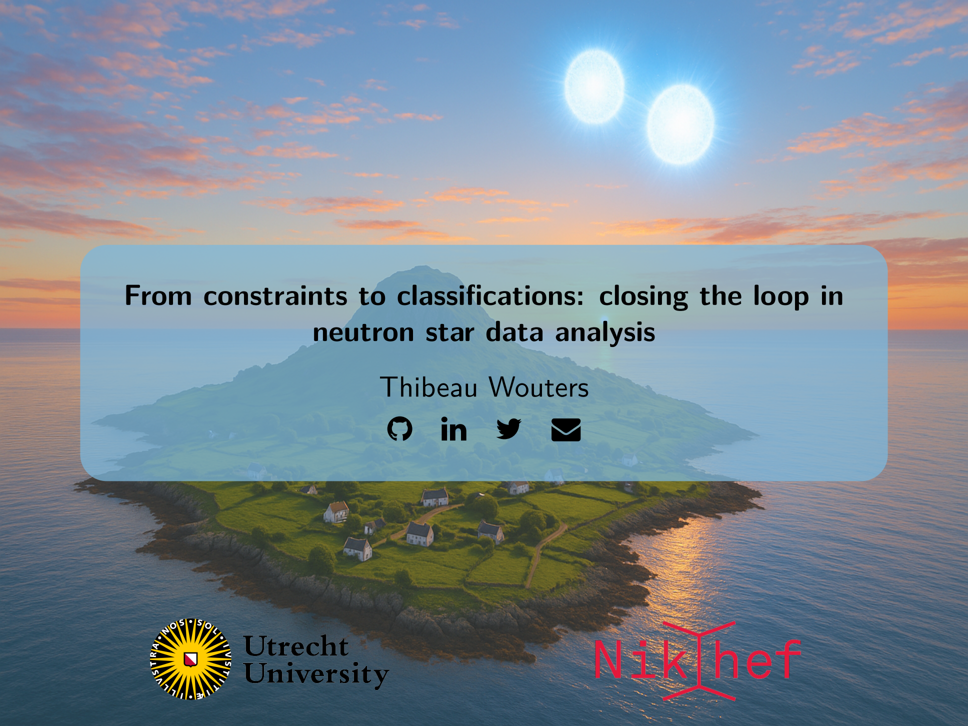

From constraints to classifications: closing the loop in neutron star data analysis

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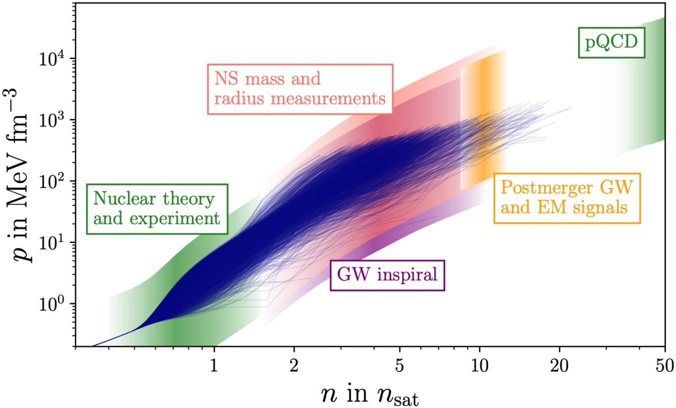
The equation of state (EOS)

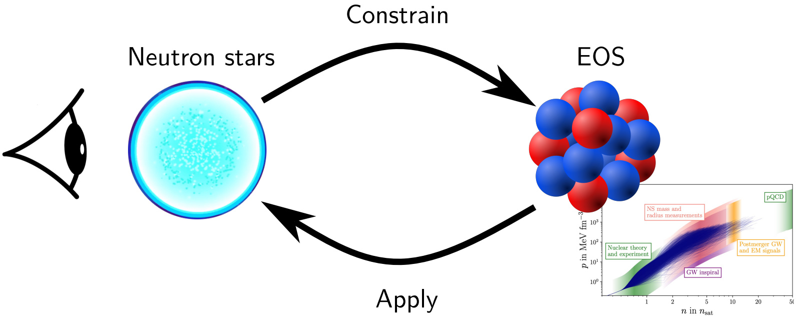
- The equation of state (EOS) of dense nuclear matter is still uncertain [1]
- Neutron star (NS) properties depend on the EOS: probe its high density regime



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

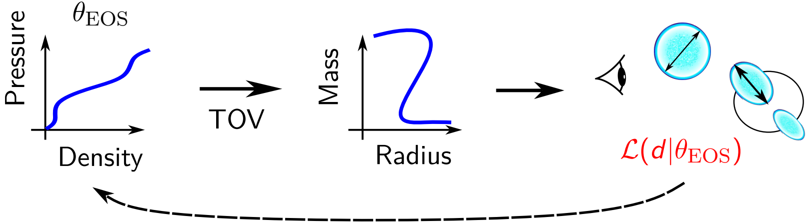
Constraining the EOS

- EOS determined with Bayesian inference:

$$\mathcal{P}(\theta_{\mathrm{EOS}}|d) \propto \mathcal{L}(d|\theta_{\mathrm{EOS}})\pi(\theta_{\mathrm{EOS}})$$

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

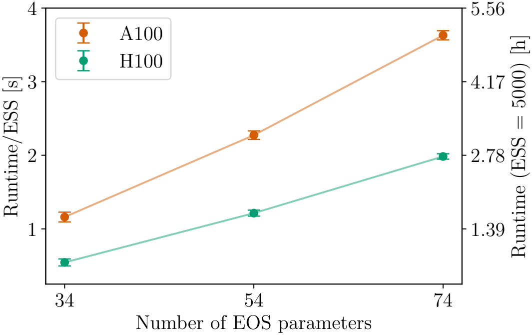
- Solve TOV equations to predict NS properties from EOS
- Solving the TOV equations is slow!



JESTER: accelerated TOV solver

JESTER [2]: JAX-based EOS code and TOV solver

- GPU acceleration, just-in-time (JIT) compilation
- Enable sampling of θ_{EOS} in high-dimensional space
- Same speed as ML surrogates of TOV solvers!



Contents

Structure of this talk

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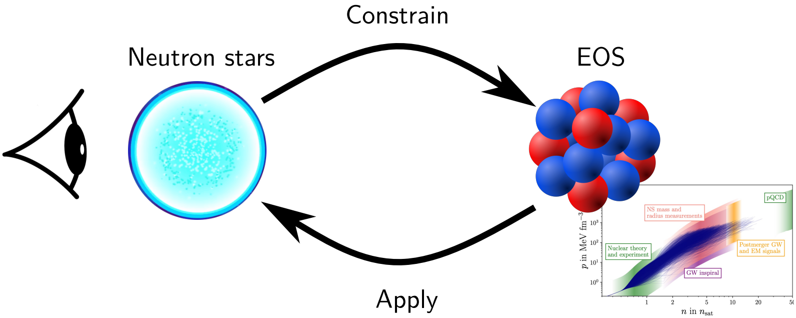
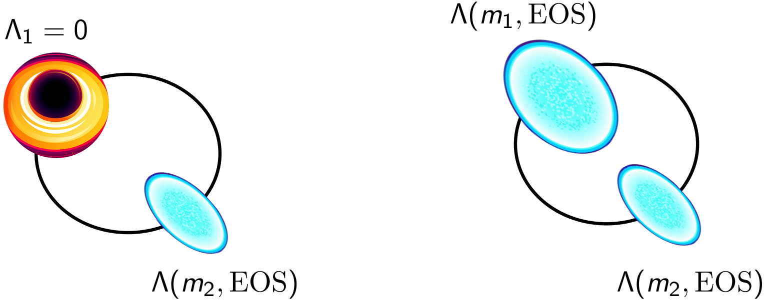


Tidal deformability

- Neutron stars are tidally deformed in a binary
- Quantified by the tidal deformability Λ
- Depends on the EOS: $\Lambda = \Lambda(m, \mathrm{EOS})$ (black holes: $\Lambda = 0$)
- Imprint in the GW phase: $\tilde{\Lambda}(m_i, \Lambda_i)$



Equation of state-informed priors

- GW parameters are determined with 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. $\Lambda_i \sim \mathcal{U}(0, 5000)$

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- **But**, we have prior knowledge from the EOS:
  - Masses m_i determined by M_{max}
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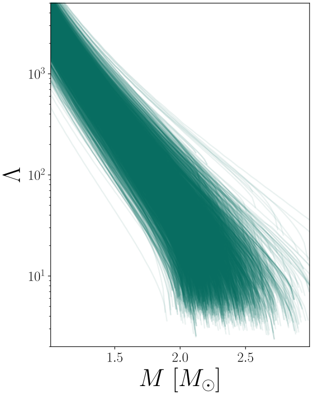
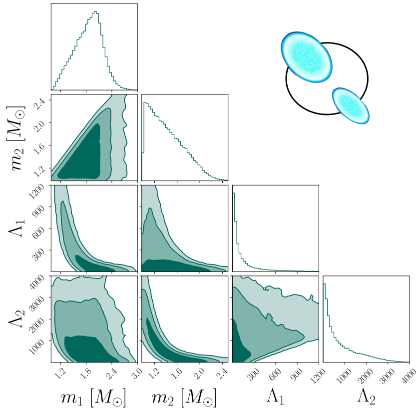
- **But**, we have prior knowledge from the EOS:
  - Masses m_i determined by M_{max}
  - Λ_i determined by m_i and EOS
- **Equation of state-informed prior**:

$$\pi(m_1, m_2, \Lambda_1, \Lambda_2) = \int \mathrm{d}\theta_{\mathrm{EOS}}\ \pi(m_1, m_2|\theta_{\mathrm{EOS}})\pi(\Lambda_1, \Lambda_2|m_1, m_2, \theta_{\mathrm{EOS}}) \times \pi(\theta_{\mathrm{EOS}})$$

Equation of state-informed priors

- Example: EOSs with $M_{\rm max} > 2.0 M_\odot$
- Emulate $\pi(m_1, m_2, \Lambda_1, \Lambda_2)$ with a **normalizing flow** (FlowJax)

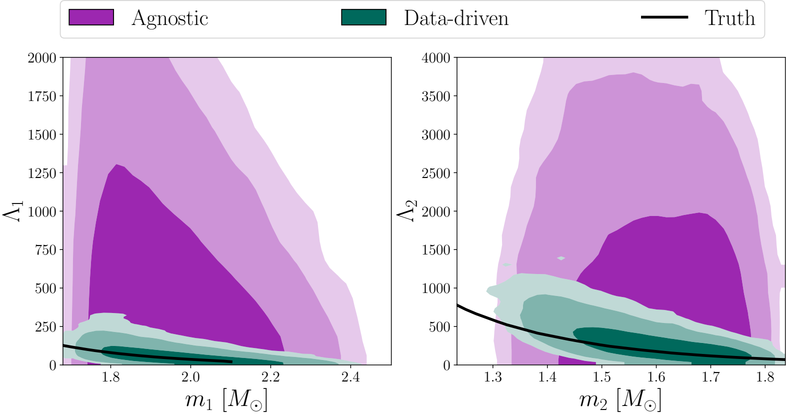




Simulated binary neutron star signal

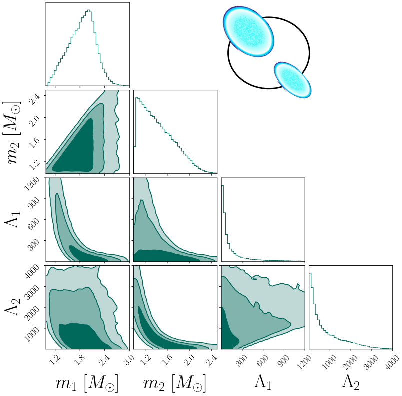
Tidal content of source more constrained (SNR $= 13$)

- **Agnostic**: uniform prior for chirp mass, mass ratio, Λ_1, Λ_2
- **Data-driven**: normalizing flow prior $\pi(m_1, m_2, \Lambda_1, \Lambda_2)$

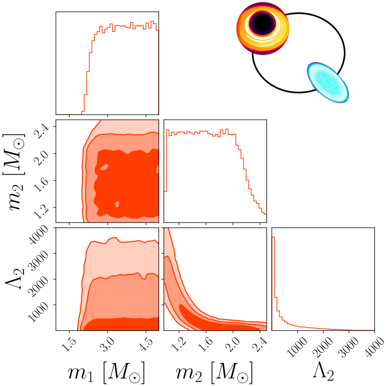


Source classification

- Similar to the **binary neutron star (BNS)** prior, we can also construct a **neutron star-black hole (NSBH)** prior
- Use EOS constraints to classify GWs with Bayesian inference



$\Lambda_1 = 0$

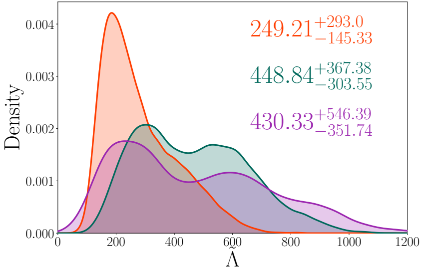


Source classification

GW170817

$$\textit{ln}\ \mathcal{B}^{\mathrm{BNS}}_{\mathrm{NSBH}} = 44.75$$

$$\textit{ln}\ \mathcal{B}^{\mathrm{BNS}}_{\mathrm{agnostic}} = 2.83$$



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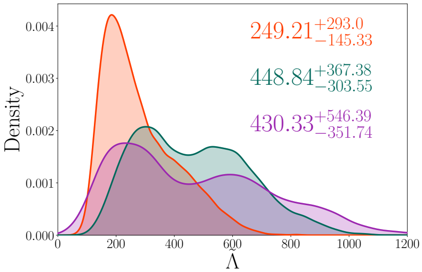
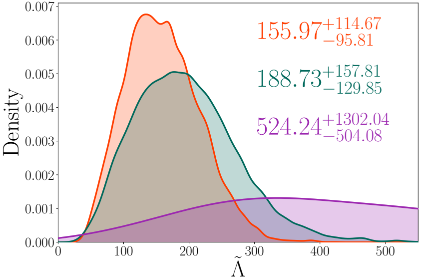


GW190425

$$ln\ \mathcal{B}^{\mathrm{BNS}}_{\mathrm{NSBH}} = 4.13$$
$$ln\ \mathcal{B}^{\mathrm{BNS}}_{\mathrm{agnostic}} = -0.30$$

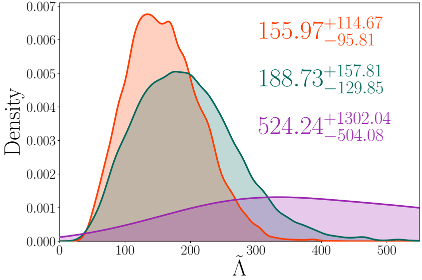


Source classification: closing the loop

GW190425

- $M_{\max} > 2M_\odot$

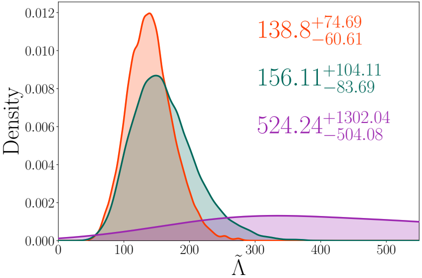
$$\ln \mathcal{B}^{\mathrm{BNS}}_{\mathrm{NSBH}} = \ \ 4.13$$
$$\ln \mathcal{B}^{\mathrm{BNS}}_{\mathrm{agnostic}} = -0.30$$



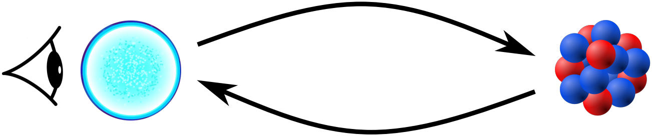
GW190425

+ mass-radius measurements
+ GW170817
+ nuclear theory predictions

$$\ln \mathcal{B}^{\mathrm{BNS}}_{\mathrm{NSBH}} = 8.20$$
$$\ln \mathcal{B}^{\mathrm{BNS}}_{\mathrm{agnostic}} = 0.28$$



Conclusion



- Neutron star observations and EOS constraints form a data analysis loop
  - TOV solvers can be accelerated with JAX, avoiding the need for machine learning surrogates
  - Normalizing flows can emulate priors on source parameters informed by EOS knowledge
- Equation of state-informed priors enable source classification: to be implemented in BILBY

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[1] 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: (Feb. 2024). arXiv: 2402.04172 [astro-ph.HE].

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

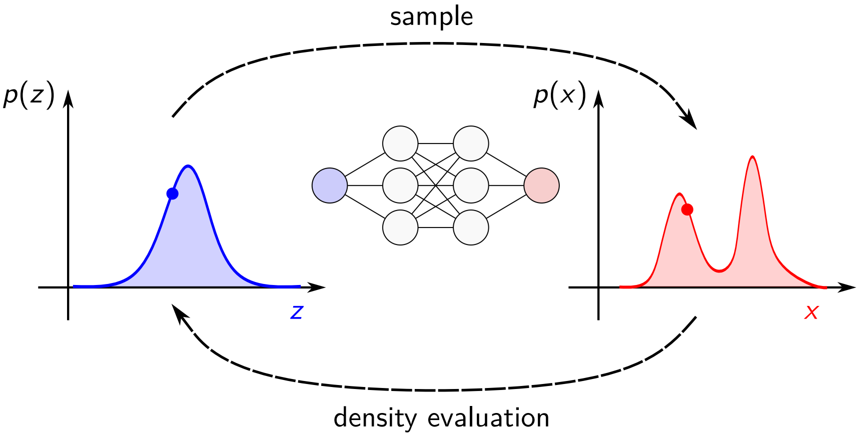
[3] Kurzgesagt. *Figures taken from "Neutron Stars - The Most Extreme Things that are not Black Holes"*. Accessed on May 14, 2025. 2019. URL: https://www.youtube.com/watch?v=udFxKZRyQt4.

[4] Kaze W. K. Wong, Maximiliano Isi, and Thomas D. P. Edwards. "Fast Gravitational-wave Parameter Estimation without Compromises". In: *Astrophys. J.* 958.2 (2023), p. 129. DOI: 10.3847/1538-4357/acf5cd. arXiv: 2302.05333 [astro-ph.IM].

[5] Thibeau Wouters et al. "Robust parameter estimation within minutes on gravitational wave signals from binary neutron star inspirals". In: *Phys. Rev. D* 110.8 (2024), p. 083033. DOI: 10.1103/PhysRevD.110.083033. arXiv: 2404.11397 [astro-ph.IM].

Normalizing flows

- Trainable, bijective transformation between latent and data space
- Emulate complicated distributions, trained from samples



Projection: 20 BNS in O5

- 20 binary neutron star signals observed with HLV and O5 sensitivity
  - Parameter estimation done with JIM [4, 5]: $\sim$ 30 mins/event
  - **Agnostic** vs **data-driven** priors
- Use resulting GW posteriors to constrain the EOS
  - $\sim$ 1 hour with JESTER [2]
- Result: constraints more robust