Accelerated Bayesian inference with machine learning

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

t.r.i.wouters@uu.nl

23 – 27 September 2024

Utrecht University

Nikhef

Nuclear Multi-Messenger Astrophysics

- `NMMA`: Nuclear Multi-Messenger Astrophysics (Peter T.H. Pang)
  - https://github.com/nuclear-multimessenger-astronomy/nmma

- A Pythonic library for probing nuclear physics and cosmology with multimessenger analysis

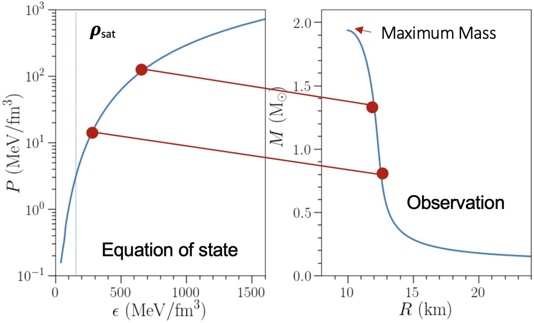
- Joint Bayesian inference on gravitational waves, kilonovae, gamma-ray bursts, supernovae

- Used for overview of EOS constraints: arXiv:2402.04172

Gravitational waves from binary neutron stars

The EOS predicts the relation between mass M and radius R or tidal deformability of neutron stars.

We can infer the tidal deformability of neutron stars from gravitational wave signals emitted by binary neutron star mergers.

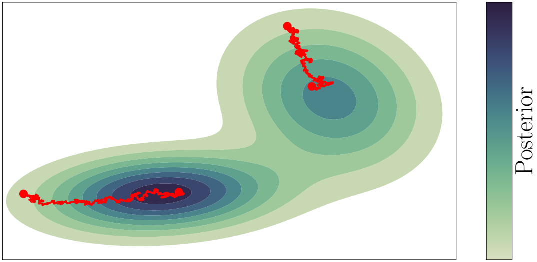


Parameter estimation of neutron star properties

Bayesian inference: get posterior of GW parameters θ (13 to 17 parameters) from gravitational wave data d:

$$p(\theta|d) = \frac{p(d|\theta)p(\theta)}{p(d)} = \frac{\text{likelihood} \times \text{prior}}{\text{evidence}}$$

Problem: Computationally expensive: $\sim 1 - 2$ months on a single CPU core for binary neutron star signal



Accelerating Bayesian inference with machine learning

- `Jim`: Accelerate Bayesian inference with (i) `jax` and (ii) normalizing flows (machine learning) (arXiv:2404.11397)
  - https://github.com/kazewong/jim/
  - Sampler: `flowMC` (https://github.com/kazewong/flowMC)

- Result: $\sim$ 30 minutes on a single GPU

- Ongoing:
  - Extend to next-generation gravitational wave detectors
  - Accelerate TOV solver with `jax` ($\sim 10 - 100\times$ faster)
  - Add electromagnetic transients – `jax` version of `NMMA`

Goal: Direct inference of nuclear physics parameters with multimessenger data.