Bayesian inference on dark matter admixed neutron stars with gravitational-wave data

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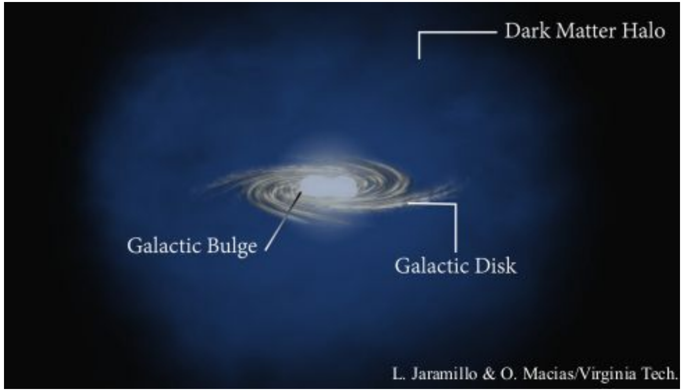
Introduction | potential presence of dark matter in neutron stars

Evidences for dark matter (DM)

- rotational curves of galaxies
- structure formation



Scenarios arguing for presence of DM in neutron stars (NSs)

- Bramante et al. (2022) argued NSs might be embedded in a DM halo or could accrete DM clumps

- due to extreme gravity, NSs may accumulate a significant amount of DM over their lifetime [Bertone & Fairbairn (2008); de Lavallaz and M. Fairbairn (2010); D. Bose and S. Sarkar (2023)]

- BNS systems may have higher amount of DM as these are old systems that went through several stages of stellar evolution [Bell et al. (2020)]

Introduction | Dark matter and impact its on neutron stars

Consequence | DM modfies NS properties:

- Gravitational Mass
- Radius
- Tidal deformability

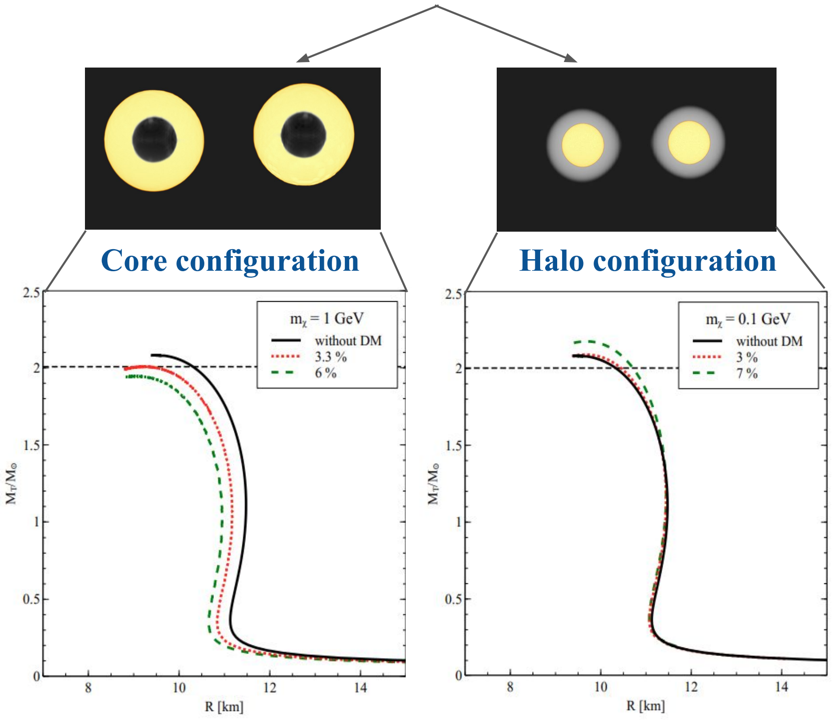
DM model | [Sagun, Giangrandi et al. 2021]

- DM is considered as fermionic gas
- neglect interaction of baryonic matter (BM) with DM
- BM and DM interact only gravitationally

→ 2 main parameters:

- DM fraction, f_χ
- DM particle mass, m_χ

DM model allows for **2 configurations**:



[Ivanytskyi, Sagun, Lopes (2020)]

Introduction | How to study DM admixed BNS mergers?

Parameter estimation through **Bayes theorem**

Likelihood *Prior*

$$p(\vec{\theta}|d,\mathcal{H}) \equiv \frac{\mathcal{L}(\vec{\theta})\pi(\vec{\theta})}{\mathcal{Z}}$$

Posterior

Evidence

Gravitational-wave likelihood

$$\mathcal{L}_{GW} \propto \exp\Big(-\frac{1}{2}\langle d - h(\vec{\theta})|d - h(\vec{\theta})\rangle\Big)$$

Data *Waveform*

Gravitational waveform

$$h(t; m_{1,2}, \Lambda_{1,2}, \vec{\theta})$$

↓

tidal deformabilities

↙ ↓ ↘

Prior informed | nuclear physics informed | nuclear physics & dark matter informed

Methods | How to study DM admixed BNS mergers?

→ we use 3 main ingredients

Step 1: use nuclear physics model to obtain baryonic Equation of State (EOS) set →

↓

- mass m,
- radius R,
- tidal deformability Λ

Step 2: model DM contribution to obtain DM EOS set →

↓

- mass m,
- radius R,
- DM informed tidal deformability Λ_{DM}

Step 3: implement conversion DM EOS $\rightarrow \Lambda_{\mathrm{DM}}$ in existing Bayesian inference libraries

NMMA

- **NMMA: Multi-messenger framework**
  [Pang, et al. (2023)]

Methods | constructing the baryonic EOS set

- construct baryonic EOS set using the metamodel of Margueron et al. (2018)

- EOS predicted by the metamodel is determined by the nuclear empirical parameters

→ obtained 5000 baryonic EOSs

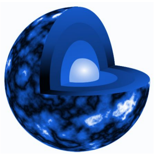
TABLE I. The distributions from which the empirical parameters are drawn to generate the EOS candidates. The parameters E_{sat} and n_{sat} are fixed at -16 MeV and $0.16\,\mathrm{fm}^{-3}$, respectively. We denote uniform distributions by $\mathcal{U}$.

Parameter	Distribution
K_{sat} [MeV]	$\mathcal{U}(210, 260)$
Q_{sat} [MeV]	$\mathcal{U}(-1000, 1000)$
Z_{sat} [MeV]	$\mathcal{U}(-1000, 1000)$
E_{sym} [MeV]	$\mathcal{U}(28, 35)$
L_{sym} [MeV]	$\mathcal{U}(30, 100)$
K_{sym} [MeV]	$\mathcal{U}(-200, 200)$
Q_{sym} [MeV]	$\mathcal{U}(-1000, 1000)$
Z_{sym} [MeV]	$\mathcal{U}(-1000, 1000)$

Koehn et al. (2024)

[arxiv: 2408.14711]

Methods | obtaining the DM EOS set



- solving 2-fluid TOV and Love equations to obtain DM NS mass, radius and tidal deformability
  [Ivanytskyi, Sagun, Lopes (2020)]

- NS configurations will now also depend on
  > DM particle mass
  > DM fraction

→ calculate NS configuration for 5000 EOSs on a grid of 12 x 12 combinations for DM masses and fractions

m_χ in MeV
170
221
286
372
483
627
814
1056
1371
1780
2311
3000

×

f_χ in %
0.01
0.015
0.023
0.035
0.053
0.081
0.123
0.187
0.285
0.433
0.658
1

Methods | Implementation in existing Bayesian inference libraries

i) Bilby [Ashton, et al. (2019)]

> Inference of gravitational-wave (GW) signals

> Add-on: Multi-banding [Morisaki, (2021)]

ii) Multi-messenger framework (NMMA) [Pang, et al. (2023)]

> Inference of GW signals

> Add-on: Multi-banding [Morisaki, (2021)]

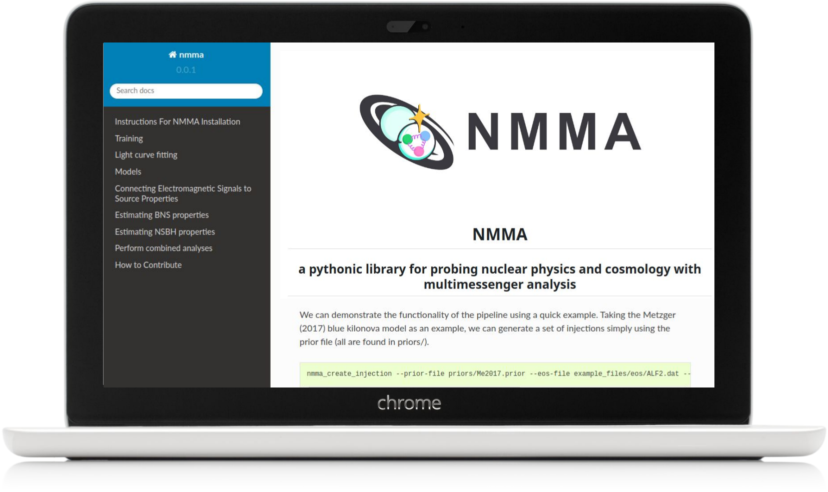
> Inference of electromagnetic (EM) signals

> Joint inference (GW + EM)

Methods | NMMA |

Nuclear physics and multi-messenger astrophysics framework

Pang et al., 2023, Nature Communications., 14, 8352



Github: https://github.com/nuclear-multimessenger-astronomy/nmma

Bayesian inference

- observational data & injections
- gravitational-wave signals
- electromagnetic signals
- joint inference of GW+ EM signals

Including nuclear physics information

- neutron star equation of state (EOS)

Estimating binary source properties

- Binary neutron star (BNS)
- Neutron star black hole (NSBH)

Other

- estimating the Hubble Constant
- **new:** sampling on Dark Matter parameters

Including nuclear physics and dark matter information

- sampling on EOS and **DM parameters** during parameter estimation

Prior

$$m_{1,2}, f_\chi, m_\chi, \mathrm{EOS}$$

↓

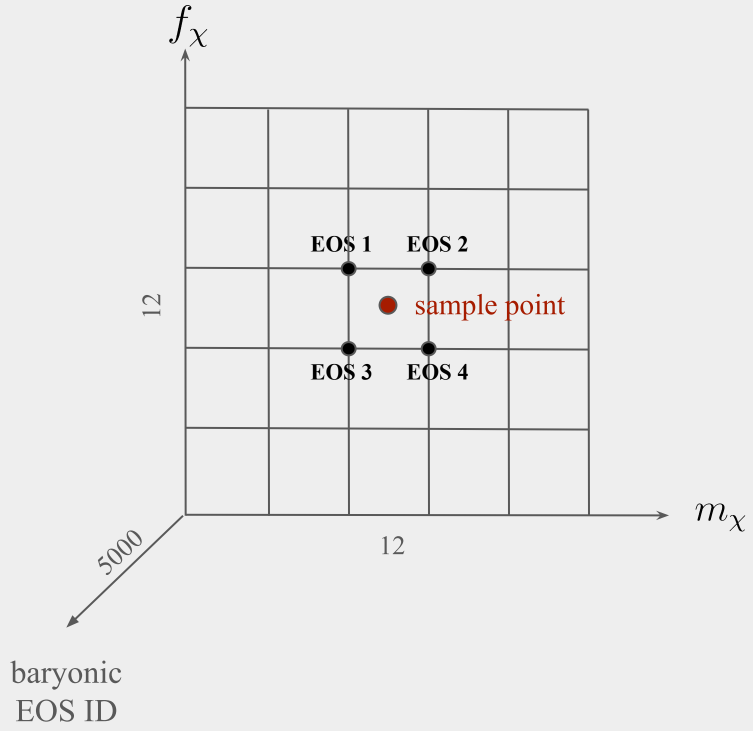
Interpolate

$$p(\Lambda_i | m_i, f_\chi, m_\chi, \mathrm{EOS}) = \delta(\Lambda_\mathrm{i} - \Lambda(\mathrm{m_i}; \mathrm{EOS}, \mathrm{f_\chi}, \mathrm{m_\chi}))$$

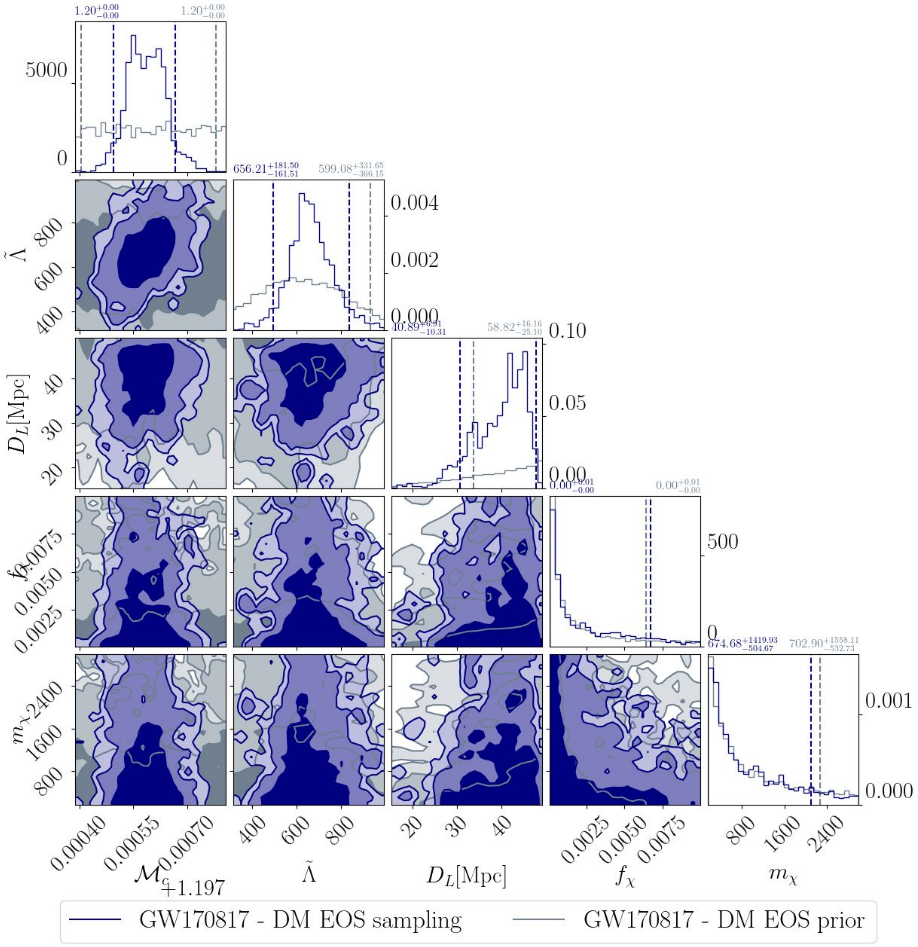
↓

GW waveform

$$h(t; m_{1,2}, \Lambda_{\mathrm{DM}_{1,2}}, \vec{\theta})$$



Results | GW170817 | assuming presence of dark matter



Data: GW170817 observation

GW model: IMRPhenomPv2_NRTidalv2

EOS set: DM EOS

Prior ranges

- dark matter fraction:
  f_χ : [0.01, 1] in % | log-uniform
- dark matter particle mass:
  m_χ: [170, 3000] in MeV | log-uniform

Results | Injections | Analyzing BNS events of Koehn et al. (2024)

→ Generation of 16 BNS population catalogues assuming Einstein Telescope (ET)

Similarities
> each has 500 BNS events
> signal-to-noise ratio, SNR > 100
> same BNS population model

Differences
> injected baryonic EOS,
> DM particle mass,
> DM fraction population

[arxiv: 2408.14711]

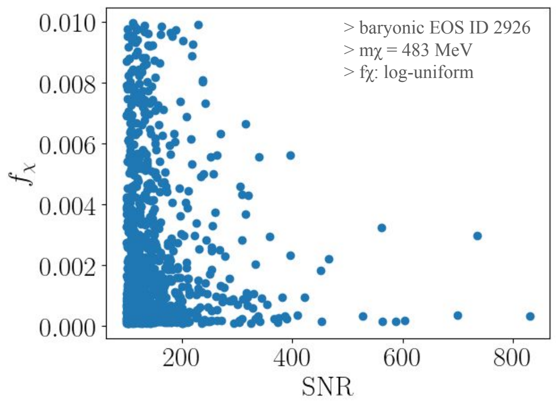
	parameter	symbol	distribution
intrinsic	Component mass [$M_\odot$]	m_1, m_2	Eq. (6)
	Spin magnitude	a_1, a_2	$\mathcal{U}(0, 0.05)$
	DM fraction	f_χ	Log or $\mathcal{U}(10^{-4}, 10^{-2})$
	Tidal deformability	Λ_1, Λ_2	from EOS, m_χ, f_χ
observational	Luminosity distance [Mpc]	d_L	$\mathcal{U}_{\text{com. vol.}}(1, 1000)$
	Sky position [rad]	φ, θ	$\mathcal{U}(0, 2\pi)$, $\text{Cos}(0, \pi)$
	Trigger time [GPS]	t_c	$\mathcal{U}(1\,\text{yr})$
	Phase [rad]	ϕ_c	$\mathcal{U}(0, 2\pi)$
	Inclination [rad]	ι	$\text{Cos}(0, \pi)$
	Polarization [rad]	ψ	$\mathcal{U}(0, 2\pi)$

Koehn et al. (2024)

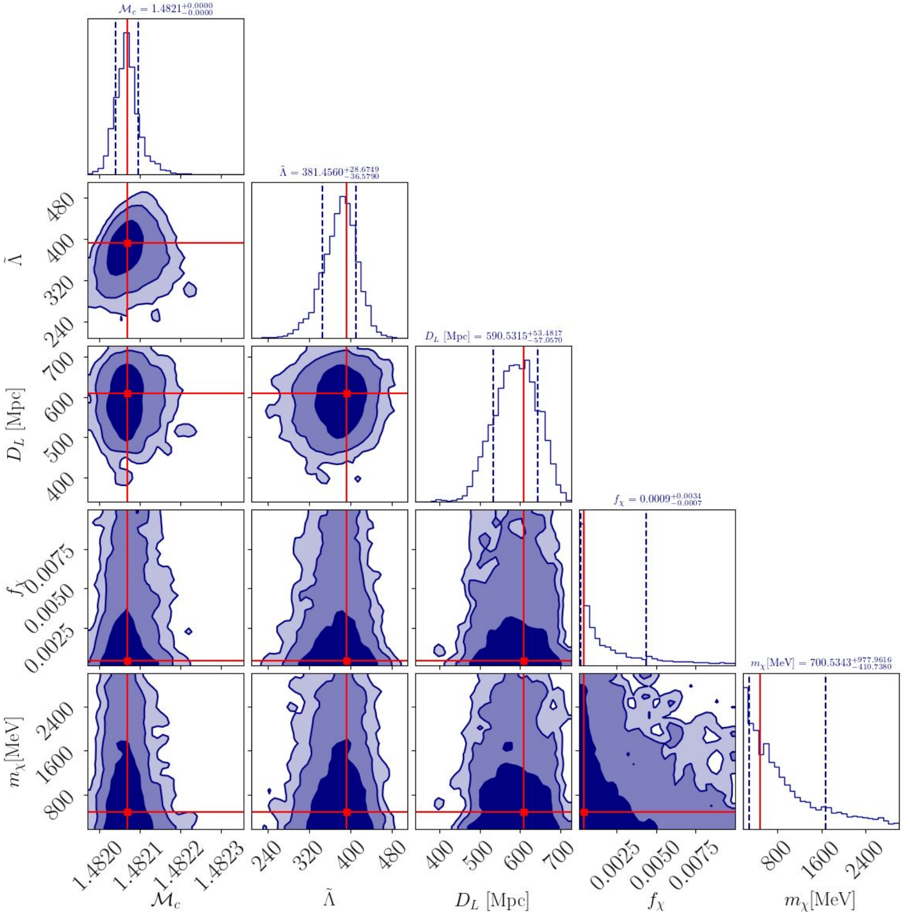
→ Posterior generation: Fisher Matrix approach with *gwfast*
[Iacovelli, et al. (2022)]

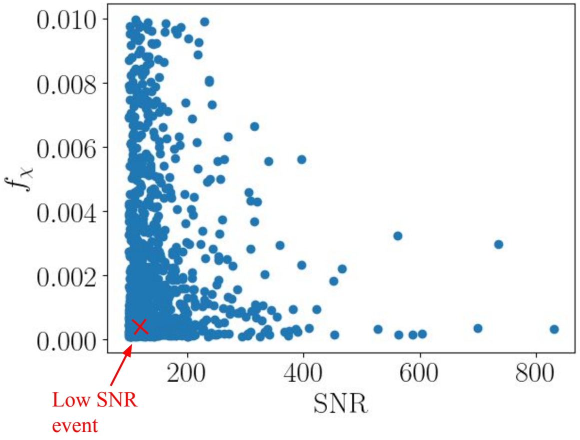
$$F_{jk} = \mathbb{E}\left(\frac{\partial \ln \mathcal{L}(\vec{\theta}|d_{\text{GW}})}{\partial \theta_j}\frac{\partial \ln \mathcal{L}(\vec{\theta}|d_{\text{GW}})}{\partial \theta_k}\right)$$

→ **For now:** Analyzing BNS events from 1 catalogue ⟶



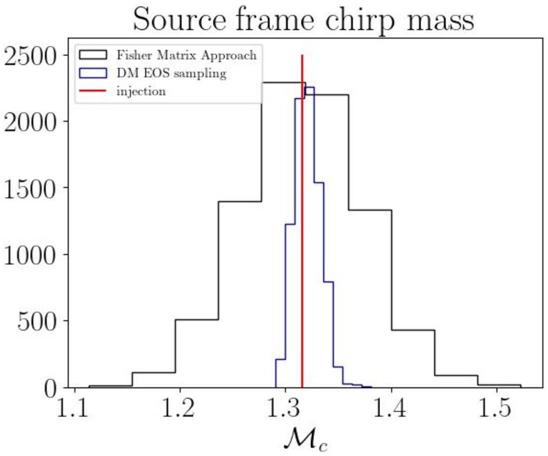
Results | Injections | DM EOS sampling

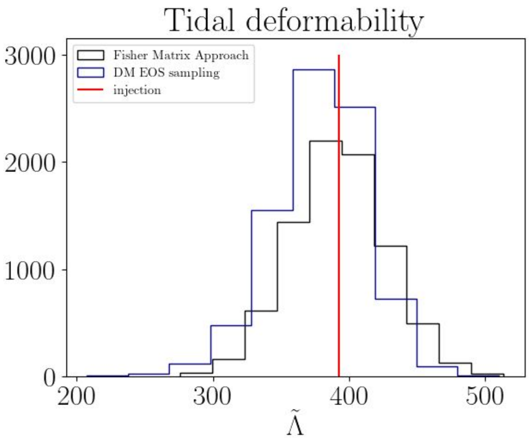


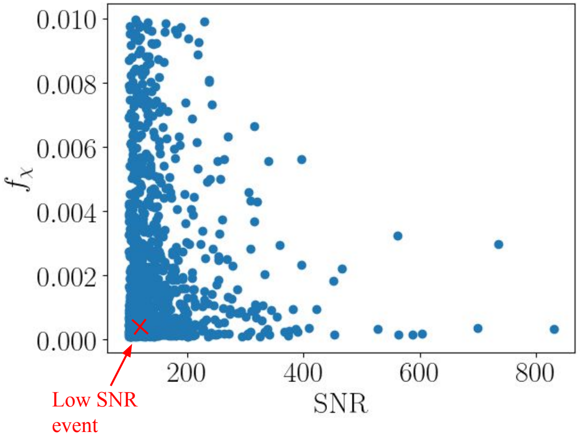


Low SNR Event	
GW model	IMRPhenomD_NRTidalv2
GW signal	f_min = 20 Hz
Sampler settings	Dynesty sampler, nlive = 2048
Speed-up factor	~ 188

Results | Injections | Comparing to Fisher Matrix Approach







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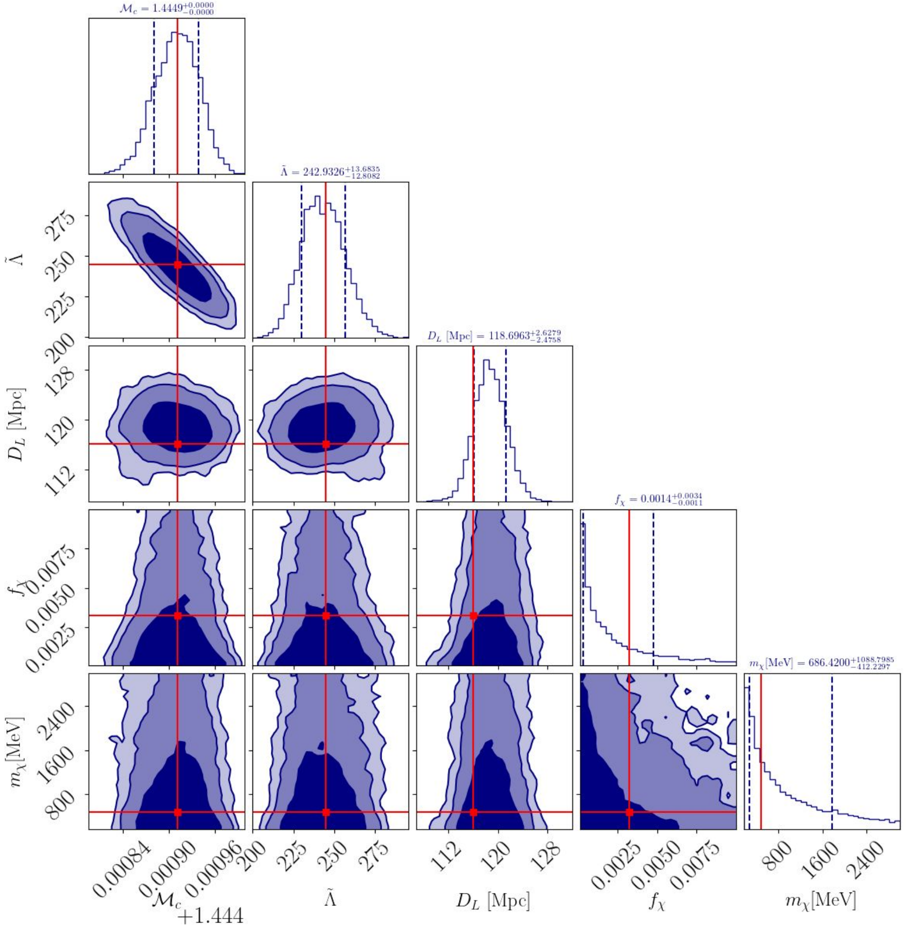
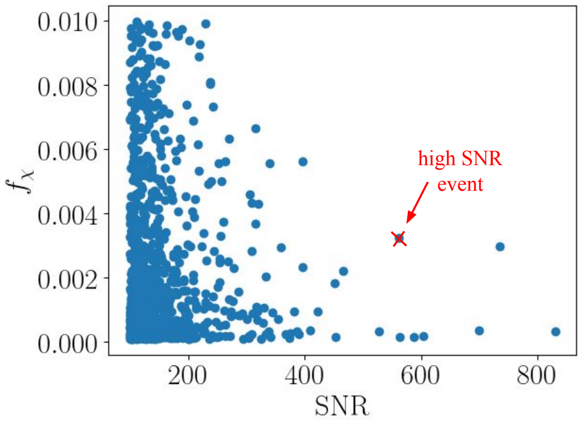
Posterior generation	Fisher matrix approach, DM EOS sampling

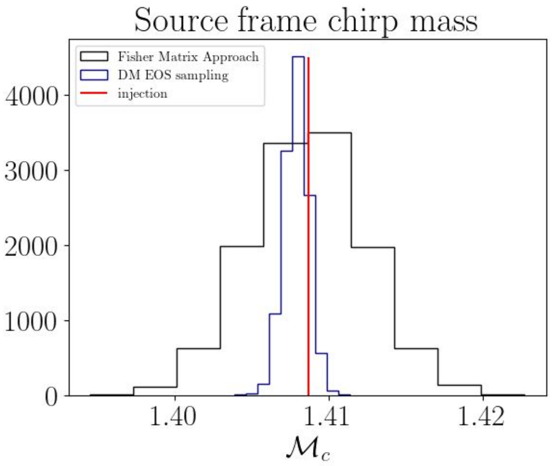
Results | Injections | DM EOS sampling

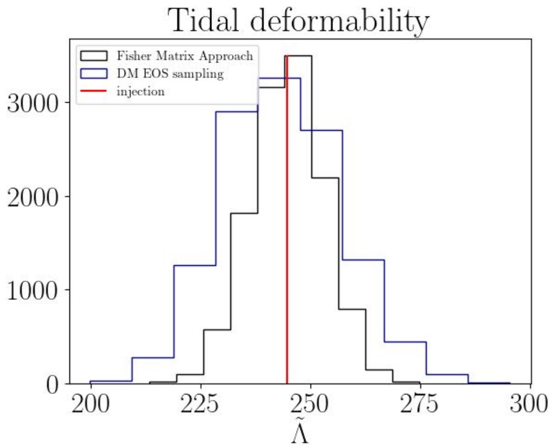


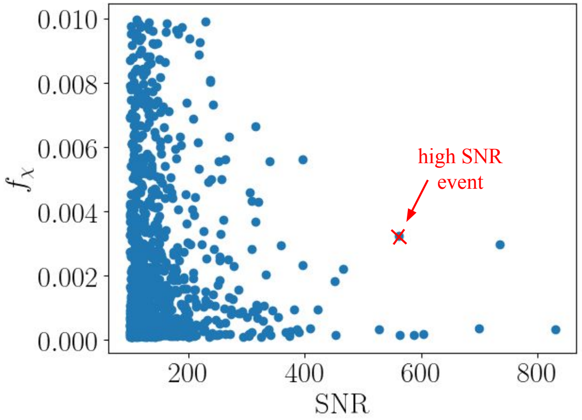


High SNR Event	
GW model	IMRPhenomD_NRTidalv2
GW signal	f_min = 20 Hz
Sampler setup	Dynesty sampler, nlive = 2048
Speed-up factor	~ 186

Results | Injections | Comparing to Fisher Matrix Approach







High SNR Event	
GW model	IMRPhenomD_NRTidalv2
GW signal	f_min = 20 Hz
Sampler setup	Dynesty sampler, nlive = 2048
Posterior generation	Fisher matrix approach, DM EOS sampling

Summary

- GW170817 has no constraining power for DM
- Injections:
  → DM EOS sampling implemented in Bilby and NMMA
  → injected parameters can be recovered with DM EOS sampling
- Fisher matrix is (so far) a reasonable approximation

Outlook

short-term | this study

- further testing required | Fisher Matrix, realistic ET setup
- model selection analysis | analyze a different DM model

long-term | future projects

- GW model construction with DM

→ requires: NR simulations of DM admixed BNSs (E. Giangrandi's talk)

Back-up slide | Investigating the impact of the speed-up method

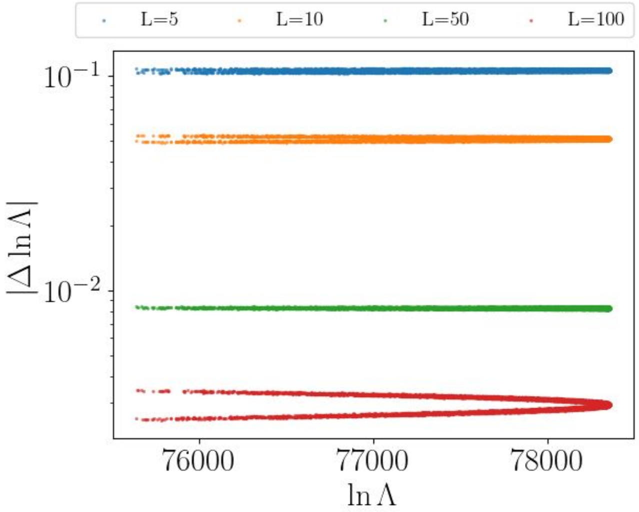
→ similar to Morisaki (2021), we compute error of log-likelihood ratio, $\ln \Lambda$

> data: posterior obtained for a high SNR event seen in ET
> investigation: varying the accuracy factor, L

Expectation:

→ error of log-likelihood ratio should decrease with increasing accuracy factor L

High SNR event seen with Einstein Telescope



Our result:

→ confirms this trend

→ PE runs with Einstein Telescope require increased accuracy factor