Kilonovae

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Table of Contents

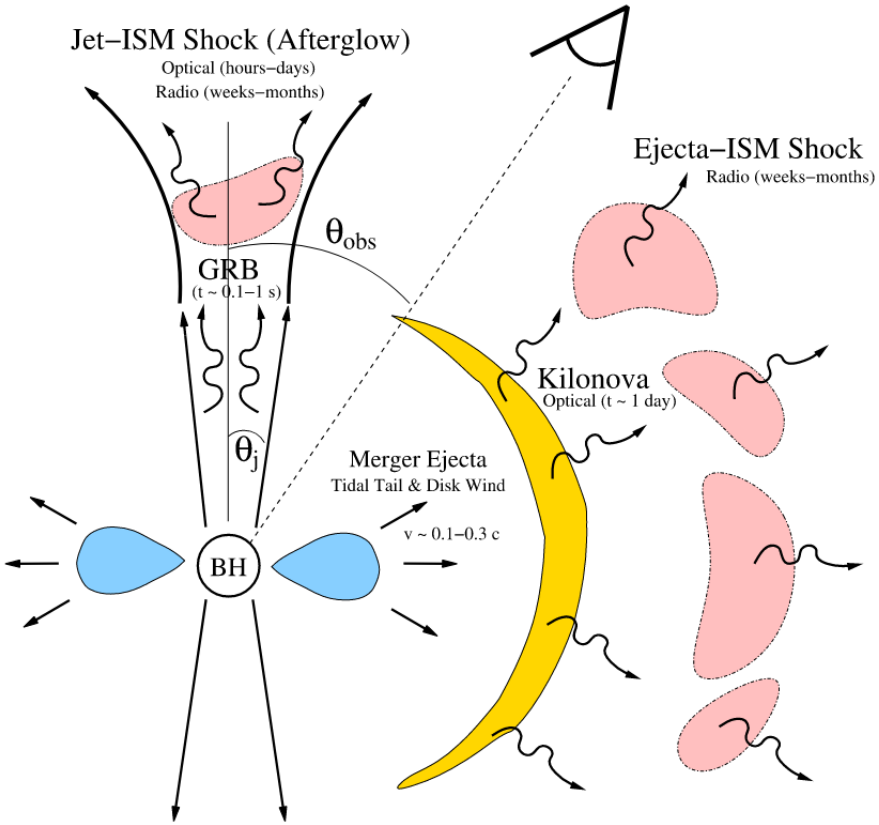
Table of Contents

Multimessenger astrophysics

- Multimessenger astrophysics: GW + **EM**: signature of NS-BH or NS-NS mergers
- Hard: sky localisation from GW is bad
- Excellent video on GW170817, the first multimessenger event
  - $t + 0$ s: GW observed by Hanford, Livingston, Virgo
  - $t + 1.7$ s: Short GRB
  - $t+$ days: kilonova

Kilonovae

"**Kilonovae** are thermal supernova-like transients lasting days to weeks, which are powered by the radioactive decay of heavy neutron-rich elements synthesized in the expanding merger ejecta" [1]



r-process

- r-process: formation heavy elements, needs neutron-rich environment
- Depends on electron fraction Y_e

$$Y_e = \frac{n_p}{n_p + n_n}$$

  - Ordinary matter: $Y_e > 0.5$
  - r-process: needs $Y_e < 0.5$

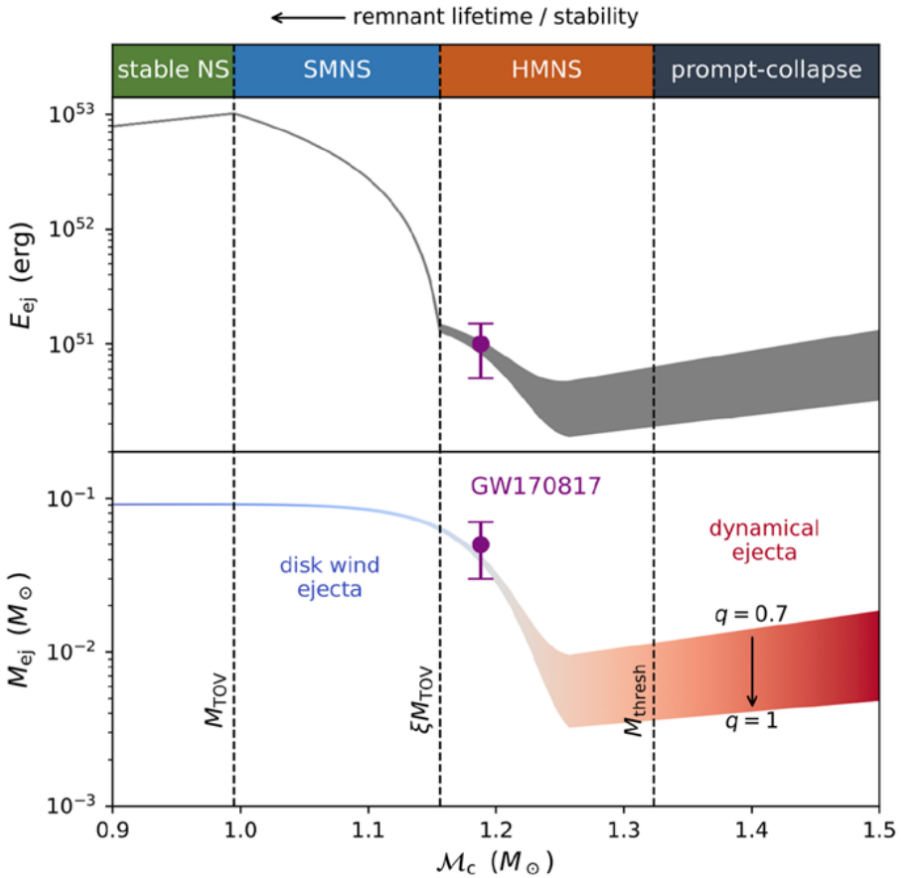
- NS mergers likely dominant source of r-process (?)

Table of Contents

Basic ingredients

Important are mass and velocity of ejecta. Type of ejecta depends on

1. Scenario (NS-BH vs NS-NS)
2. For NS-NS: mass of NSs and **EOS quantities** (TOV mass)



Red and blue kilonovae

- Red kilonovae: low Y_e, lanthanide-rich
- Blue kilonovae: high Y_e, no lanthanides
- Longer-lived remnants: higher Ye: bluer kilonovae

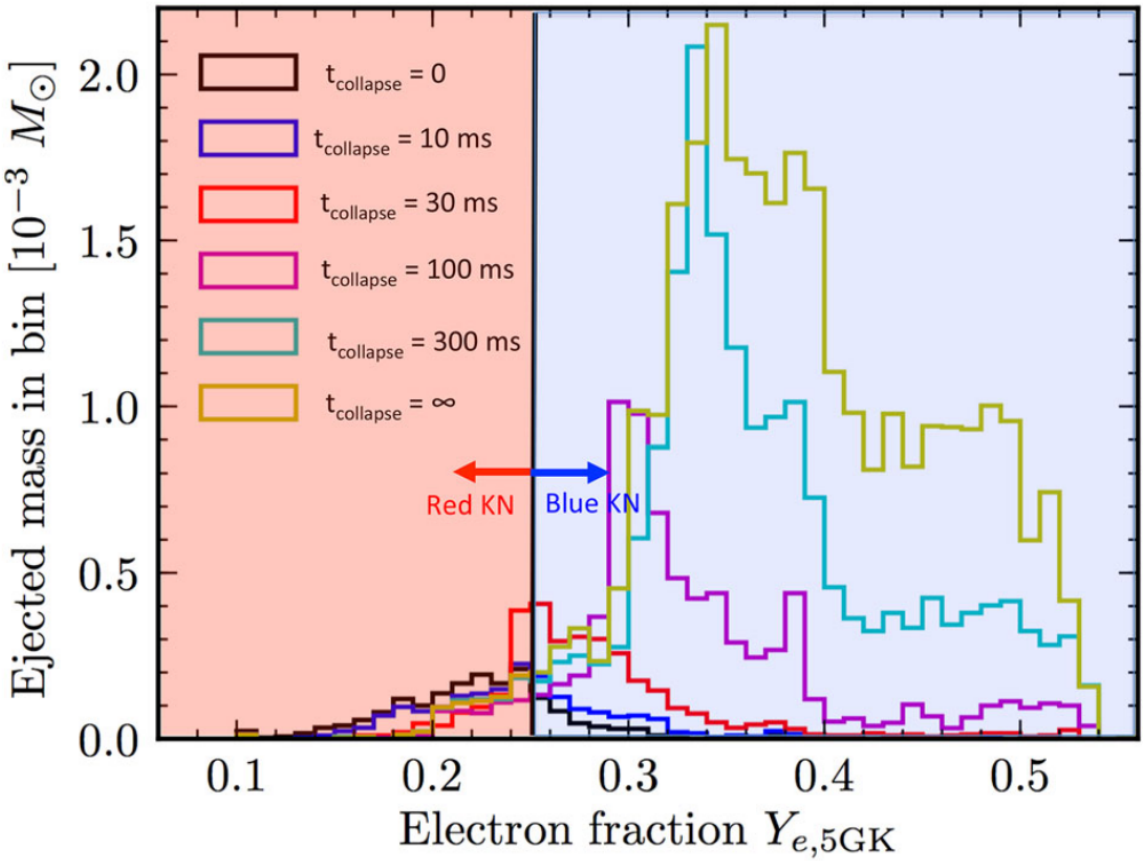
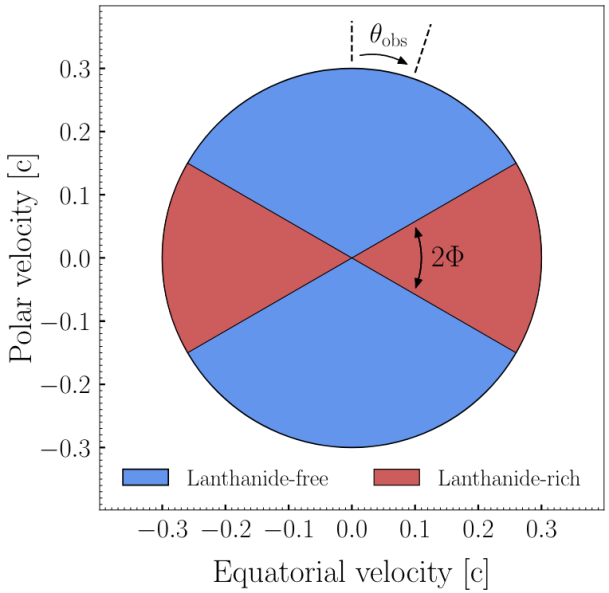


Table of Contents

POSSIS

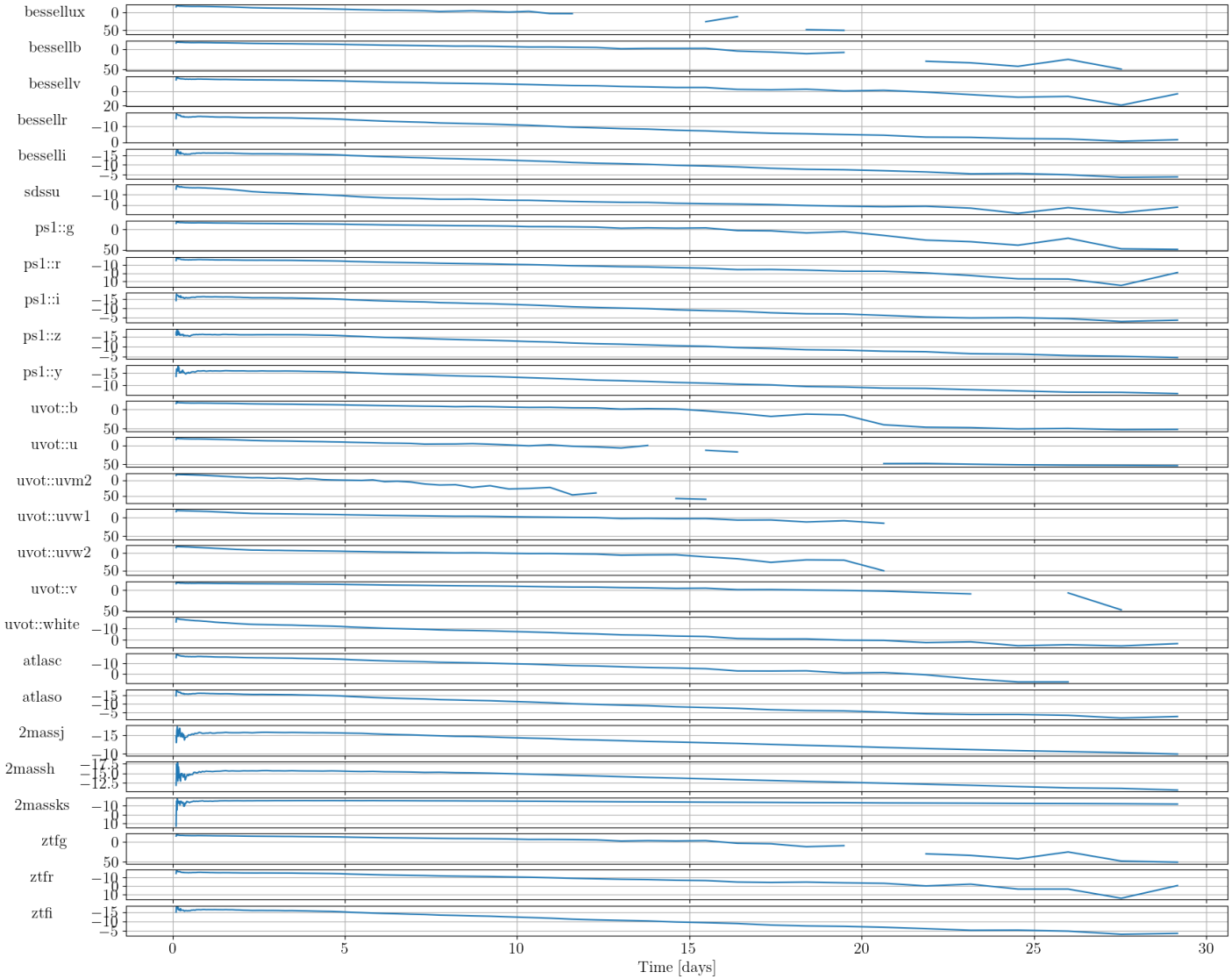
POSSIS [2]: time-dependent 3D Monte Carlo radiative transfer code

- Monte Carlo packets of photons
- Packets propagated until interaction with matter
- Can handle arbitrary geometry for ejecta
- Time- and wavelength-dependent opacities
- Synthetic observables: light curves, spectra, polarisation



Example light curve

Example light curve – how to use in Bayesian analysis?



Surrogate models

Train a surrogate model:

1. Training data: grid of `POSSIS` light curves: $\{(\theta_{\mathrm{KN}}; m_i)\}$
2. Reduce dimensionality: SVD: $m_i \mapsto \tilde{m}_i$ $(\mathbb{R}^{100} \to \mathbb{R}^{10})$
3. Train neural network: NN: $\theta_{\mathrm{KN}} \mapsto \tilde{m}_i$

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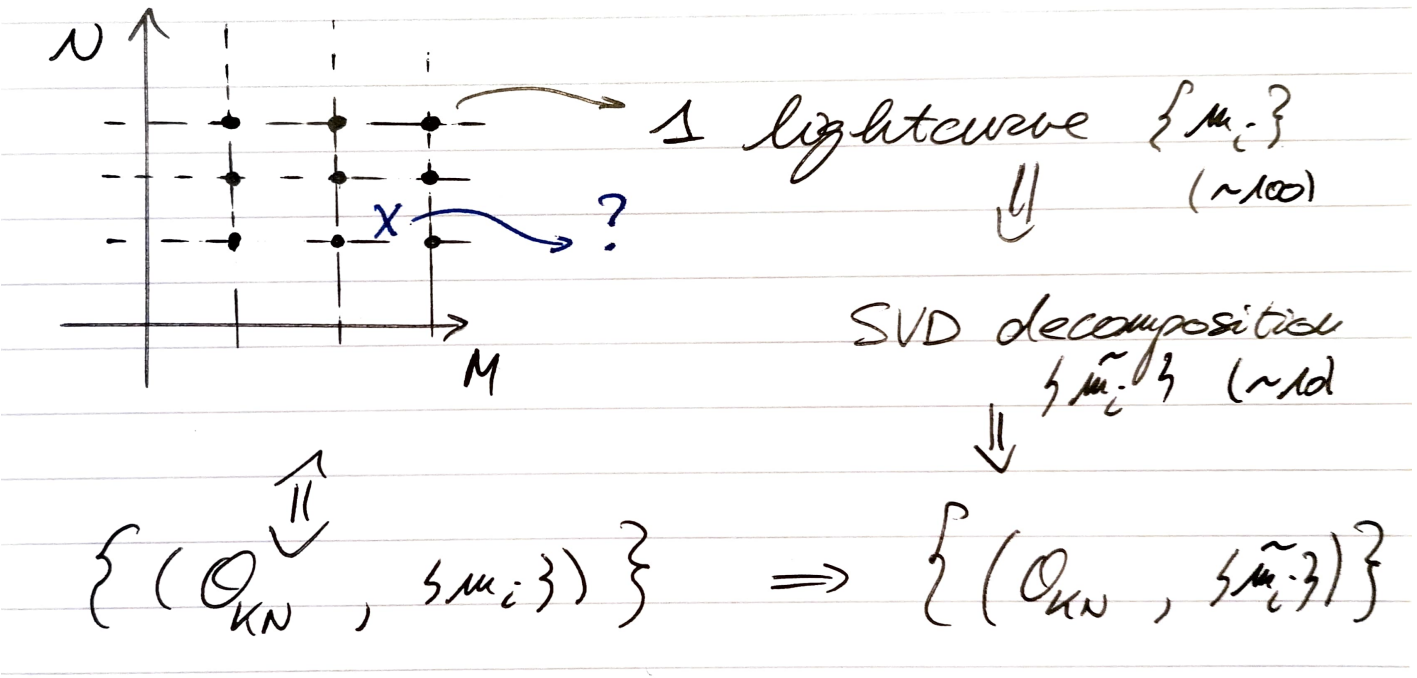

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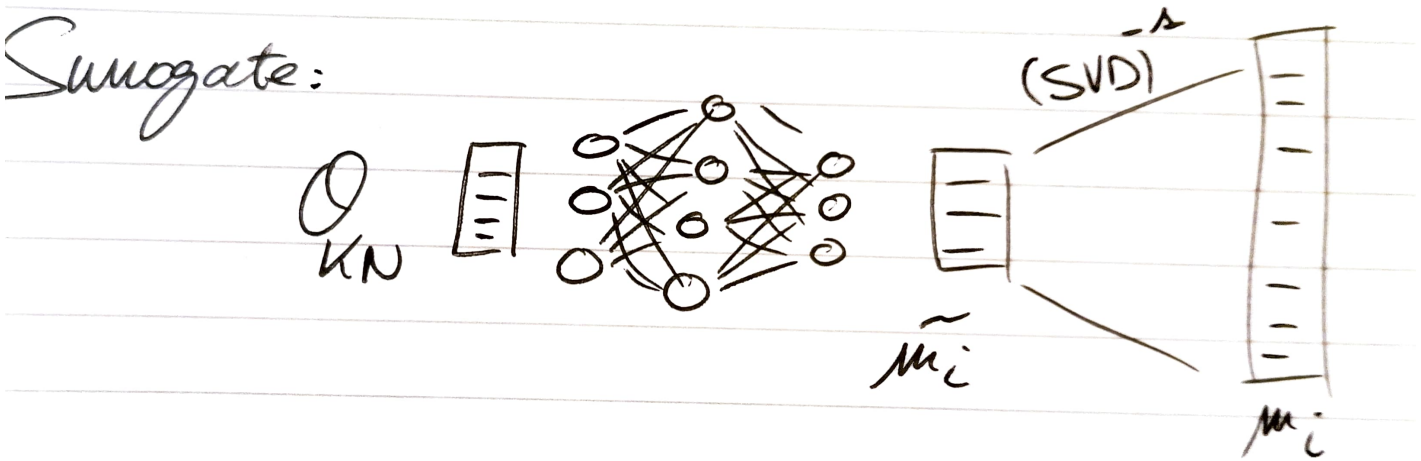

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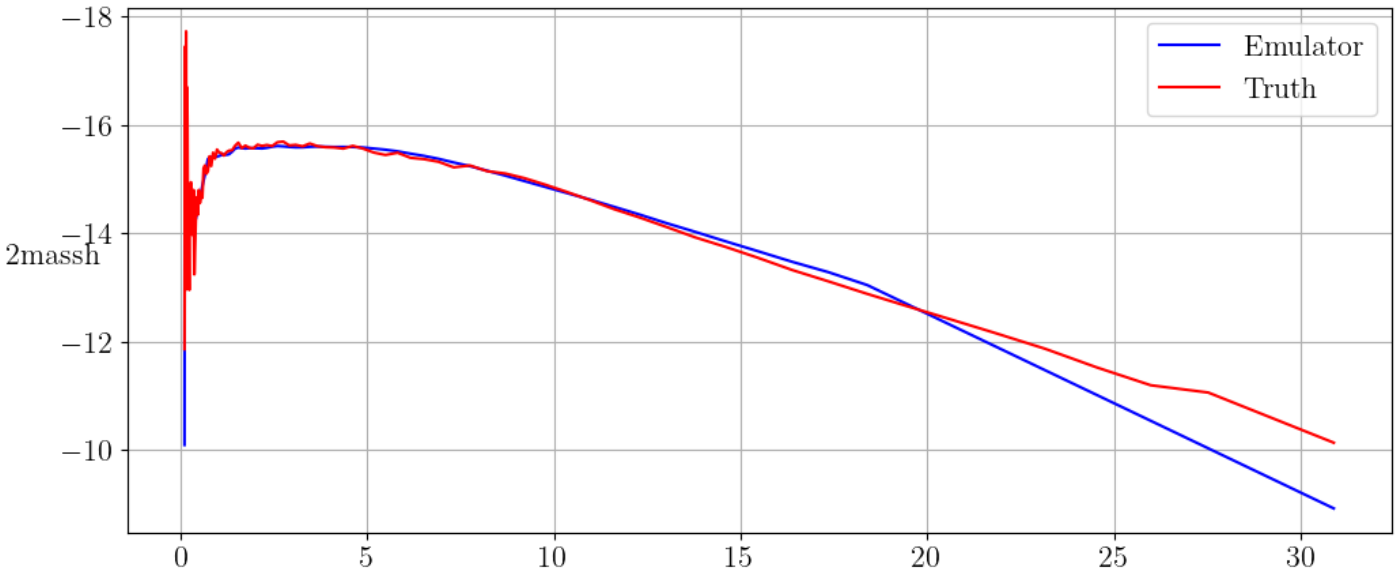

Example: end result AT2017gfo

Result from `NMMA` (with GW and GRB) [3]

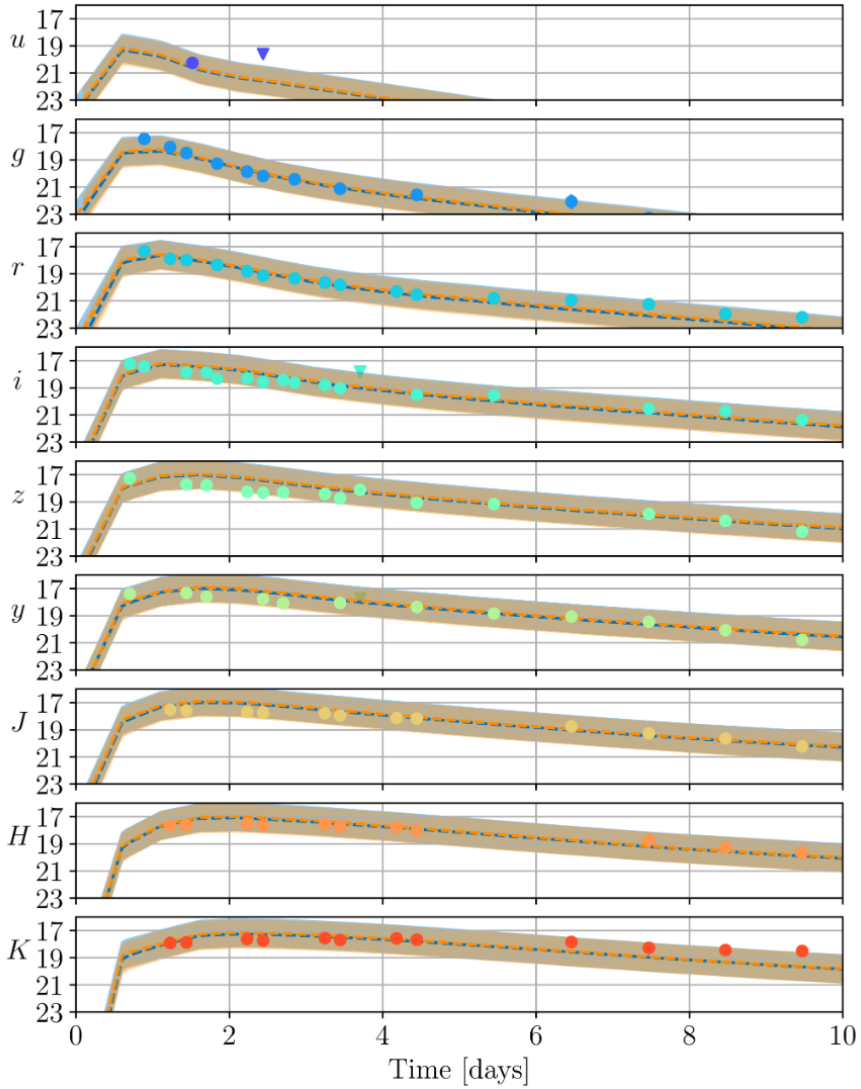

Table of Contents

Conclusion and outlook

Conclusion:

- Kilonovae: important EM counterpart to GW events, EOS dependent
- Important for understanding *r*-process (Jasper next week)
- `POSSIS` and surrogate models: tools to model kilonovae

Outlook:

- Bayesian analysis over KN models
- GRB counterparts
- Joint inference over GW & EM (KN + GRB)
- EOS constraints from GW170817

References

[1] Brian D. Metzger. "Kilonovae". In: *Living Rev. Rel.* 23.1 (2020), p. 1. DOI: 10.1007/s41114-019-0024-0. arXiv: 1910.01617 [astro-ph.HE].

[2] Mattia Bulla. "POSSIS: predicting spectra, light curves and polarization for multi-dimensional models of supernovae and kilonovae". In: *Mon. Not. Roy. Astron. Soc.* 489.4 (2019), pp. 5037–5045. DOI: 10.1093/mnras/stz2495. arXiv: 1906.04205 [astro-ph.HE].

[3] Peter T. H. Pang et al. "An updated nuclear-physics and multi-messenger astrophysics framework for binary neutron star mergers". In: *Nature Commun.* 14.1 (2023), p. 8352. DOI: 10.1038/s41467-023-43932-6. arXiv: 2205.08513 [astro-ph.HE].