Numerical modeling of IR SEDs of dusty core-collapse supernovae with a **Bayesian approach**

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Motivation

Supernova (SN) explosions provide an exceptional opportunity to investigate both the final explosions of massive stars and their impact on their circumstellar environment. Astronomical dust plays a key role in fundamental astrophysical processes; furthermore, theoretical expectations as well as observations advocate that a considerable amount of dust can be produced during/ before SN explosions. According to our understanding, late-time mid-infrared (mid-IR) excess of SNe can be explained by newly-formed and/or pre-existing dust grains, thus mid-IR analysis may reveal precious information about SN dust. We aimed to investigate the multidimensional parameter space of SN dust (e.g. the dust mass, grain sizes and species, location) through mid-IR SED modeling. However, complex model assumptions and numerous model parameters support the use of a statistical approach. Therefore, we applied a Bayesian data inference framework to interpret our models. This approach enables us to characterize the posterior probability distribution of models, hence, not only determine the most probable regions of the parameter space, but also reveal the possible degeneracies between parameters.

Models of SN 1980K (II-L, 23yrs & 28yrs averaged)



IR SED modeling of dusty core-collapse SNe

Throughout our analysis, we investigated the late-time mid-IR Spitzer data of type II-L SN 1980K (Sugerman+2012), type IIb SN 1993J (Zsíros+2022) and type IIn SN 1996cr (unpublished data). To reveal the physical properties of the dust in the vicinity of the SNe, we fit both analitical and numerical models to the SEDs.

Analitical dust models: adopted from Hildebrand (1983) (also applied by e.g. Zsíros et al., 2022). The models describes the thermal emission of dust grains assuming a modified blackbody radiation from optically thin dust with at a single equilibrium temperature. We applied pure amorphous carbon and silicate-based (C-Si-PAH) composition throughout modeling (Zsíros+2022).

Numerical models: computed using the MOCASSIN (MOnte CArlo SimulationS of Ionized Nebulae) radiative transfer code (Ercolano+2003, 2005, 2007). The code follows the possible light-matter interactions (emission, absorption) and scattering) and describes the re-emission of the dust grains. We used both a point and a diffuse radiation source compass about with a shell-like dust containing region with a smooth dust density distribution. We applied a mixture of amorphous carbon and silicate dust composition. Nevertheless, while numerical models provide more relevant representation of the possible physical background, they require more free parameters. We focused on the crucial parameters of the models, including the luminosity of the radiation source, the dust mass, the inner radius of the dust containing shell and the ratio of the inner and outer radii of the shell.









The Bayesian approach

To interpret the numerical modeling thoroughly, we applied a Bayesian inference procedure linked to a Markov Chain Monte Carlo (MCMC) algorithm (De Looze+2019). This approach is a powerful tool to characterize the parameter space of complex multidimensional models and, moreover, to expose and describe possible parameter degeneracies. For sampling, the method applies an affin invariant ensemble sampler (Goodman & Weare 2010) implemented by a Markov Chain Monte Carlo (MCMC) algorithm through the "*emcee*" package in *Python* (Foreman-Mackey+2013). The sampling is executed by random walks of a selection of walkers which preferred to have a higher likelihood in each new position. The posterior probabilities are drawn from the positions of the walkers, while the priors determined from the respective numerical models. We analysed both point source and diffuse source models with a smooth dust distribution.

Our best-fit amorphous carbon and C-Si-PAH composition analitical dust models (left column) with the numerical dust models (right column) assuming a diffuse source on mid-IR SEDs of SN 1980K (Sugerman+2012), SN 1993J (Zsíros+2022) and SN 1996cr. In order to have a representative sample of SNe, we choose various types of well-observed SNe with late-time Spitzer data.



✓ The observed late-time mid-IR emission can be described with dust models, thus supports the presence of significant amount of dust in the vicinity of all three SNe in accordance with previous studies.

✓ In case of different types of SNe, numerical dust models with a shell-like geometry can be reconciled with analitical models, resulting a deeper insight of dust parameters. However, on account of the shortage of data, we may consider other possible solutions regarding dust parameters and also physical processes (e.g. clumpy dust, IR echo).

✓ Our analysis provides preliminary results of large scale numerical modeling of IR SED of dusty SNe, which is proved to prepare an in-depth analysis of SNe with more available data.

Work in progress



A corner plot derived from an IR SED fitting process assuming numerical dust models with a smooth dust distribution. Corner plots correspond to the charachteristic of the parameter field along with the relationship of certain parameters. histograms coincidence the 1D The marginalized posterior distribution plots showing the likelihood if a certain value will be given to a particular parameter. The contour plots accord to the 2D posterior distributions revealing the probability of two parameters. The posterior contours were smoothen and also individual data points are not plotted. The contours display the 0.5σ , 1.0σ , 1.5σ and 2.0σ likelihoods, respectively, and the blue curve indicate the mean solution.

To reveal more details about the properties of SN dust, we have been working on more precise application of the Bayesian inference framework. Moreover, since, dust grains are more likely to accumulate in clumps (e.g. Wesson+2015), we have been testing more complex dust models with clumpy dust distribution.

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