Simulation-based inference applied to Kilonova SED modeling

A case of study with AT2017gfo

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Summary:

- Simulation-Based Inference (SBI)
  - Amortized Neural Posterior Estimation (ANPE)

- The Astrophysical Parameters of Kilonovae
  - *Kilonovanet* Simulator

- Results:
  - Simulated Data
  - Validation with Real Observations (GW170817)

Likelihood-based Methods:

The main objective of our Bayesian spectral energy distribution (SED) model is to estimate the posterior distribution p(A|B) of kilonova parameters A, given an observable B.

The “problem”

$$\underbrace{\boxed{P(A|B)}}_{\text{posterior}} = \underbrace{\boxed{P(A)}}_{\text{prior}} \times \frac{\boxed{P(B|A)}\ \text{likelihood}}{\boxed{P(B)}\ \text{marginal}}$$

Our Objective

Traditional Methods:

Monte Carlo Markov Chain(MCMC)

Nested Sampling techniques

Limitations

- You need to be able to write the likelihood
- <u>Time consuming</u>
- Difficult to assess the faithfulness of the posterior approximations
- Scales poorly with the dimensionality of the explored parameter space

Simulation-Based Inference

Simulation-based inference, also referred to as likelihood-free inference, encompasses a set of techniques aimed at conducting Bayesian inference without the need for directly computing the likelihood function numerically.

Amortized Neural Posterior Estimation (NPE)

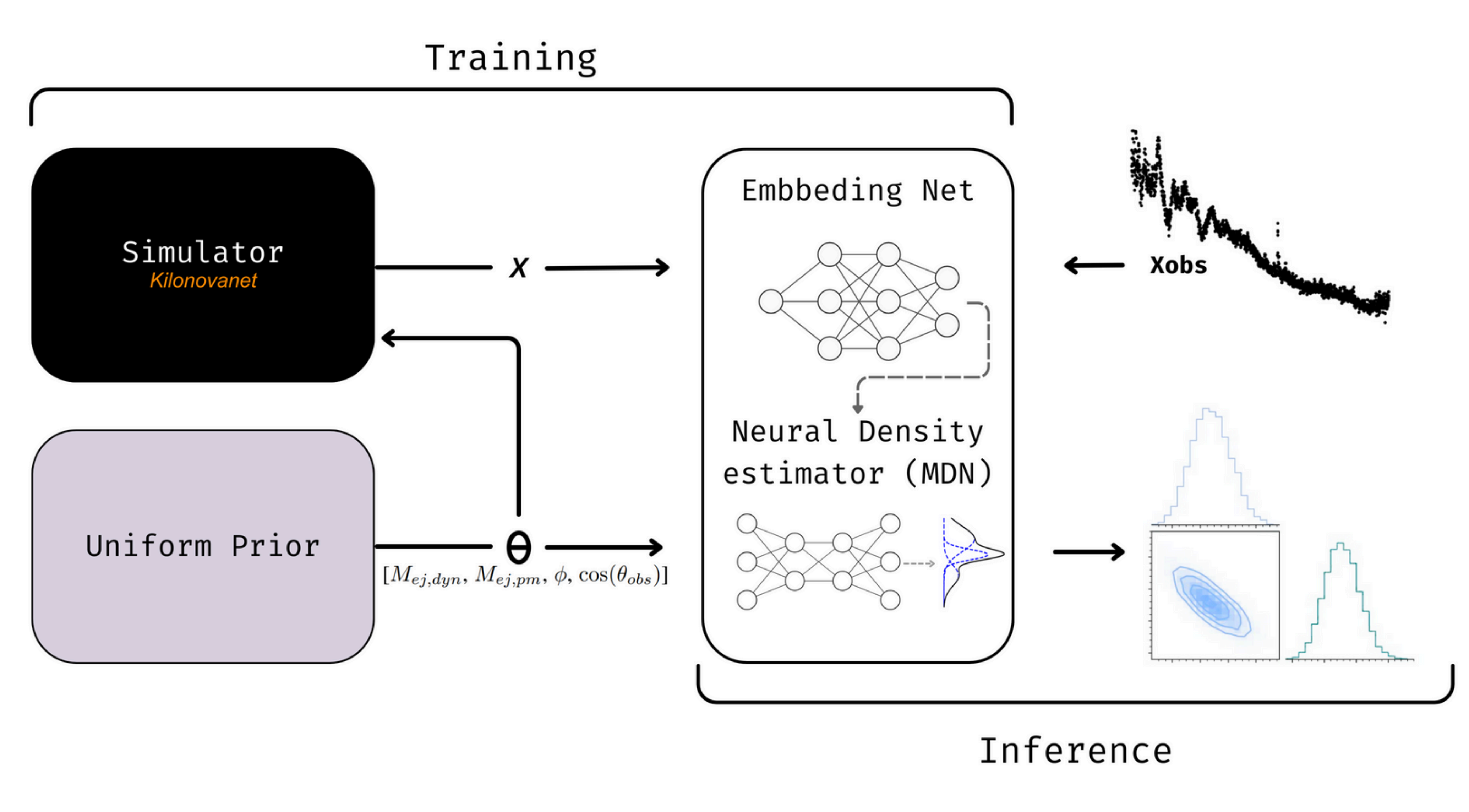


Fig.1) Inference pipeline using Amortized Neural Posterior Estimation

Advantages

- Fast - Once trained, the density estimator can, in the next phase (inference), quickly and continually infer parameters of BNS kilonovae for any data supported by our prior.
- Testable - It’s possible to make repeated and sequential inference to a large amount of data.
- Scalable - It can target the marginal posterior distribution, rather than the full joint posterior.

Simulator - Kilonovanet*

A conditional variational autoencoder trained on three different datasets of simulated kilonova observables from BNS or NSBH mergers :

- Dietrich et al 2021 (BNS)
- Kasen et al 2017 (BNS)
- Annand et al 2020 (BHNS)

Kilonova Parameters:

- Mass of the Dynamical Ejecta: $\boxed{M_{ej,dyn}}$
  - Polar Dynamical (lanthanide Free)
  - Tidal Dynamical (lanthanide Rich)
- Mass of the Post merger ejecta (Disk wind) $\boxed{M_{ej,pm}}$
- the half-opening angle of the lanthanide-rich tidal dynamical ejecta $\boxed{\phi}$
- Cosine of the observer viewing angle $\boxed{\cos(\theta_{obs})}$

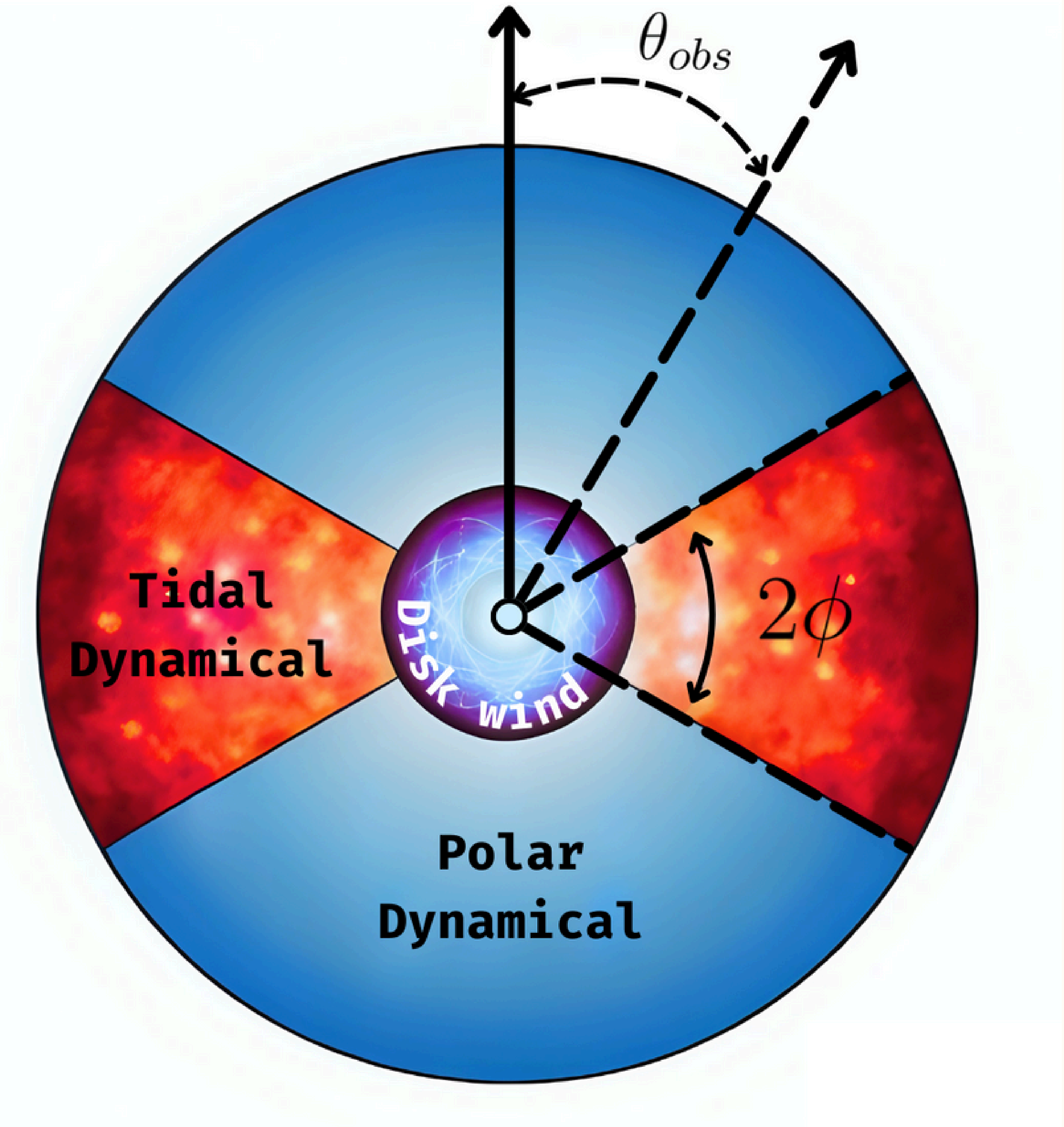


Fig. 2) Geometry employed in the kilonova description of Dietrich-based simulation model (see also Dietrich et al. 2020). Different colors refer to the different lanthanide fractions of the individual ejecta components: tidal dynamical (red), polar dynamical (blue), and disk wind (purple).

*Lukosiute et al (2022)

- Retrieving Kilonova Parameters
- Assessing Reliability of The Posterior Approximations
- Validation with Real Observations GW170817 (ATf2017gfo)

Retrieving Kilonova Parameters

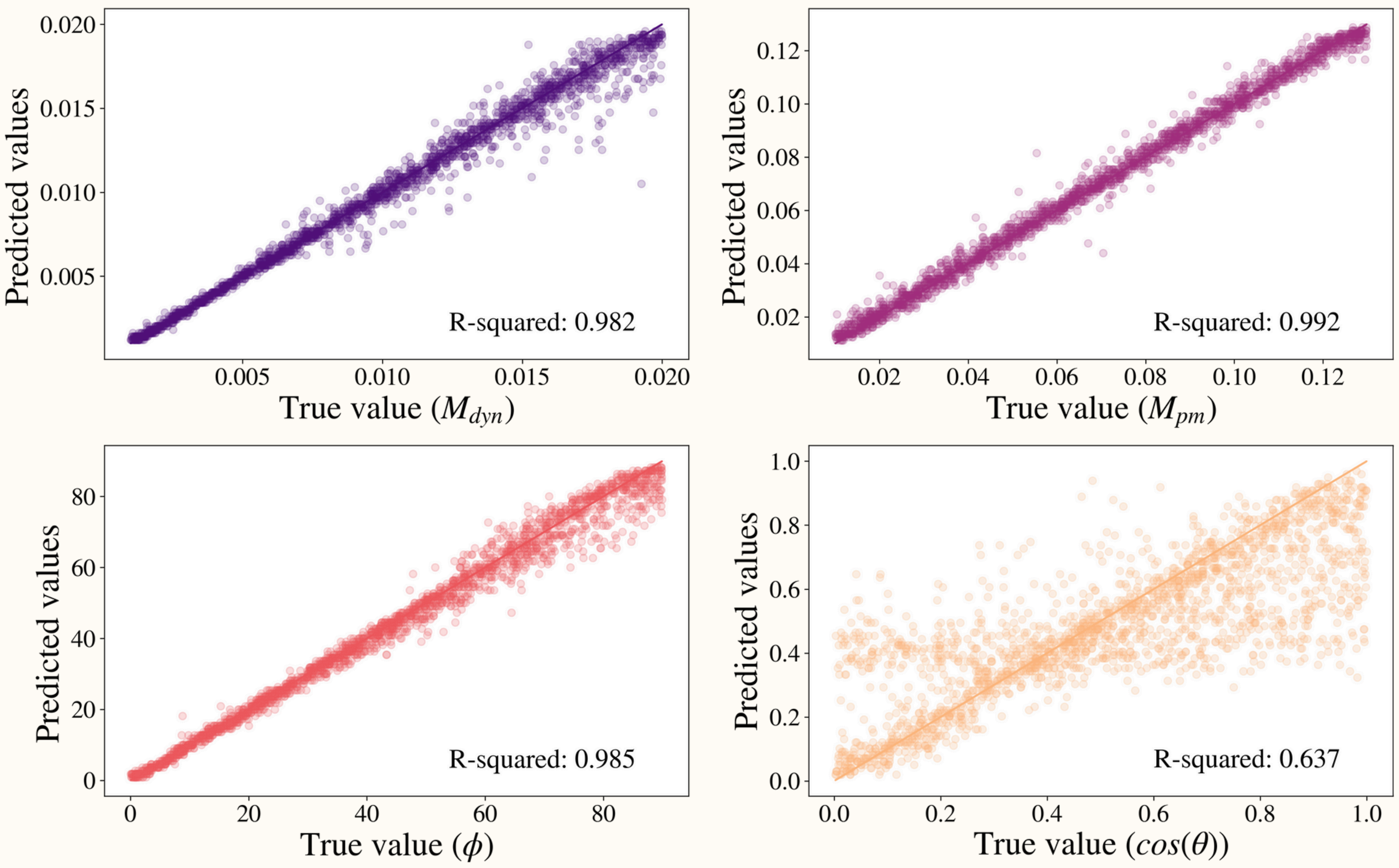


Fig. 3) True vs. recovered values for kilonovas parameters in the test set of 2000 spectra. The diagonal solid line is the ideal scenario where the θpred is equal to θtrue.

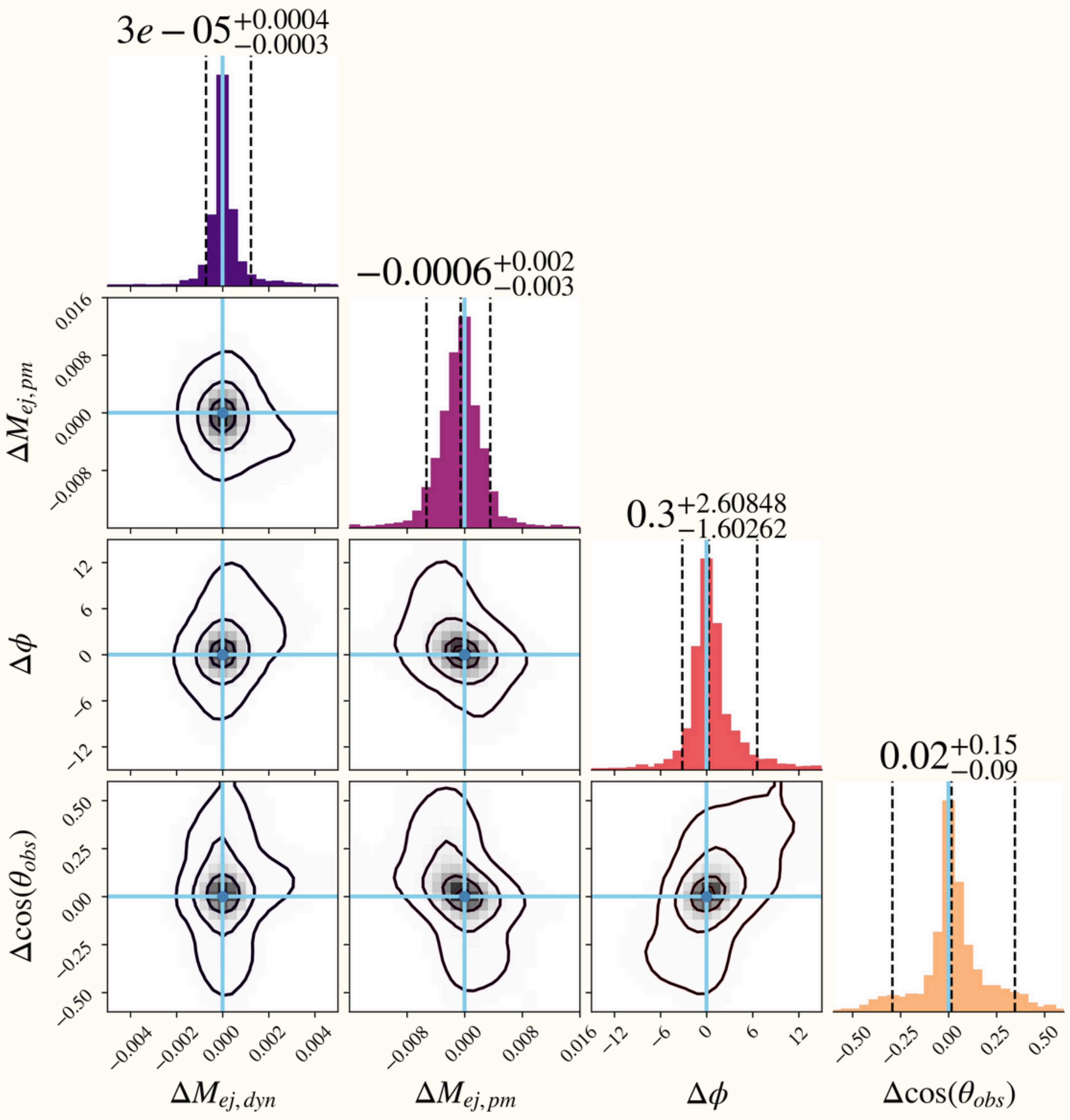


Fig. 4) Residual Corner Plot shows the 1d and 2d residual distributions obtained by subtracting θtrue from θpred.

Posterior Diagnostic:

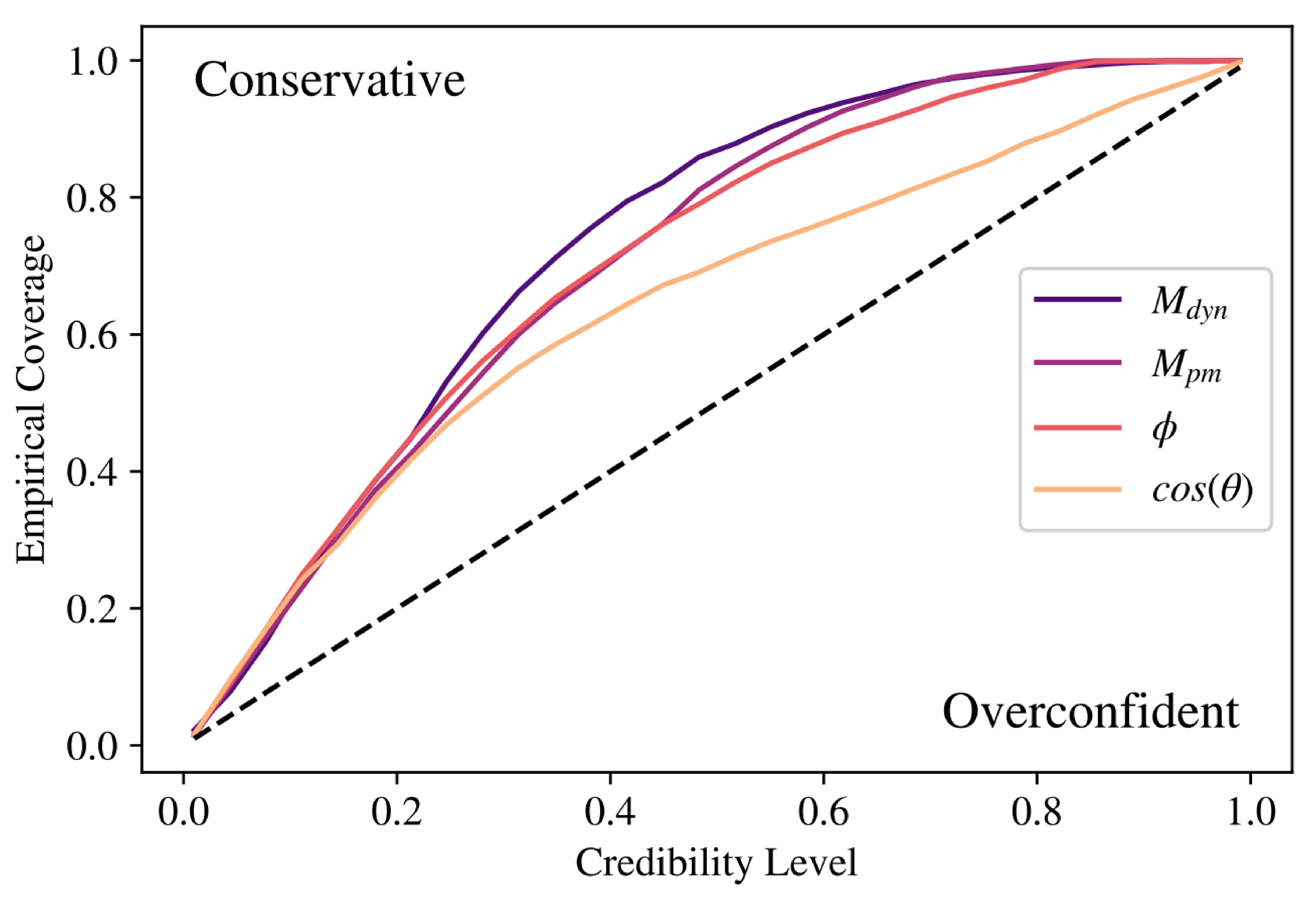


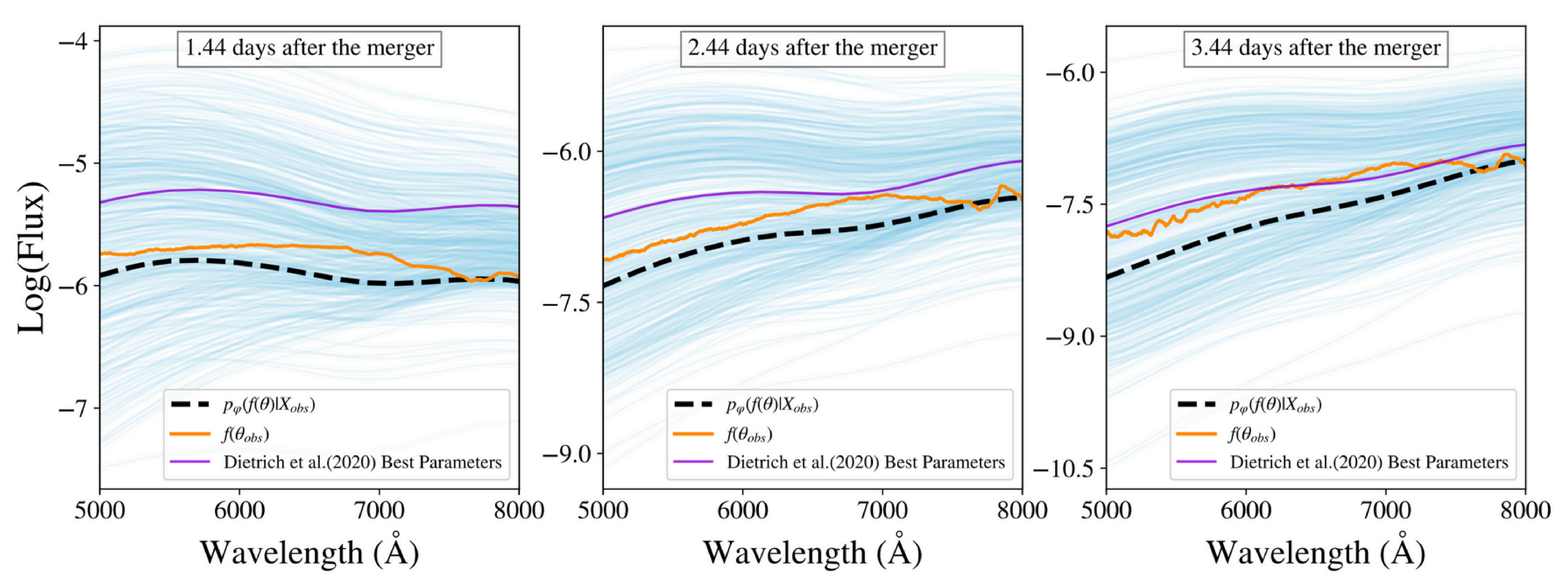
Fig. 5) Coverage plot for each kilonova parameter. A conservative posterior estimator will produce curves above the dashed line, and an overconfident posterior estimator will produce curves below the diagonal.

GW170817

Table 2. Kilonova Parameters

Model	$\log(M_{\mathrm{ej,dyn}}/M_\odot)$	$\log(M_{\mathrm{ej,pm}}/M_\odot)$	ϕ [deg]	θ_{obs} [deg]
Dietrich et al. (2020)	$-2.27^{+1.01}_{-0.54}$	$-1.28^{+0.42}_{-0.35}$	$49.50^{+21.16}_{-26.65}$	$42.80^{+40.62}_{-36.51}$
Lukošiute et al. (2022)	$-2.31^{+0.22}_{-0.22}$	$-1.13^{+0.11}_{-0.21}$	$47.98^{+20.21}_{-12.90}$	$64.55^{+17.39}_{-22.34}$
ANPE	$-2.42^{+0.59}_{-0.09}$	$-1.20^{+0.17}_{-0.26}$	$34.08^{+30.98}_{-7.82}$	$65.58^{+19.84}_{-38.01}$

NOTE—Median values and 90% credible intervals for kilonova parameters reported in various studies.



- Spectroscopic time series of AT2017gfo (orange solid line)
- Spectra generated using the values reported bDietrich et al. (2020).
- Spectra generated by KilonovaNet using the Best fit of our ANPE model (pϕ(f(θ)|Xobs), black dashed line)
- Spectra generated by 500 parameters set randomly sampled from the inferred posterior distribution (light blue solid line)

Conclusion

- Simulation-based inference is a viable approach to Kilonova SED modelling
- We demonstrate the reliability of our posterior approximations using diagnostic tools (such as coverage test).
- Our model agrees with previous likelihood-based methods while reducing the inference time down to a few seconds


QUESTIONS?