Multimessenger analysis with *xkn* & *bajes*

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Multimessenger Astronomy in the ET era

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xkn: a semi-analytic framework for KN modelling

Goals:

- to provide a flexible, robust & computationally feasible KN model for
  - extensive parameter estimation analysis
  - multimessenger frameworks
- incorporate the relevant physics with a connection to the outcome of first principle simulations
  - heating rates
  - thermalization efficiency
  - atomic opacities
  - matter ejecta properties

xkn documented in Ricigliano et al 2024, available at https://github.com/GiacomoRicigliano/xkn

xkn: hypothesis and method

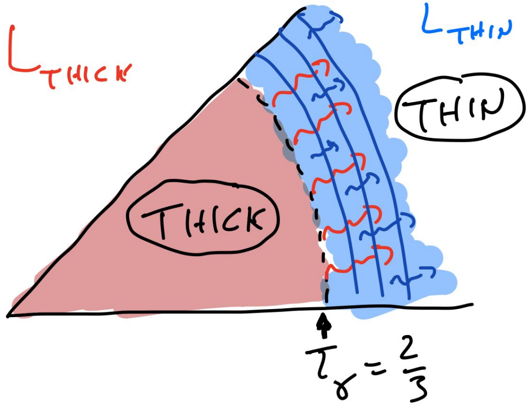
Basic hypothesis:

- homologously expanding ejecta
- spherical symmetry
- photospheric conditions (within a few days post-merger, for GW170817-like KNe)
- gray, spatially homogeneous opacity

Method:

- distinction between optically thick and optically thin conditions

$$\rho(t) = \rho_0 \left(\frac{t_0}{t}\right)^3 \qquad \rho_0 = \frac{M_{\rm ej}}{\frac{4}{3}\pi(v_{\max} t_0)^3}$$



$$L(t) = L_{\rm thick}(t) + L_{\rm thin}(t)$$

xkn: calculation of photospheric luminosity

optically thick part

- radiation diffusion problem
- photospheric luminosity: solution of eigenvalue problem
- precise solution depends on temporal behavior of thermalization (f_{th}), nuclear energy rate and gray opacity

$$\frac{DE}{Dt} - \frac{c}{3r^2}\frac{\partial}{\partial r}\left(\frac{r^2}{\chi}\frac{\partial E}{\partial r}\right) + \frac{4\dot{R}}{R}E = \dot{E}_{\rm heat}$$

$$F = -\frac{c}{3\chi}\frac{\partial E}{\partial r}$$

$$L(t) = 4\pi R^2(t)\left[x^2 F(x,t)\right]_{x=1} = \frac{4\pi\,(v_{\max}t_0)^3\sqrt{2}E_0}{\tau}\sum_{n=1}^{\infty}(-1)^{n+1}n\pi\phi_n(t)$$

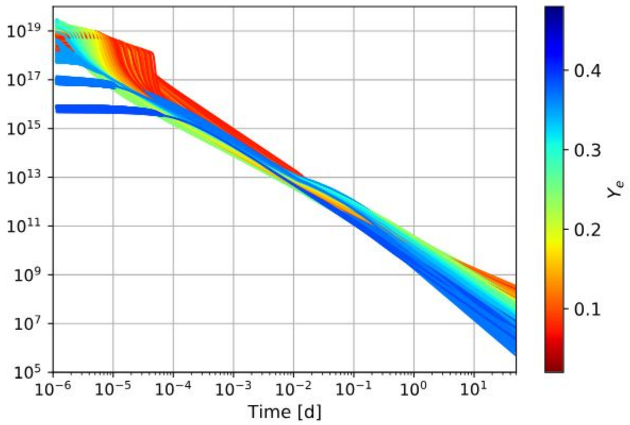
$$\phi_n'(t) + \left(\frac{t}{t_0\tau}\right)(n^2\pi^2)\phi_n(t) = \frac{(-1)^{n+1}\rho_0\sqrt{2}}{n\pi E_0}\left(\frac{t}{t_0}\right)\dot{\epsilon}\, f_{\rm th} \qquad \dot{\epsilon} = \dot{\epsilon}_0\left(\frac{t}{t_0}\right)^{-\alpha}, \quad f_{\rm th} = f_{\rm th,0}\left(\frac{t}{t_0}\right)^{-\beta}, \quad \kappa = \kappa_0\left(\frac{t}{t_0}\right)^{-\gamma}$$

first proposed by Pinto & Eastman (2000) and later extended to KN by Wollaeger et al (2018)

xkn: optically thin part and input physics

$$L_{\mathrm{thin}}(t) = \sum_{i=1}^{N_{\mathrm{thin}}} f_{\mathrm{th},i}(t)\dot{\epsilon}(t)\mathrm{d}M_i$$

<u>Relevant input physics:</u>



Wu et al 2022

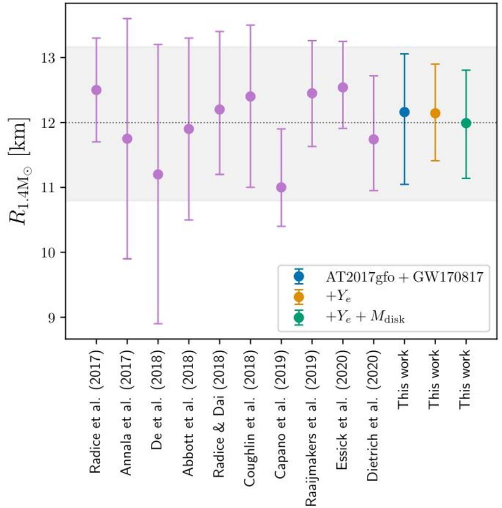
optically thin part

- free streaming contribution from optically thin (Lagrangian) shells

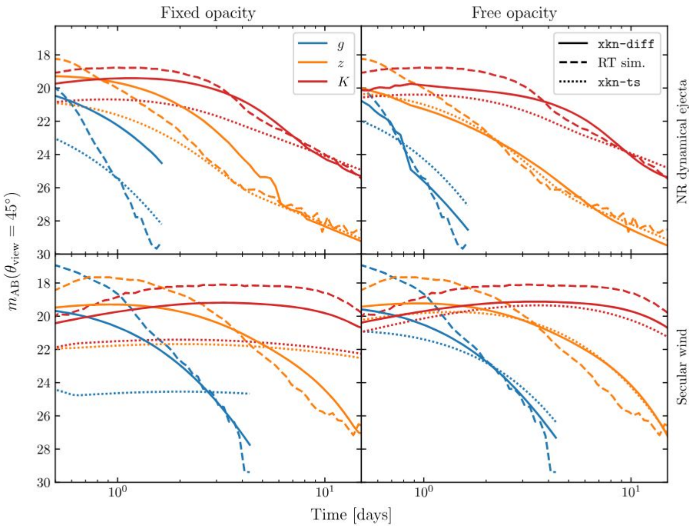
- heating rates: numerical fit of the outcome of detailed nuclear network trajectories in (s,t_{exp},Y_e) space
- thermalization efficiency: physically motivated fitting formula
- gray opacity: simple relation with elemental composition

see Chiesa et al 2024, Barnes et al 2016, Tanaka et al 2020

xkn: from 1D luminosity to KN framework



- extension to 2D: ray-by-ray approach
- anisotropic density, opacity and speed profiles
- implemented alongside a simpler time scale KN models (Grossmann model)



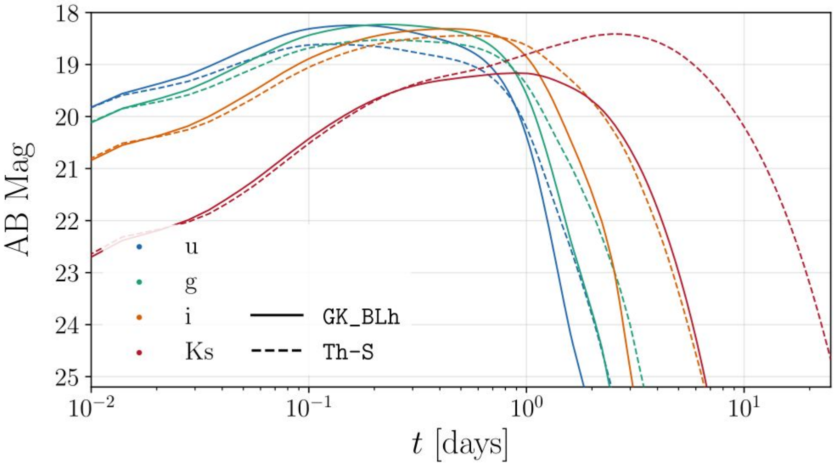
Breschi et al 2022

- photometry: broad band light curves
- black body emission, both from photosphere & optically thin shells
- validated against RT simulations

Radiation hydrodynamics models with nuclear network

SNEC ⇒ KNEC+NN

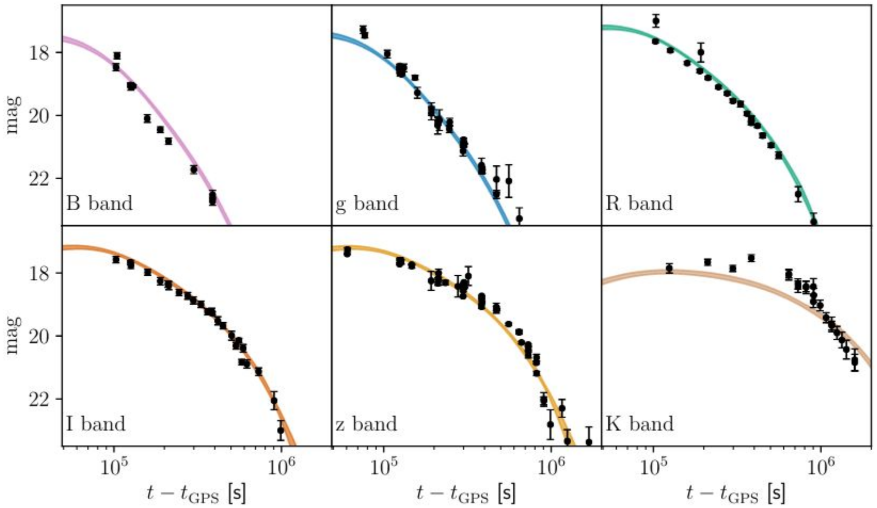
- radiation hydrodynamics of the ejecta
- energy-dependent photon transport
- online nuclear network:
  - detailed spectral atomic opacities
  - nuclear energy
  - thermalization efficiency
- 2D or 3D ray-by-ray
- F. Magistrelli & S. Bernuzzi (Jena U), G. Ricigliano (TU Darmstat →Tokyo U)



Magistrelli et al, arxiv

bajes: an open source nested sampling algorithm

- parallel & lightweight framework for Bayesian inference of MM transients
- nested sampling →**model selection**
- Python modular package
  - minimal dependencies on external libraries
  - adaptable to the majority of the Bayesian models
  - various sampling methods
- developed and tested in the context of GW data analysis: 1 full analysis in 1 day on 128 CPUs



LC bands from GW+KN inference, from Breschi et al 2024

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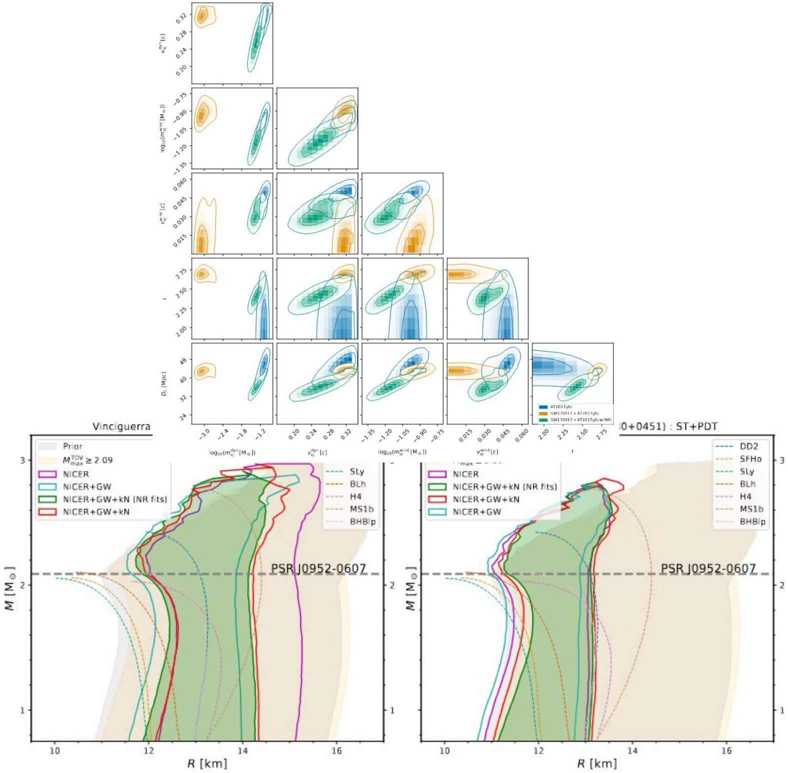

EOS constraints from GW+KN inference, from Breschi et al 2024

bajes: status of MM (GW+EM) analysis capabilities

- Nester sampling:
  - *bajes*
- GW models
  - *TEOBResumSPA*
  - *IMPRhenomPv2_NRTidal*
- KN models
  - Grossmann
  - *xkn*
- GRB afterglow model:
  - *afterglowpy*

- additional key features:
  - joint likelihood for multiple datasets
  - NR-informed relations for ejecta properties
- First tests and calibration procedure
  - M. Breschi & S. Bernuzzi (Jena U)
  - V. Fusaro (MSc student in Trento)
  - G. Huez (PhD student in Jena)
  - collaboration with G. Stratta and A. Rossi (INAF-OAS Bologna)

Pros & Cons of *bajes+xkn*

Pros

- flexible & transparent
- easily extendable
- no need of interpolation inside large parameter space
- direct connection with first principle calculations concerning
  - ejecta properties
  - nucleosynthesis yields

Cons

- accuracy bounded to performance
- limited accuracy in opacity & RT
  - no energy dependence
  - limited time evolution behavior
- lack of lateral motion & lateral fluxes
- systematic uncertainties in *xkn* (difficult to quantify)
- actual meaning and usage of NR fitting formulae