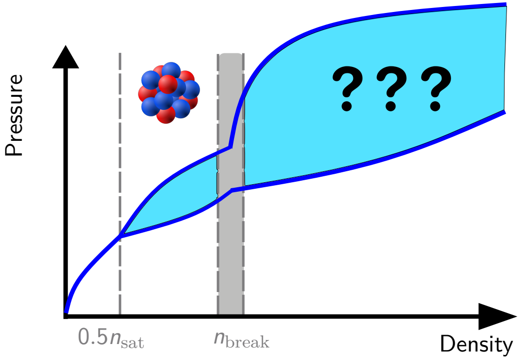
Parameter estimation on GW231109_235456

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



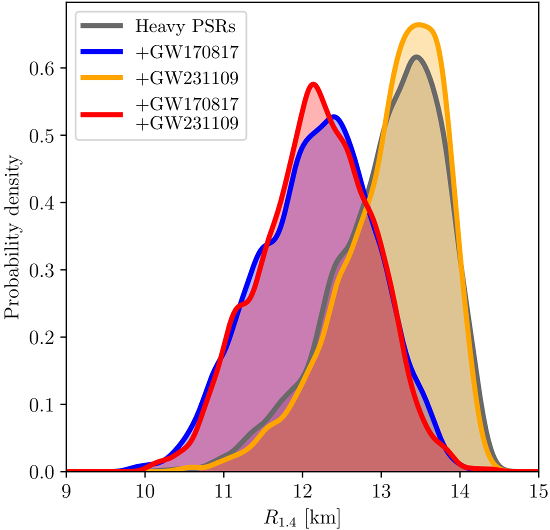
Constraining EOS from GW231109_235456

- Parametrized EOS inference: 26 parameters in total
  - Fixed crust
  - Metamodel
  - Speed-of-sound extension
- Accelerate with GPUs: JESTER [6]: ~ 1 hour



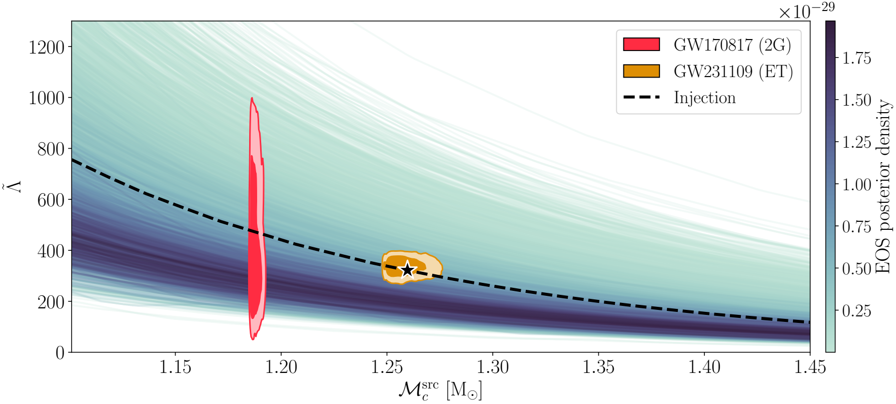
Constraining EOS from GW231109_235456

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



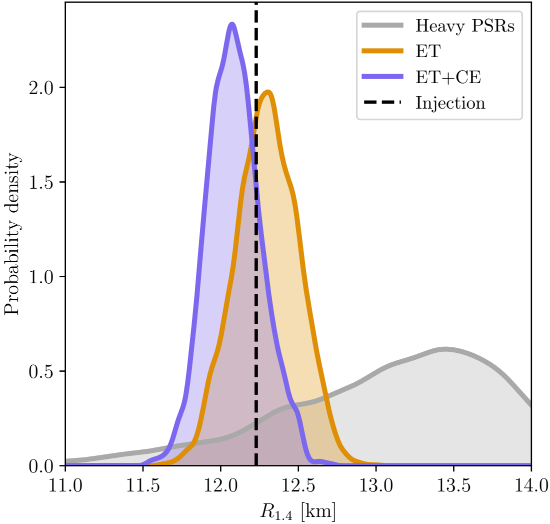
Projection: Einstein Telescope & Cosmic Explorer

- Simulate GW231109-like event with third-generation detectors
- Einstein Telescope: SNR ~ 134, with Cosmic Explorer: SNR ~ 294
- Recovery of tidal deformation improved



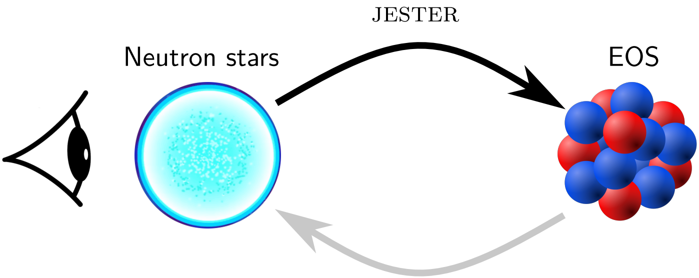
Projection: radius constraints

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: constrain EOS from 3G BNS in $\sim$ 1 hour



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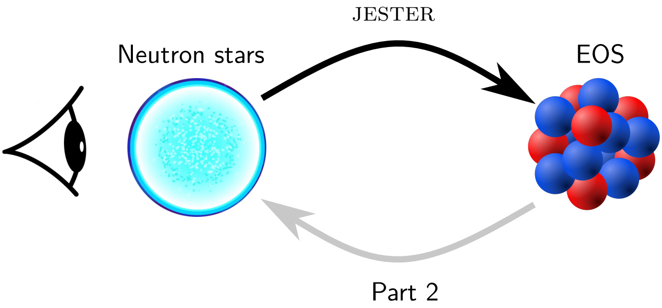


Neural priors: motivation

- Bayesian inference depends on choice of priors:

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

- By default, we use agnostic priors, but what if we *do* have non-trivial prior information?

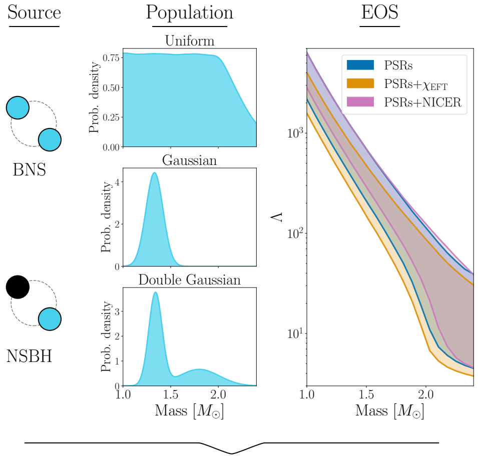
- Case study: neutron stars (NSs) and information from
  - Population models
  - Equation of state (EOS) constraints

Neural priors

Flexible way to encode NS physics into GW inference

Neural priors: key idea

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



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

NS population models

Three fiducial population models for NS masses:

1. **Uniform** [7–9]:
   - Only use EOS constraints for maximum mass (M_{TOV})
   - NS mass $\sim U[1\,\mathrm{M}_\odot, M_{\mathrm{TOV}}]$

2. **Gaussian** [10]:
   - NS mass $\sim \mathcal{N}(1.33\,\mathrm{M}_\odot, (0.09\,\mathrm{M}_\odot)^2)$

3. **Double Gaussian** [11, 12]:
   - Weighted mixture of two Gaussians
   - $0.65 \times \mathcal{N}(1.34\,\mathrm{M}_\odot, (0.07\,\mathrm{M}_\odot)^2) + 0.35 \times \mathcal{N}(1.80\,\mathrm{M}_\odot, (0.21\,\mathrm{M}_\odot)^2)$

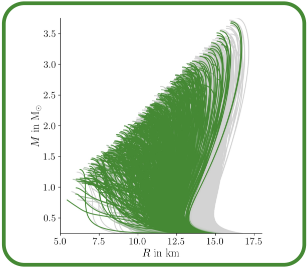
For NSBH systems:

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

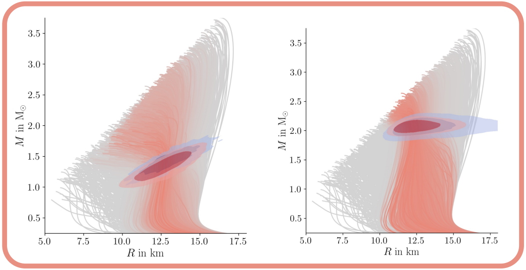
EOS constraints

- We use three EOS constraints [13]:
  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 [6]

Chiral EFT



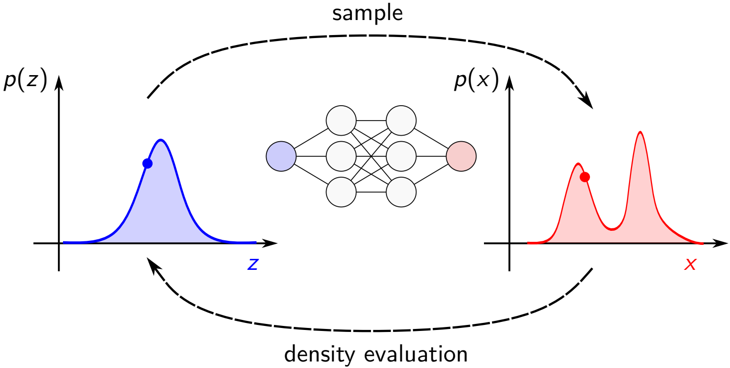
NICER



Normalizing flows

Normalizing flows [14, 15]

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



Construction of neural priors

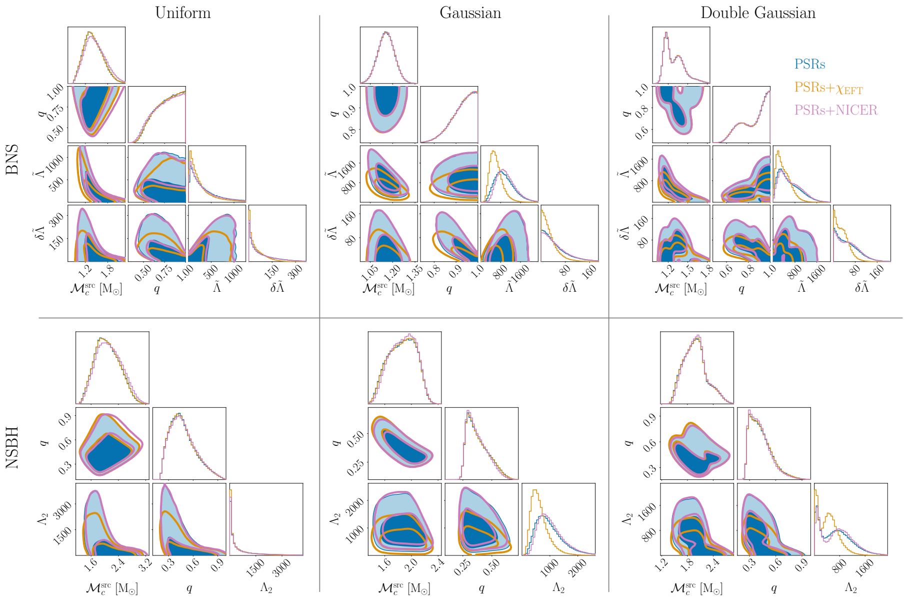
Steps to generate training data:

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 $\xrightarrow{\mathrm{NF}}$ data space

All neural priors



Setup

Analyze GW170817, GW190425, GW230529 with:

- `IMRPhenomXP_NRTidalv3`
- Neural priors for m_i, Λ_i (standard priors for other parameters)

Two contributions:

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

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

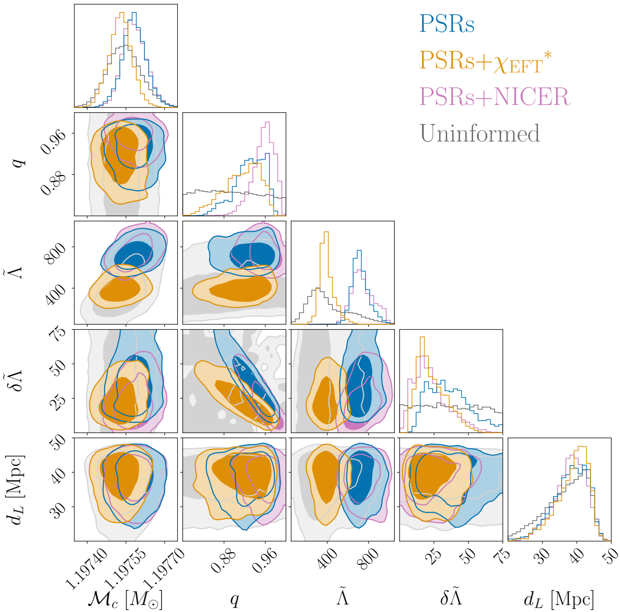
$\log_{10}(\mathcal{B}_1^2)$	Interpretation	Color
$[0, \frac{1}{2}]$	Barely worth mentioning	
$[\frac{1}{2}, 1]$	Substantial	
$[1, \frac{3}{2}]$	Strong	
$[\frac{3}{2}, 2]$	Very strong	
> 2	Decisive	

Source classification: All events

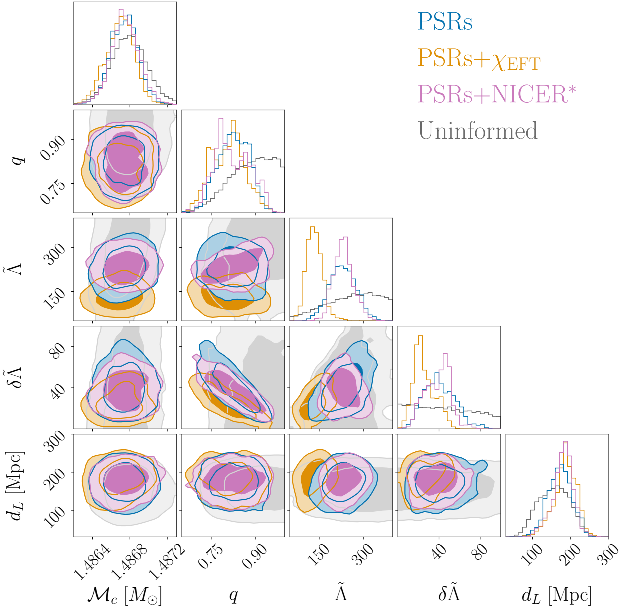
$\log_{10}$ Bayes factors relative to model with highest evidence ('ref.')

Source	Population	EOS	GW170817	GW190425	GW230529
BNS	Uniform	PSRs	−1.83	−0.07	−13.14
		PSRs+χ_{EFT}	−0.80	−0.11	−13.12
		PSRs+NICER	−1.58	**ref.**	−12.92
	Gaussian	PSRs	−0.68	−6.89	−18.82
		PSRs+χ_{EFT}	**ref.**	−8.47	−18.83
		PSRs+NICER	−0.76	−5.45	−18.81
	Double Gaussian	PSRs	−1.36	−0.55	−13.75
		PSRs+χ_{EFT}	−0.59	−0.79	−13.77
		PSRs+NICER	−0.92	−0.57	−13.71
NSBH	Uniform	PSRs	−224.65	−1.52	−0.08
		PSRs+χ_{EFT}	−224.66	−1.35	−0.02
		PSRs+NICER	−224.66	−1.63	−0.25
	Gaussian	PSRs	−224.67	−0.82	−0.05
		PSRs+χ_{EFT}	−224.66	−1.11	−0.20
		PSRs+NICER	−224.66	−1.43	**ref.**
	Double Gaussian	PSRs	−224.67	−4.11	−0.14
		PSRs+χ_{EFT}	−224.68	−3.83	−0.13
		PSRs+NICER	−224.67	−24.31	−0.05

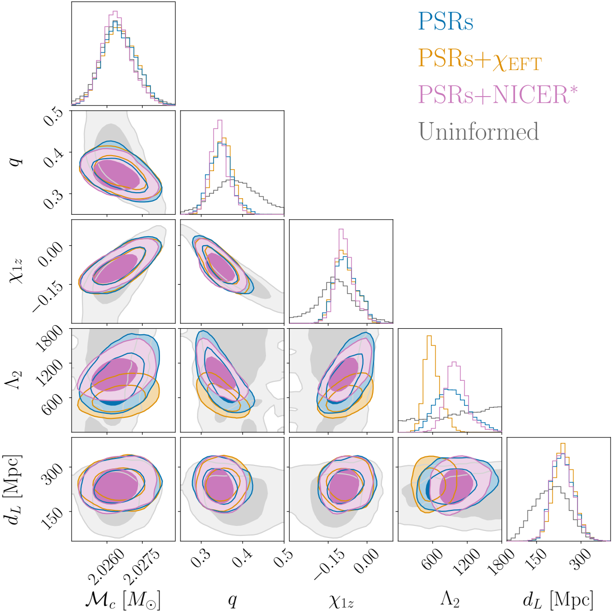
Parameter constraints: GW170817 (Gaussian population)



Parameter constraints: GW190425 (uniform population)



Parameter constraints: GW230529 (Gaussian population)



Discussion: Parameter constraints

GW170817:

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

GW190425:

- Less equal masses: $q \leq 0.9$; $\tilde{\Lambda} \approx 200$ (prior-dominated, low SNR)
- Higher luminosity distance: 182^{+41}_{-49} Mpc vs. 157^{+64}_{-65} Mpc

GW230529:

- Mass ratio more constrained: $q \leq 0.4$ (improved spin constraints)
- Tidal posteriors dominated by priors
- Higher luminosity distance: 235^{+59}_{-58} Mpc vs. 201^{+84}_{-97} Mpc

Conclusion (part 2)

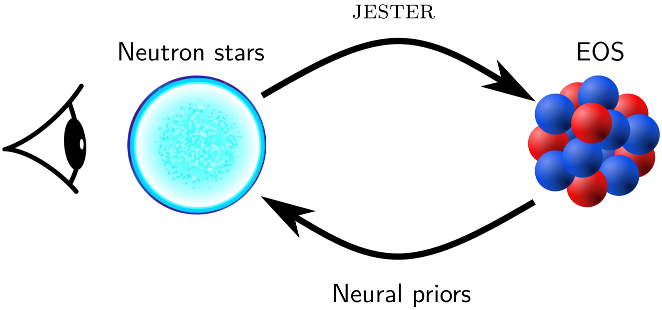
- **Neural priors**: Flexible way to encode non-trivial prior information
- Two highlights:
  1. Bayesian model selection
  2. Informed parameter constraints
- Implemented in BILBY
- Data-driven approach: easy to extend/generalize
- Future work: apply to 3G BNS

Contents

Conclusion

Methods for closing the neutron star data analysis loop:

1. JESTER: from NS observations to EOS constraints
2. Neural priors: incorporate EOS knowledge into GW inference



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Posterior distributions for ET/ET+CE injections