

# Incorporating neutron star physics into gravitational wave inference with neural priors

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# Motivation

- Bayesian inference depends on choice of **priors**:

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

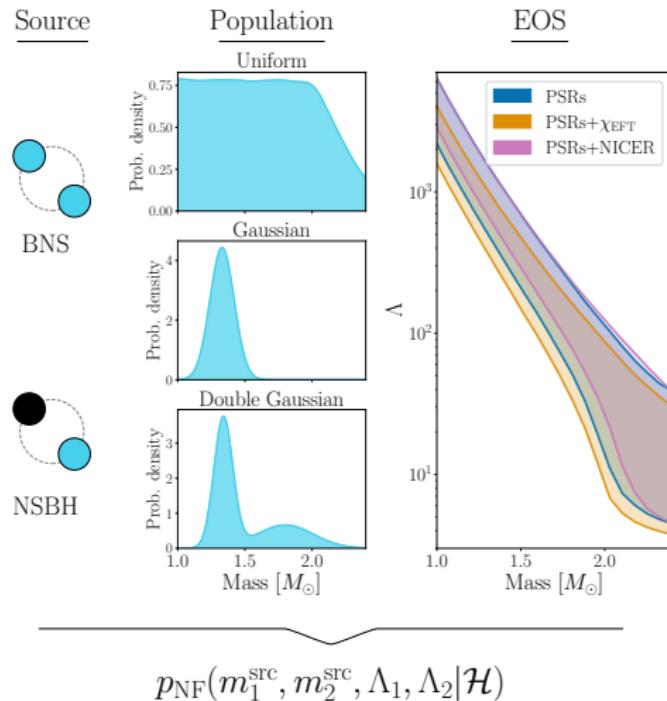
- By default, we use **agnostic priors**, but what if we *do* have non-trivial prior information?
- Case study: neutron stars (NSs) and information from
  - Population models
  - Equation of state (EOS) constraints

Neural priors

Flexible way to encode NS physics into GW inference

# Key idea

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



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# NS population models

Three fiducial population models for NS masses:

## ① Uniform [1–3]:

- Only use EOS constraints for maximum mass ( $M_{\text{TOV}}$ )
- NS mass  $\sim U[1 \text{ M}_\odot, M_{\text{TOV}}]$

## ② Gaussian [4]:

- NS mass  $\sim \mathcal{N}(1.33 \text{ M}_\odot, (0.09 \text{ M}_\odot)^2)$

## ③ Double Gaussian [5, 6]:

- Weighted mixture of two Gaussians
- $0.65 \times \mathcal{N}(1.34 \text{ M}_\odot, (0.07 \text{ M}_\odot)^2) + 0.35 \times \mathcal{N}(1.80 \text{ M}_\odot, (0.21 \text{ M}_\odot)^2)$

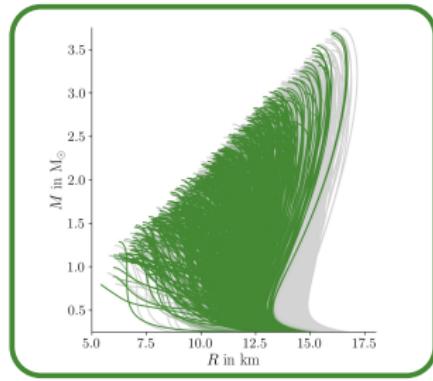
For NSBH systems:

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

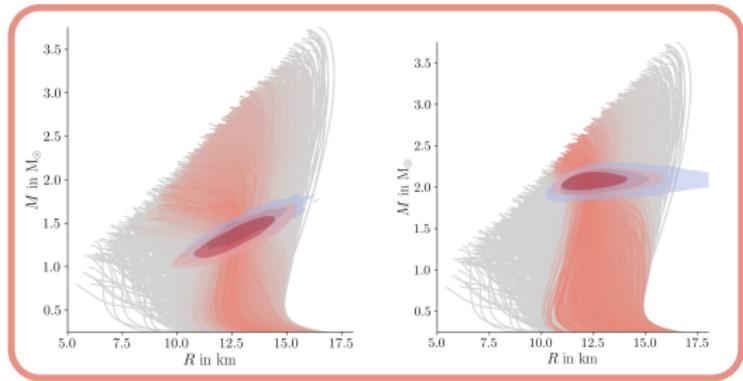
# EOS constraints

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

Chiral EFT



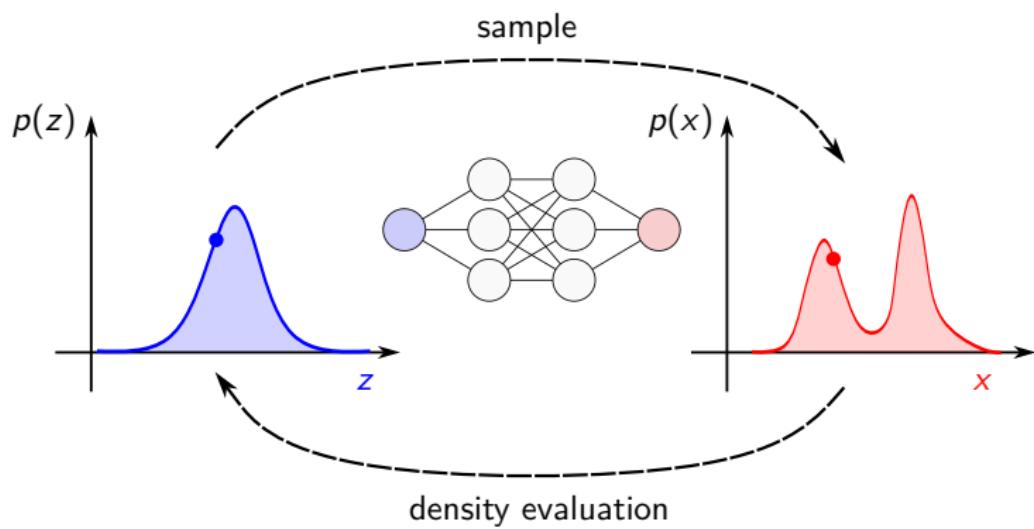
NICER



# Normalizing flows

## Normalizing flows [9, 10]

- Neural density estimators: trainable bijections
- Often used in PE, e.g., DINGO [11, 12], NESSAI [13, 14]
- Generate samples, evaluate density: can be used as priors [15]



# Construction of neural priors

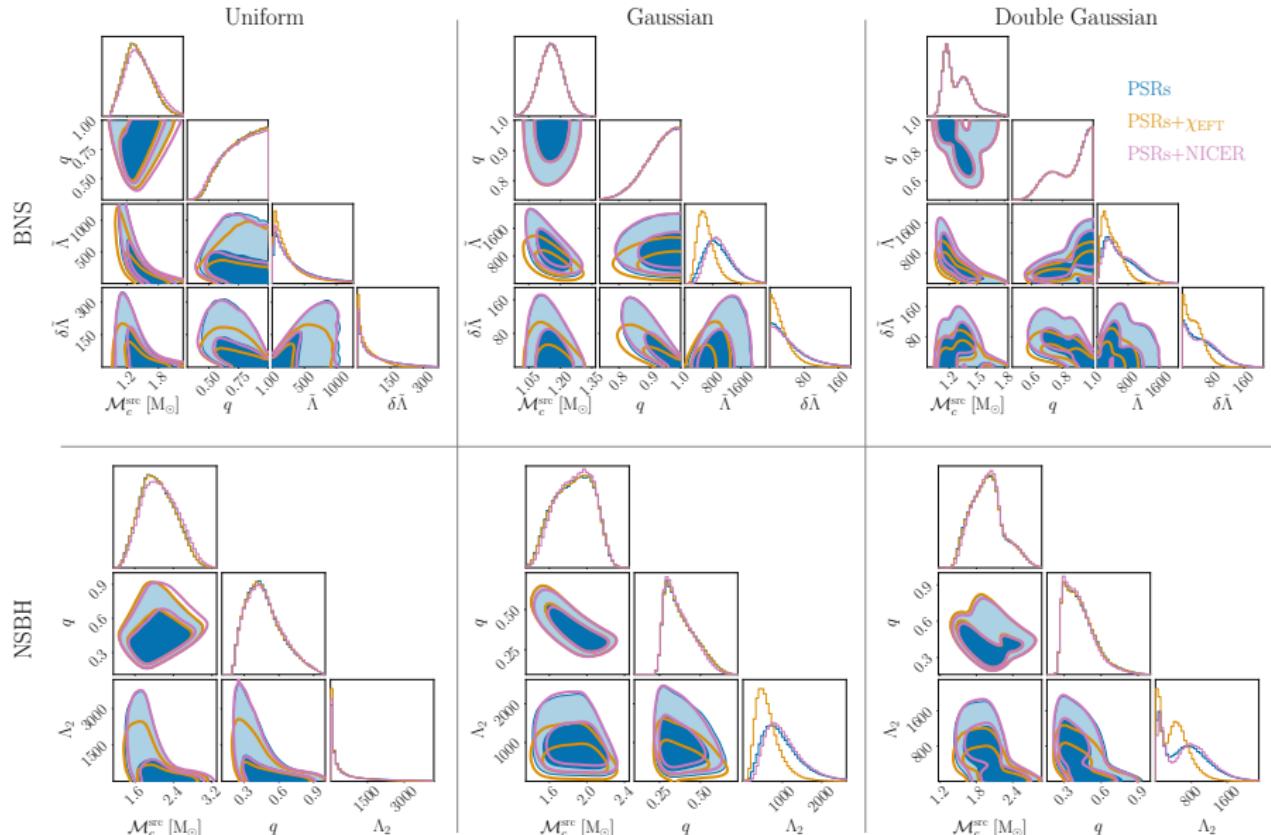
Steps to generate training data:

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

Implementation:

- Created with GLASFLOW [16, 17]
- CouplingNSF architecture (neural spline flows [18])
- 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



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# Setup

Analyze GW170817, GW190425, GW230529 with:

- 4096 live points, multibanding likelihood
- IMRPhenomXP\_NRTidalv3
- Neural priors for  $m_i, \Lambda_i$  (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	Light orange
$[\frac{1}{2}, 1]$	Substantial	Orange
$[1, \frac{3}{2}]$	Strong	Red-orange
$[\frac{3}{2}, 2]$	Very strong	Dark red
$> 2$	Decisive	Red

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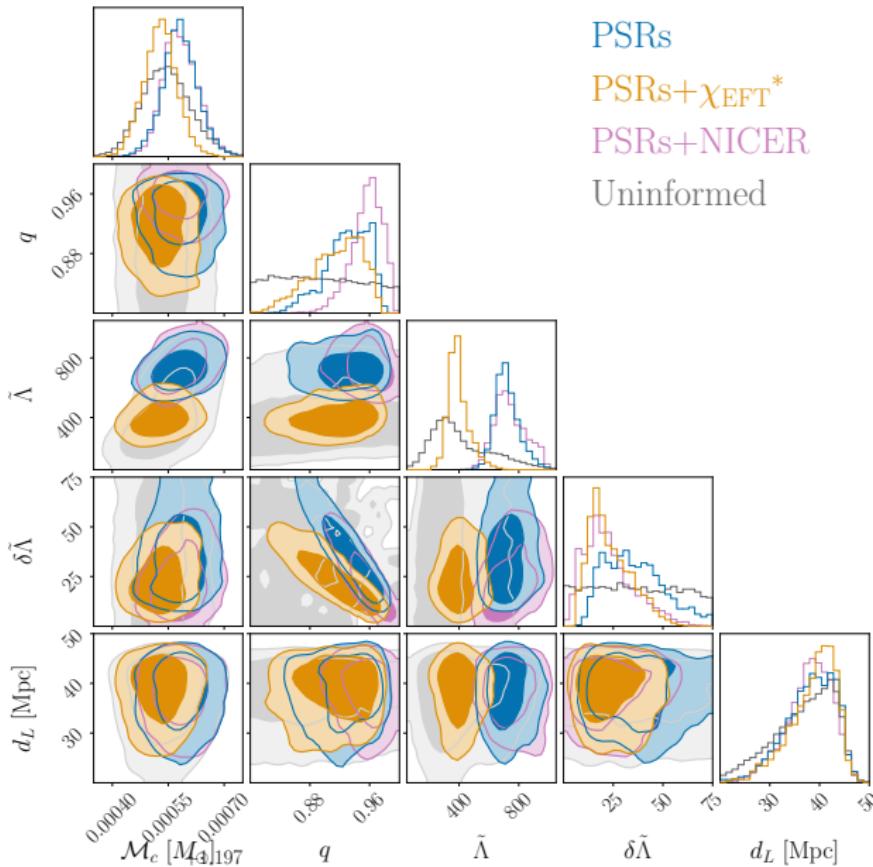
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# GW170817: Source classification

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

Source	Population	EOS	GW170817
BNS	Uniform	PSRs	-1.83
		PSRs+ $\chi$ EFT	-0.80
		PSRs+NICER	-1.58
	Gaussian	PSRs	-0.68
		PSRs+ $\chi$ EFT	ref.
		PSRs+NICER	-0.76
	Double Gaussian	PSRs	-1.36
		PSRs+ $\chi$ EFT	-0.59
		PSRs+NICER	-0.92
NSBH	Uniform	PSRs	-224.65
		PSRs+ $\chi$ EFT	-224.66
		PSRs+NICER	-224.66
	Gaussian	PSRs	-224.67
		PSRs+ $\chi$ EFT	-224.66
		PSRs+NICER	-224.66
	Double Gaussian	PSRs	-224.67
		PSRs+ $\chi$ 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+ $\chi_{\text{EFT}}$ )

## 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 [19–23]

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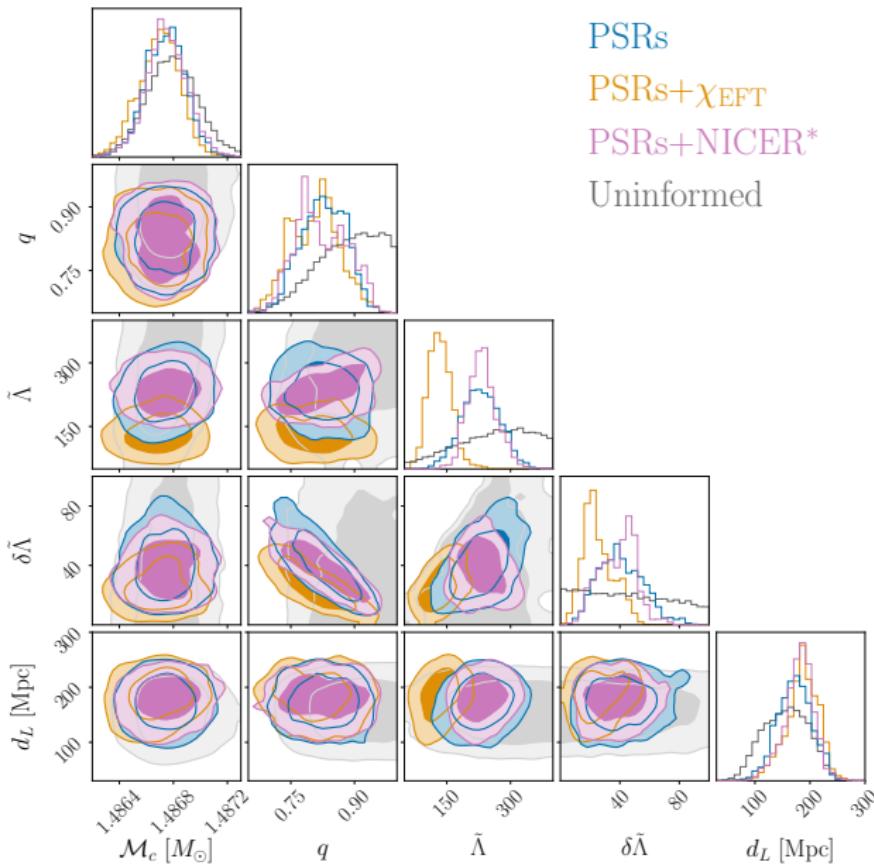
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# GW190425: Source classification

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

Source	Population	EOS	GW190425
BNS	Uniform	PSRs	-0.07
		PSRs+ $\chi$ EFT	-0.11
		PSRs+NICER	ref.
	Gaussian	PSRs	-6.89
		PSRs+ $\chi$ EFT	-8.47
		PSRs+NICER	-5.45
	Double Gaussian	PSRs	-0.55
		PSRs+ $\chi$ EFT	-0.79
		PSRs+NICER	-0.57
NSBH	Uniform	PSRs	-1.52
		PSRs+ $\chi$ EFT	-1.35
		PSRs+NICER	-1.63
	Gaussian	PSRs	-0.82
		PSRs+ $\chi$ EFT	-1.11
		PSRs+NICER	-1.43
	Double Gaussian	PSRs	-4.11
		PSRs+ $\chi$ 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:  $182_{-49}^{+41}$  Mpc vs.  $157_{-65}^{+64}$  Mpc (90% credibility)

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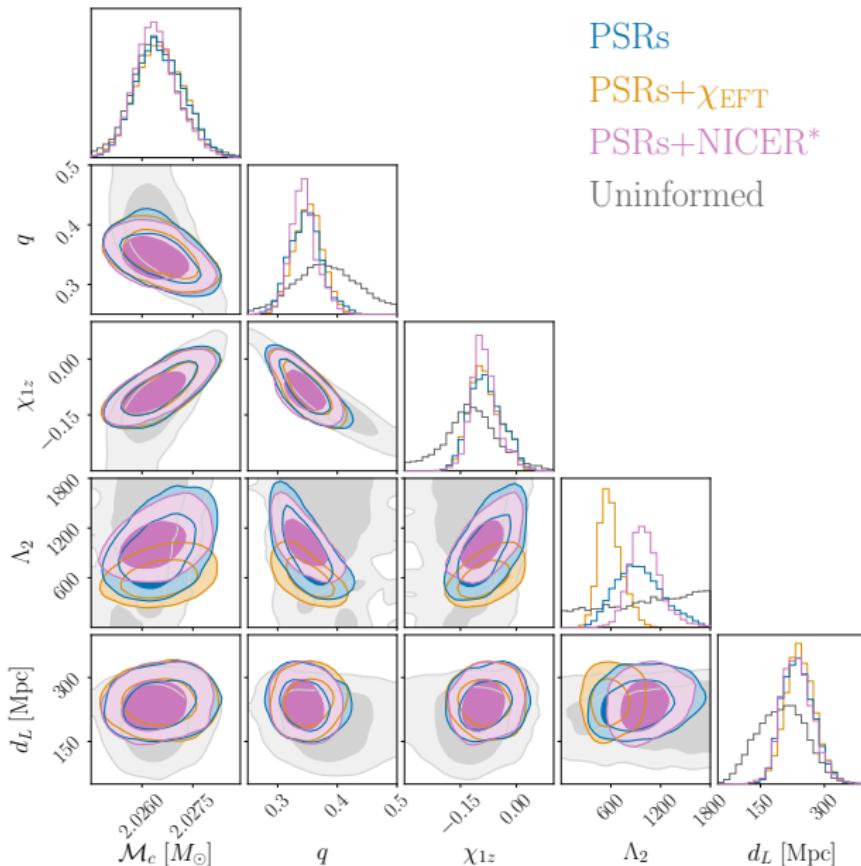
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# GW230529: Source classification

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

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

# GW230529: Parameter constraints (Gaussian)



# GW230529: Discussion

## Source classification:

- Decisive evidence for NSBH over BNS (agrees with LVK [24])
- No evidence between hypotheses (low SNR)

## Parameter constraints:

- Mass ratio more constrained:  $q \leq 0.4$ 
  - As a result, improved spin constraints ( $\chi_{1z}$  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)

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# Conclusion

- PE often uses agnostic priors, missing valuable information
- **Neural priors**: flexible way to encode non-trivial prior information
- Case study: neutron star physics from
  - Population models
  - EOS constraints
- Two highlights:
  - ① **Bayesian source classification** (BNS vs. NSBH)
  - ② **Informed parameter constraints** (narrower posteriors)
- Implemented in BILBY
- Data-driven approach: easy to extend/generalize



**Thanks for listening!**



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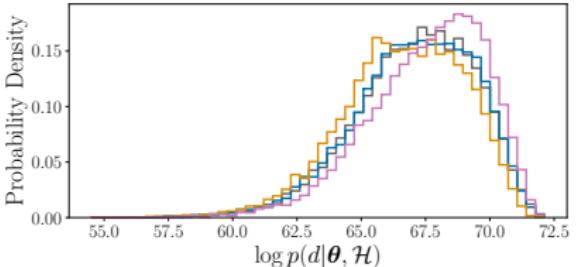
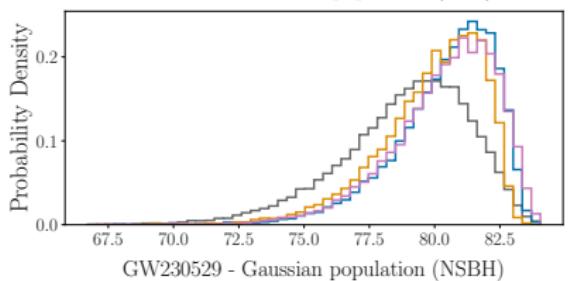
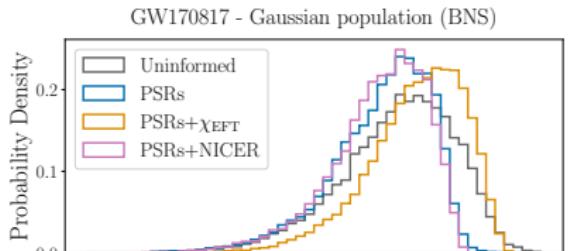
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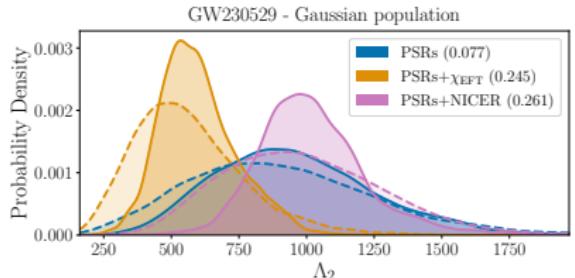
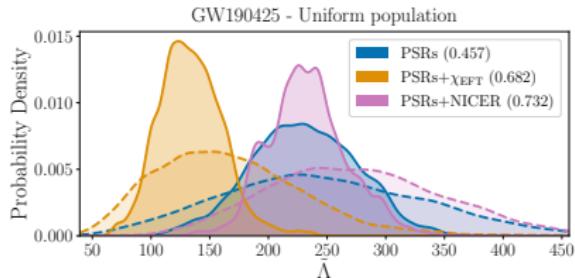
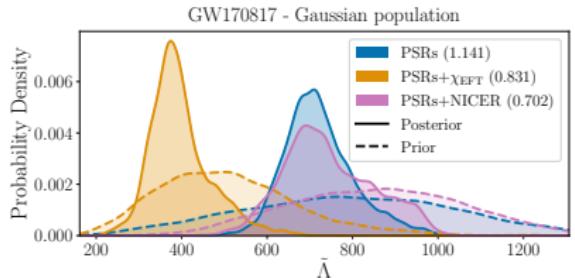
# Likelihood distributions

- Likelihood distributions, obtained from final posterior samples



# Information gain

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



# More posteriors

Event	Pop	EOS	$m_1^{\text{src}} [M_{\odot}]$	$m_2^{\text{src}} [M_{\odot}]$	$q$	$\Lambda_1$	$\Lambda_2$	$\bar{\Lambda}$	$\delta\bar{\Lambda}$	$d_L [\text{Mpc}]$	
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+ $\chi_{\text{EFT}}$	$1.52^{+0.08}_{-0.07}$	$1.23^{+0.06}_{-0.06}$	$0.81^{+0.08}_{-0.07}$	$215^{+87}_{-111}$	$712^{+219}_{-175}$	$390^{+98}_{-93}$	$58^{+19}_{-25}$	$40^{+6}_{-8}$	
		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+ $\chi_{\text{EFT}}$	$1.42^{+0.05}_{-0.04}$	$1.31^{+0.03}_{-0.04}$	$0.92^{+0.05}_{-0.06}$	$298^{+130}_{-99}$	$495^{+173}_{-118}$	$385^{+141}_{-85}$	$21^{+19}_{-13}$	$40^{+6}_{-9}$	
		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+ $\chi_{\text{EFT}}$	$1.39^{+0.02}_{-0.02}$	$1.34^{+0.02}_{-0.02}$	$0.96^{+0.03}_{-0.03}$	$382^{+148}_{-111}$	$507^{+153}_{-152}$	$444^{+136}_{-131}$	$11^{+12}_{-9}$	$39^{+7}_{-7}$	
		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+ $\chi_{\text{EFT}}$	$1.83^{+0.12}_{-0.10}$	$1.48^{+0.07}_{-0.10}$	$0.81^{+0.09}_{-0.09}$	$58^{+40}_{-28}$	$259^{+174}_{-107}$	$132^{+44}_{-40}$	$23^{+21}_{-12}$	$187^{+48}_{-49}$	
		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+ $\chi_{\text{EFT}}$	$1.94^{+0.07}_{-0.06}$	$1.40^{+0.04}_{-0.05}$	$0.72^{+0.04}_{-0.05}$	$51^{+23}_{-24}$	$408^{+125}_{-100}$	$156^{+37}_{-45}$	$37^{+10}_{-9}$	$190^{+41}_{-47}$	
		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+ $\chi_{\text{EFT}}$	$3.52^{+0.46}_{-0.45}$	$1.46^{+0.18}_{-0.14}$	$0.41^{+0.12}_{-0.08}$	—	$322^{+206}_{-202}$	$26^{+8}_{-7}$	$13^{+4}_{-4}$	$220^{+70}_{-64}$	
		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+ $\chi_{\text{EFT}}$	$3.83^{+0.25}_{-0.25}$	$1.35^{+0.07}_{-0.07}$	$0.35^{+0.04}_{-0.04}$	—	$582^{+261}_{-198}$	$30^{+7}_{-8}$	$15^{+3}_{-4}$	$242^{+59}_{-57}$	
		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+ $\chi_{\text{EFT}}$	$3.85^{+0.18}_{-0.21}$	$1.34^{+0.05}_{-0.06}$	$0.35^{+0.03}_{-0.03}$	—	$516^{+194}_{-205}$	$26^{+8}_{-8}$	$13^{+4}_{-4}$	$237^{+66}_{-71}$	
		PSRs+NICER	$3.86^{+0.15}_{-0.16}$	$1.34^{+0.04}_{-0.04}$	$0.35^{+0.02}_{-0.02}$	—	$1026^{+254}_{-306}$	$52^{+11}_{-13}$	$26^{+6}_{-6}$	$229^{+65}_{-68}$	