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# *Fast and Automated Characterization of Core-Collapse Supernovae with Machine Learning and HPC-Driven Modeling*

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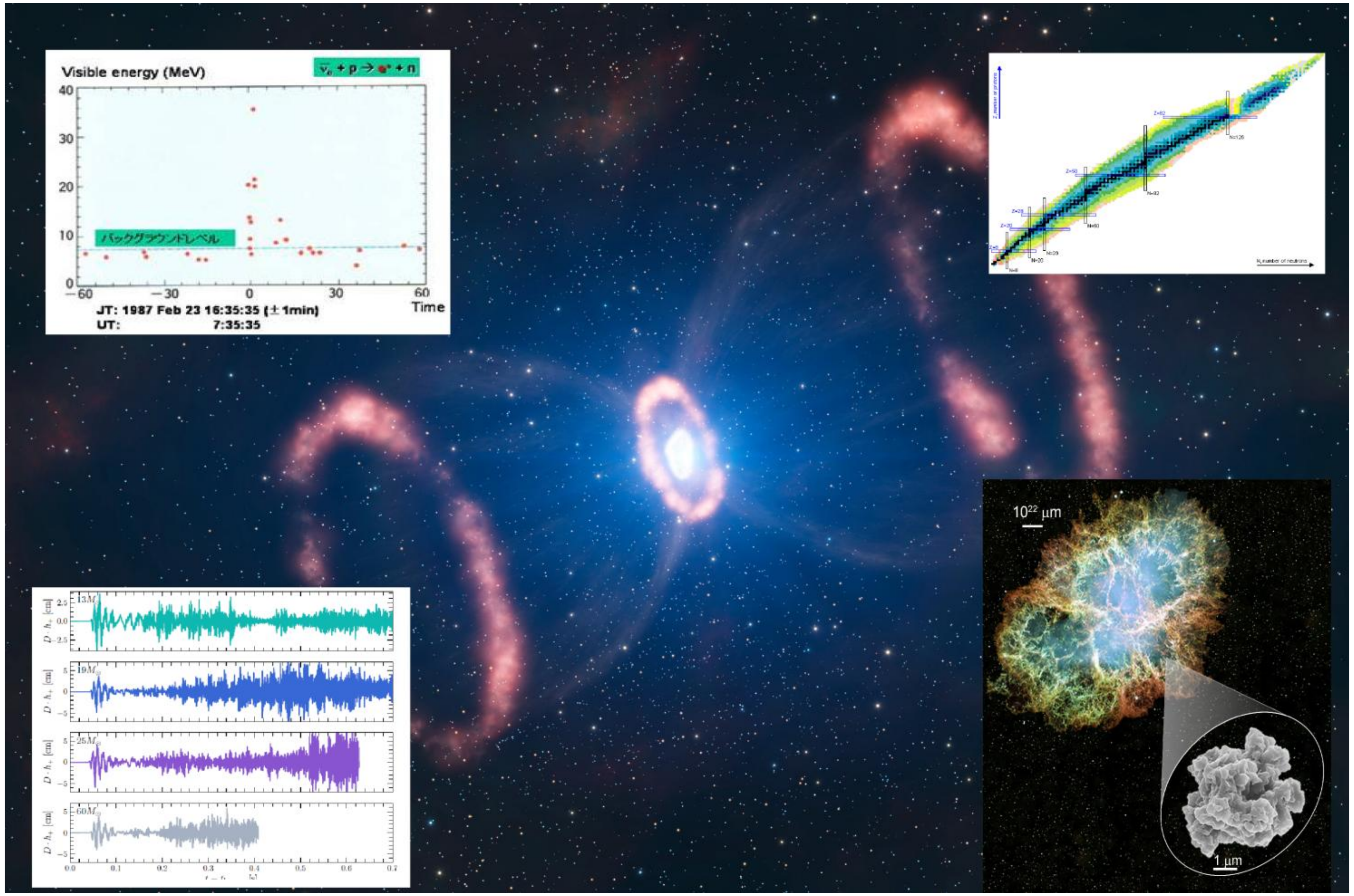
# Core-Collapse Supernovae

Neutrino Emission

Stellar Nucleosynthesis




Gravitational Waves

Molecular & Dust production

Composite image with artistic representation of SN 1987A (Ref. ESO Website)

# Physical Characterization of Supernova events

## Electromagnetic Observation:

- Light Curves → Bolometric Luminosity;
- Spectra → Photospheric Velocity.

## Theoretical Models:

- Hydrodynamic numerical models;
- Scaling Equations;
- Semi-/Analytical models.

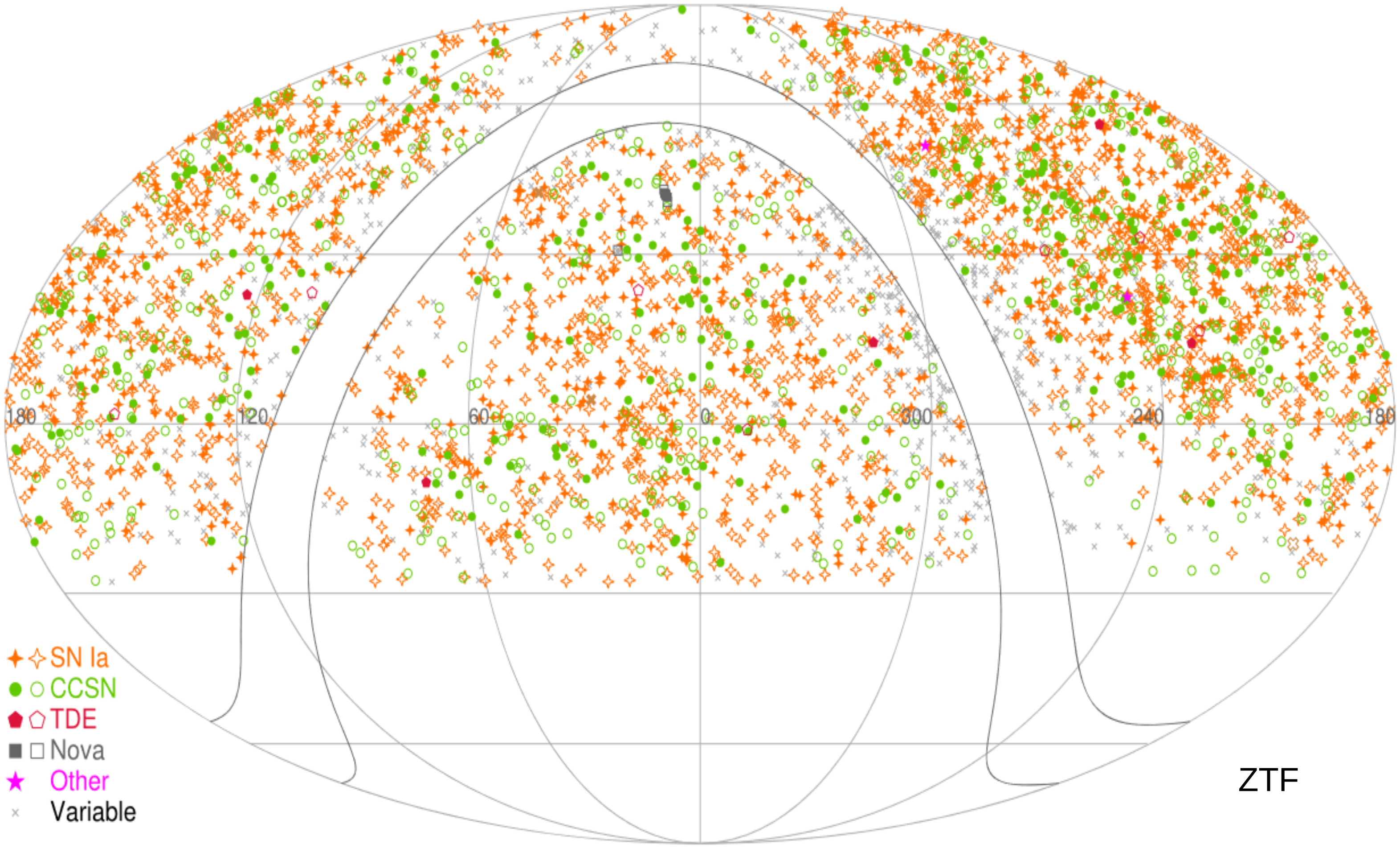
## Explosion parameters:

- Explosion energy ($E$);
- Ejected mass ($M_{ej}$) ;
- Radius at explosion ($R_0$) ;
- Source mechanism –$^{56}$Ni mass, magnetar, CSM interaction, etc.– parameters (e. g. $M_{Ni}, B_M, P_M$, $M_{CSM}$, $R_{CSM}$, s, etc.).

# Discovery, classification, characterization rates:

- Transients $\approx 10^4 yr^{-1}$
- SN Classifications $\approx 10^3 yr^{-1}$
- Type II SNe $\approx 2 \cdot 10^2 yr^{-1}$
- **Characterized** SNe II $\approx 20 yr^{-1}$

LSST survey will increase the discovery rates of **$\times$ 1000 – 2000**




Ivezić, Ž et al., ApJ, Vol. 873, 2, id. 111, 44 pp. (2019).

Perley D.A., Fremling C., Sollerman et al., 2020, ApJ, 904:35

# Scientific Rationale:

- Hydrodynamical models capable of characterizing SN events are very **computationally expensive**, limiting their application to fewer SNe than those observed by the surveys (e.g. ZTF, LSST);
- **Coherent statistical studies** of SNe properties using large data samples require fast, general, and accurate post-explosion models applicable to many SN types;

## «Fast» modeling procedures for CC-SNe

# «Fast» modeling procedures for CC-SNe:

- Post-explosive (semi-)analytical models;
- Modeling procedures for physical characterization of H-rich SNe.

# Analytic Light Curve Model

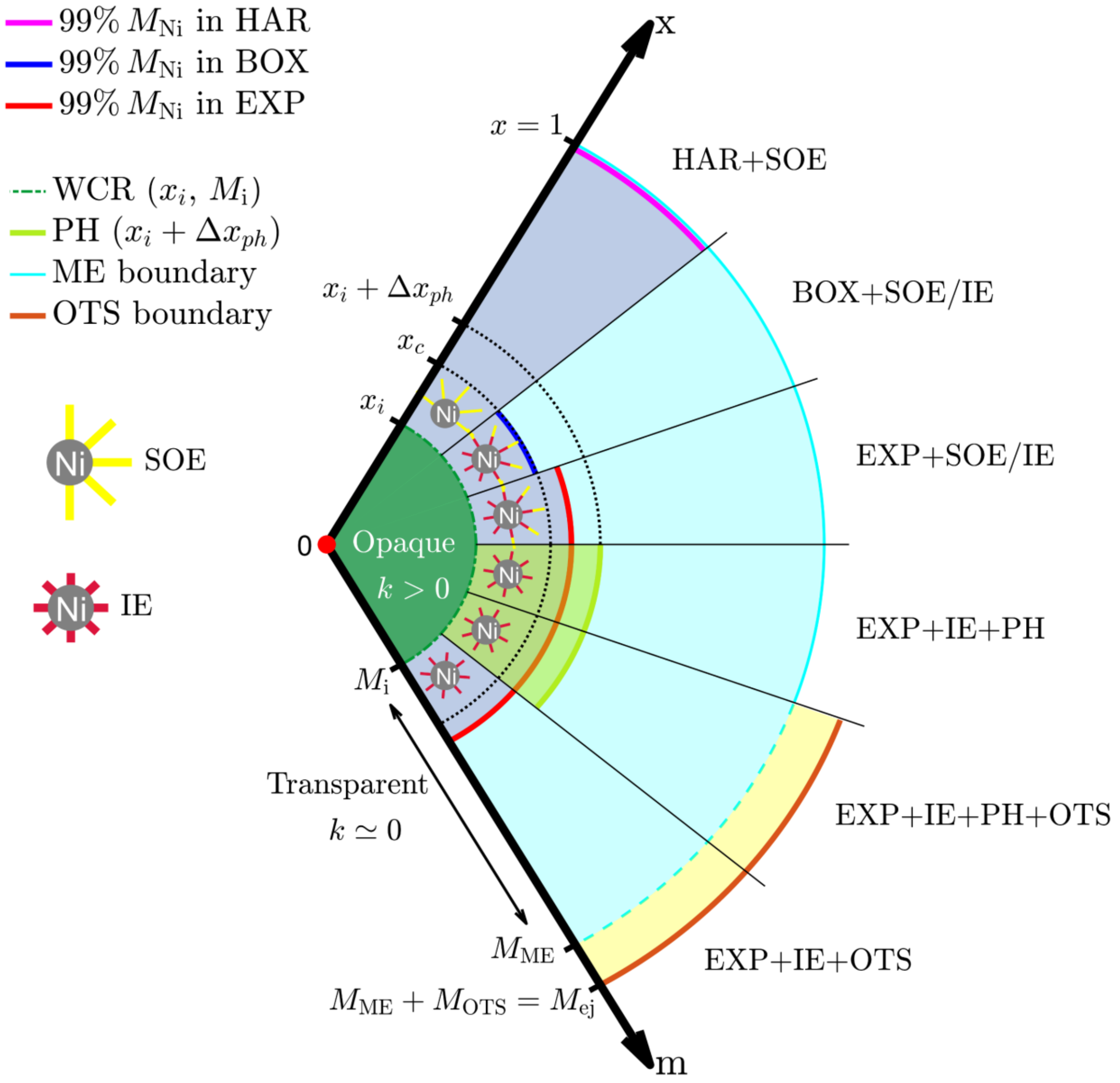
## Common hypothesis for SN ejecta:

- spherical symmetry;
- homologous expansion;
- uniform density profile;
- dominant rad. pressure;
- strictly adiabatic solution (like ***Arnett 1980-1982***);
- two-zone opacity model (like ***Popov 1993***).

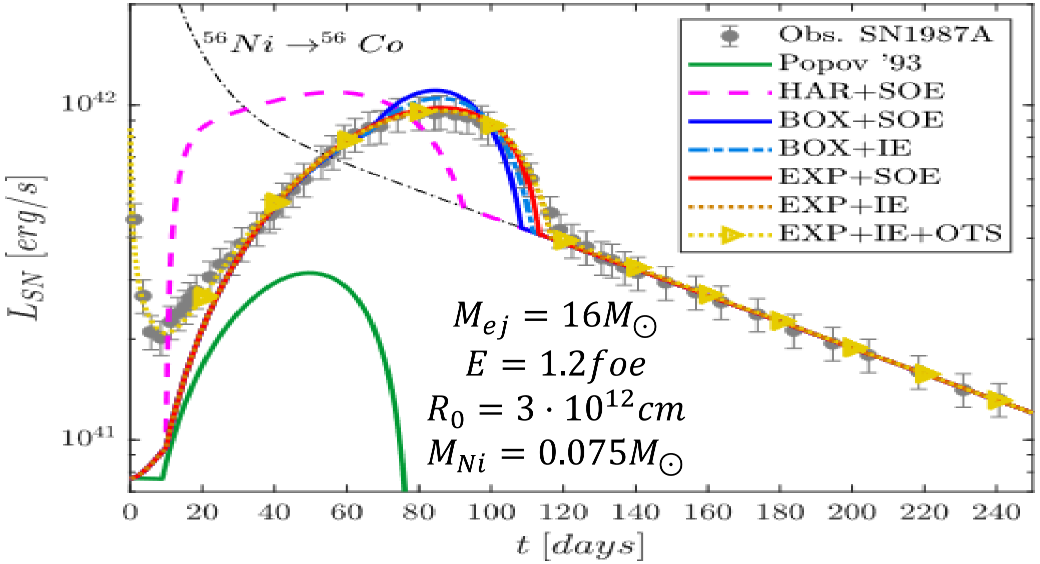
## New analytical model:

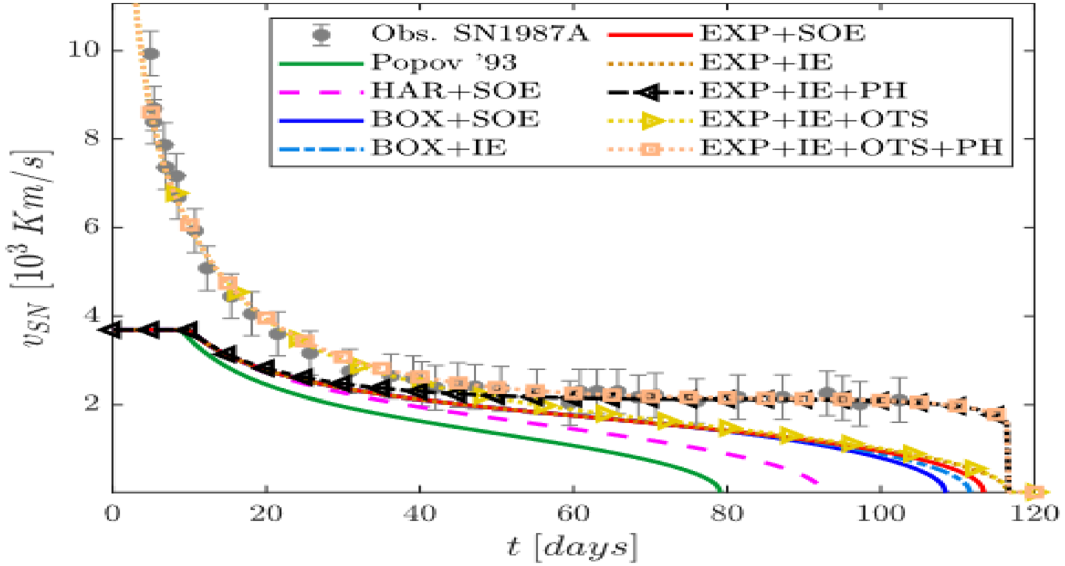
Pumo & Cosentino, MNRAS, Vol. 538, 1, pp.223-242 (2025)

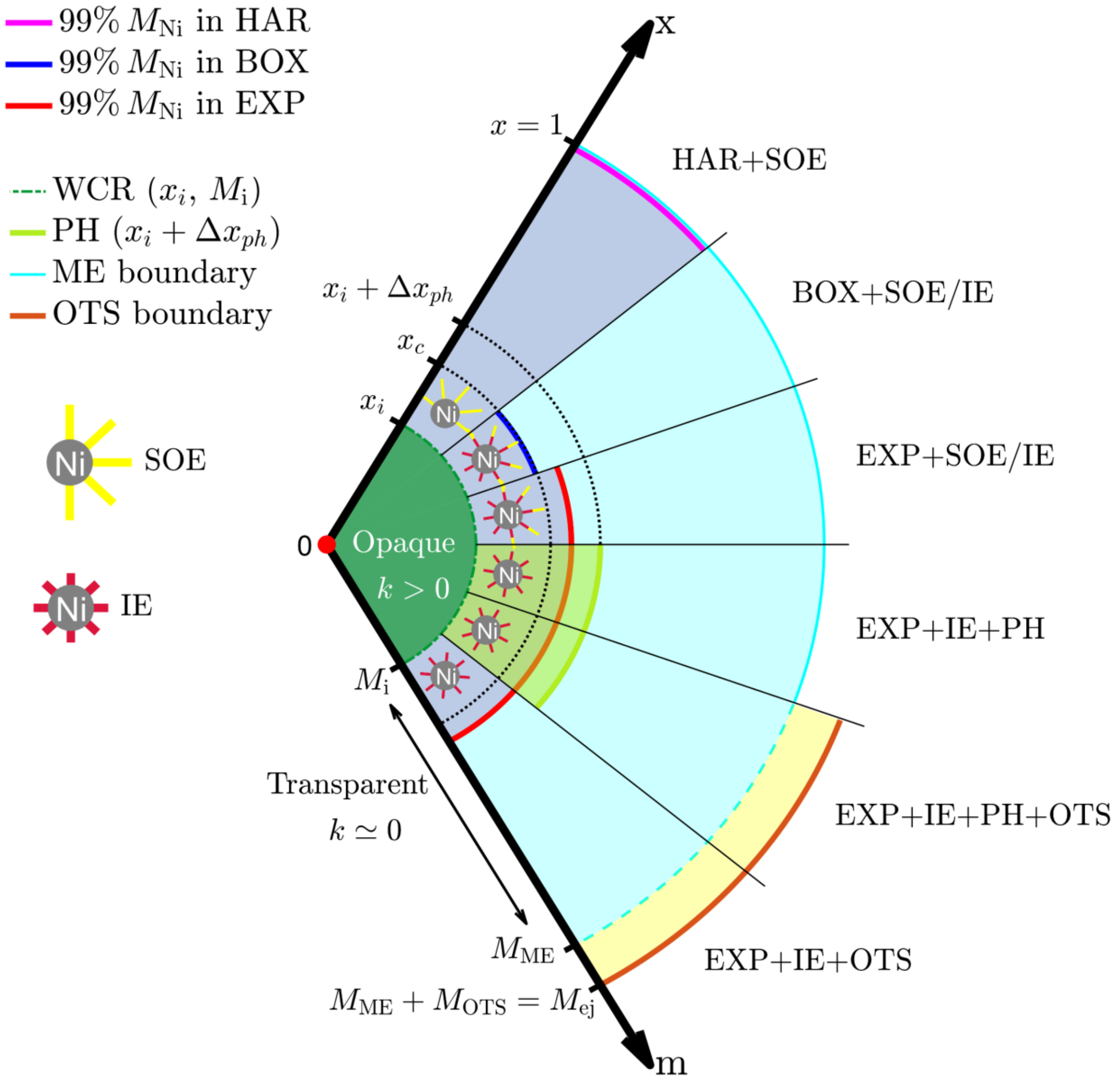
- Heating effects of $^{56}$**Ni decay during the recombination phase**:
  → Ni distribution and emission hypothesis (BOX, EXP, SOE, IE)
- Presence of an **Outer Thin Shell** (OTS) above the homologous ejecta:
  → further shell parameters (at least two more)



Pumo & Cosentino, MNRAS, Vol. 538, 1, pp.223-242 (2025)



# Shock luminosity in interacting Supernovae

- CSM configuration

$$M_{CSM}, R_{CSM}, s, f_{\Omega}$$

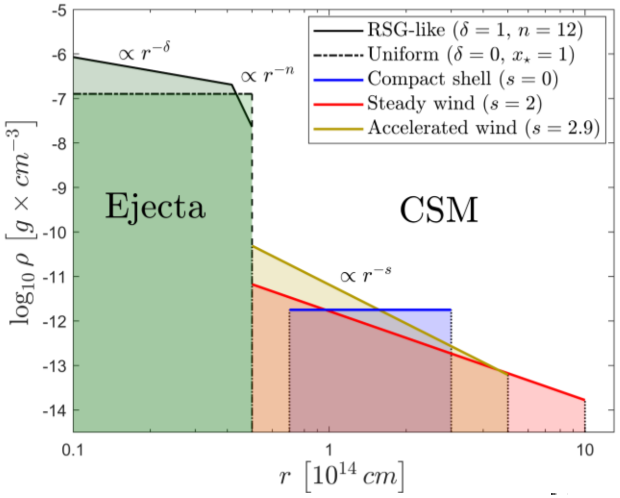
- Energy source & Diffusion time:

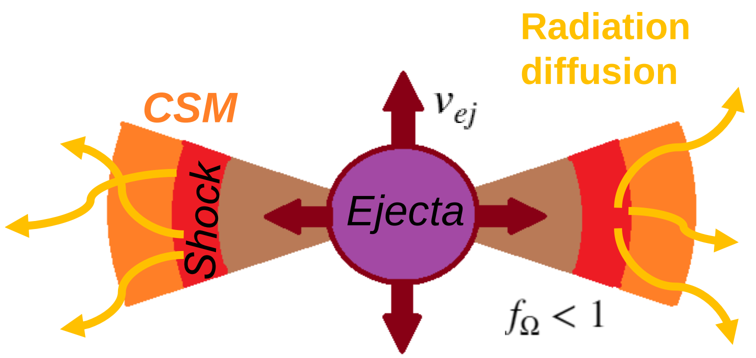
$$S_{\rm sh} \equiv \frac{9}{2}\pi f_{\Omega}\epsilon_{\rm rad}\ \rho_{\rm CSM}|_{R_{\rm sh}(t)}\ v^3_{\rm sh}(t)\, R^2_{\rm sh}(t)$$

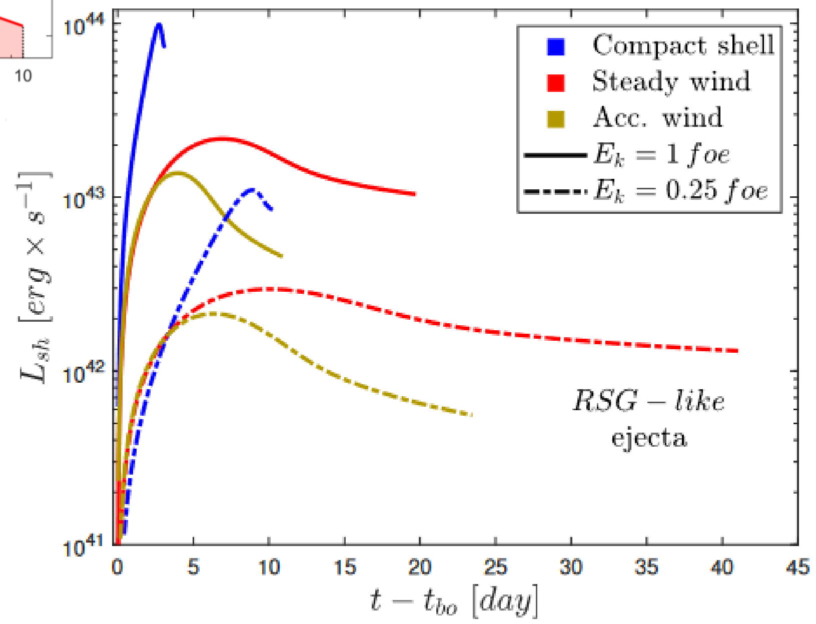
$$t_{\rm d} \equiv \frac{k_{\rm T}}{c} \times \int_{R_{\rm sh}}^{R_{\rm ph}} \rho_{\rm CSM}(r)\, d\left[(r - R_{\rm sh})^2\right]$$

- Shock luminosity:

$$L_{\rm sh}(t) = \int_{t_{\rm bo}}^{t} \frac{S_{\rm sh}(t')}{t_{\rm d}(t')} \times e^{-(t-t')/t_{\rm d}(t')}\, dt',$$



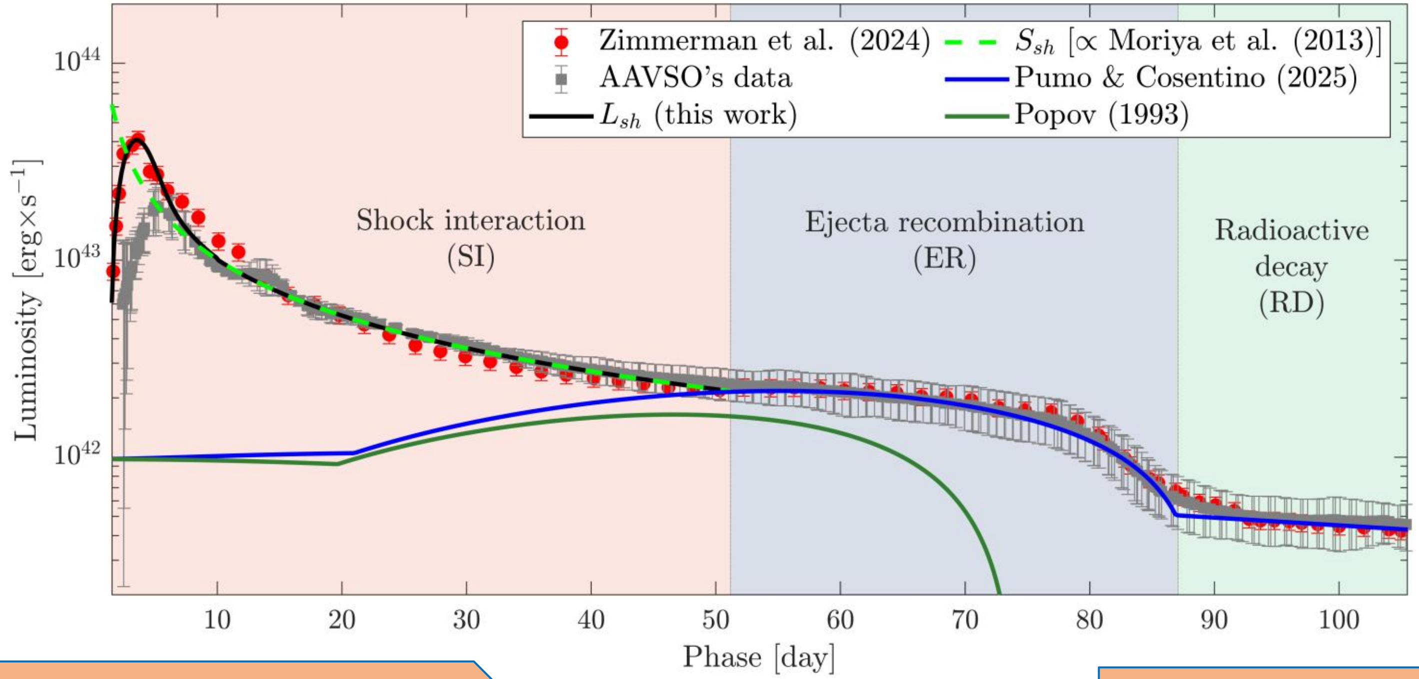




S.P. Cosentino, M.L. Pumo & S. Cherubini, MNRAS (2025).

# Application to other H-rich SNe: The case of SN 2023ixf

S.P. Cosentino, M.L. Pumo & S. Cherubini, MNRAS (2025)




## SN ejecta parameters

$M_{ej} = 9 \pm 0.5 M_\odot$, $E = 1.8 \pm 0.2 foe$

$R_0 = (1.6 \pm 0.6) \cdot 10^{13} cm$

$M_{Ni} = 7.3^{+1}_{-0.5} \times 10^{-2} M_\odot$

## CSM parameters

$M_{CSM} = 6.5^{+1.5}_{-1} \cdot 10^{-2} M_\odot$

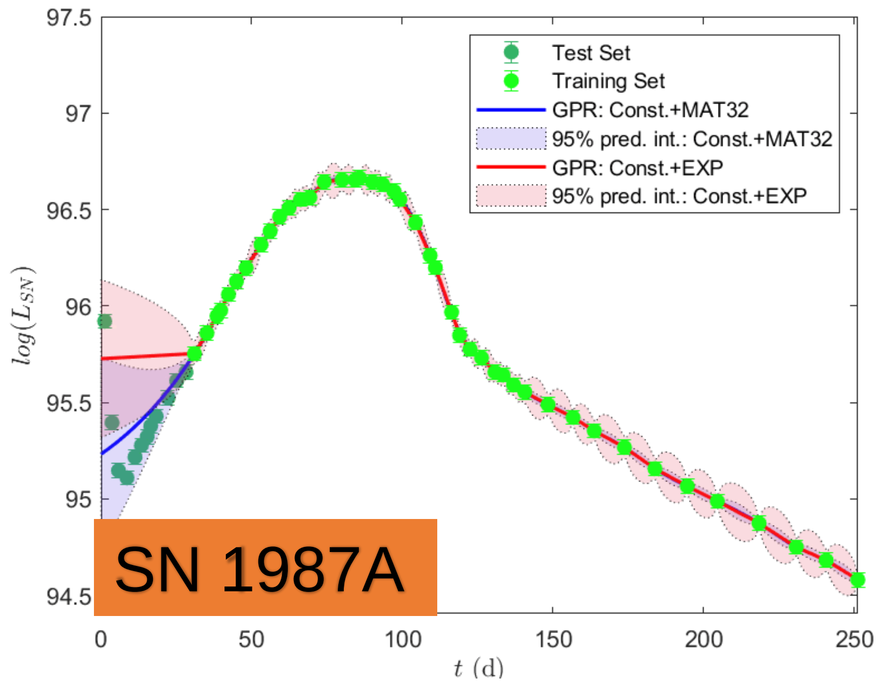
$R_{CSM} = (3.6 \pm 0.5) \cdot 10^{15} cm$

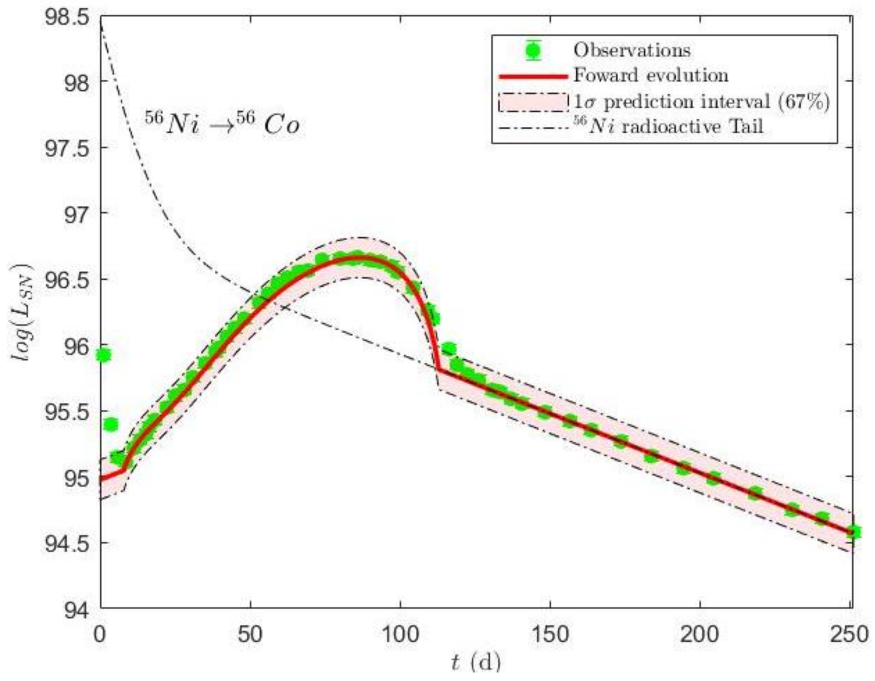
$s = 2.90 \pm 0.03$

# Technical Objectives, Methodologies and Solutions

## Data reduction and analysis:

- Sample choice and spectrophotometric reduction;
- Time series reconstruction (Gaussian Process).




## Modelling procedures:

- Monte-Carlo Bayesian Analysis (SuperBAM);
- Machine Learning solutions (Inception-Time model).

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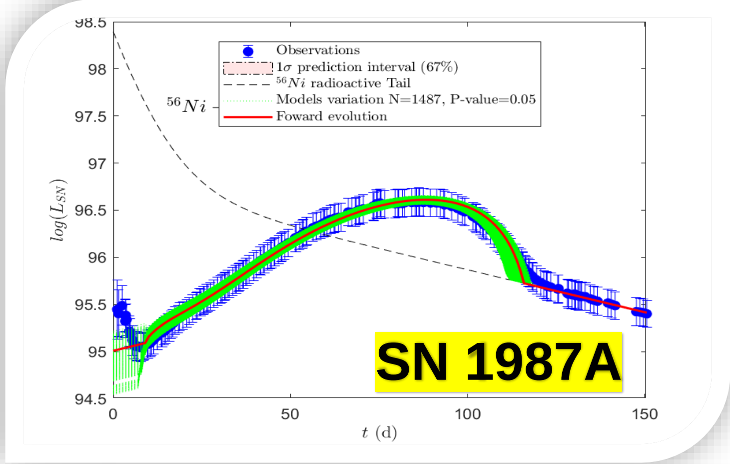
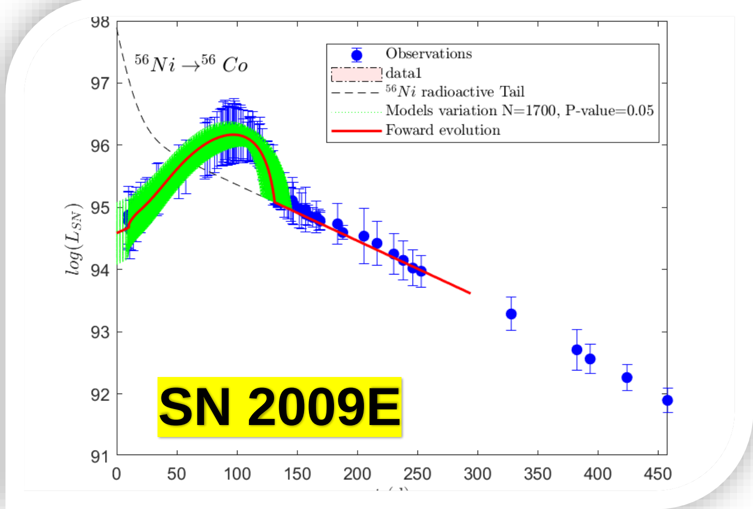
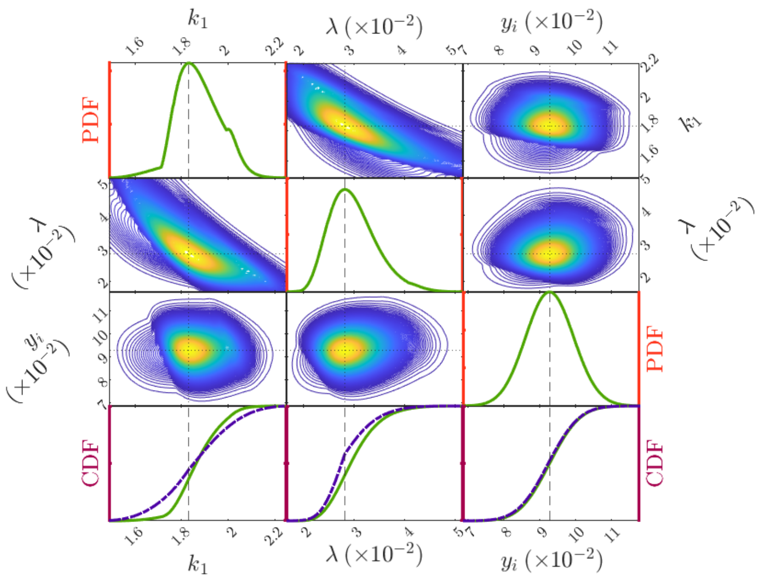
# Supernova Bayesian Analytic Modeling - SuperBAM

S.P. Cosentino, C. Inserra, M.L. Pumo (A&A, to be submitted)




SuperBAM

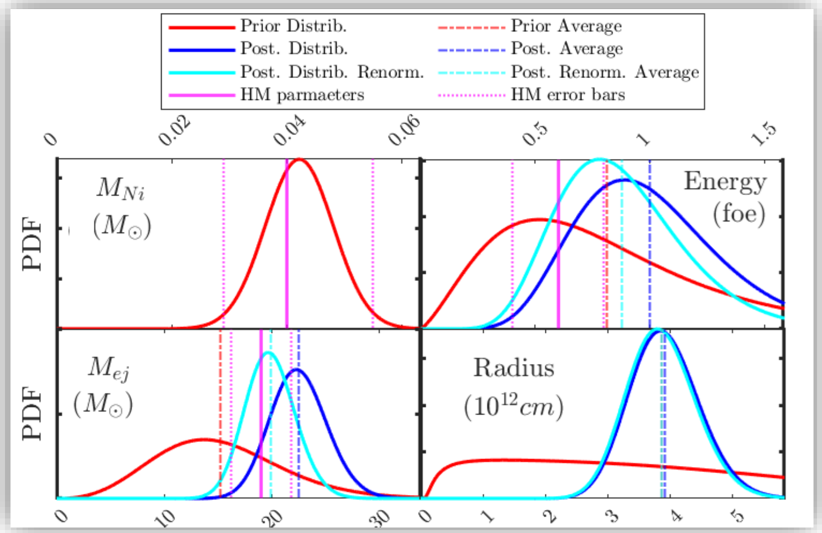
Prior probabilities from scaling relation of
[Pumo, Cosentino, Pastorello et al., MNRAS 521, 4801–4818 (2023)];
Likelihood function model based on
[Pumo & Cosentino, MNRAS, Vol. 538, 1, pp.223-242 (2025)].

## Likelihood Function

$$P(\bar{L}|\theta) = \frac{1}{\sqrt{2\pi}\,\sigma}\cdot\prod_{Obs.}\exp\left\{-\frac{\left[log\bar{L}_{Obs.} - log\bar{L}_{Mod.}(y_{Obs.},k_1,\lambda,y_{i/f})\right]^2}{2\sigma^2}\right\}$$

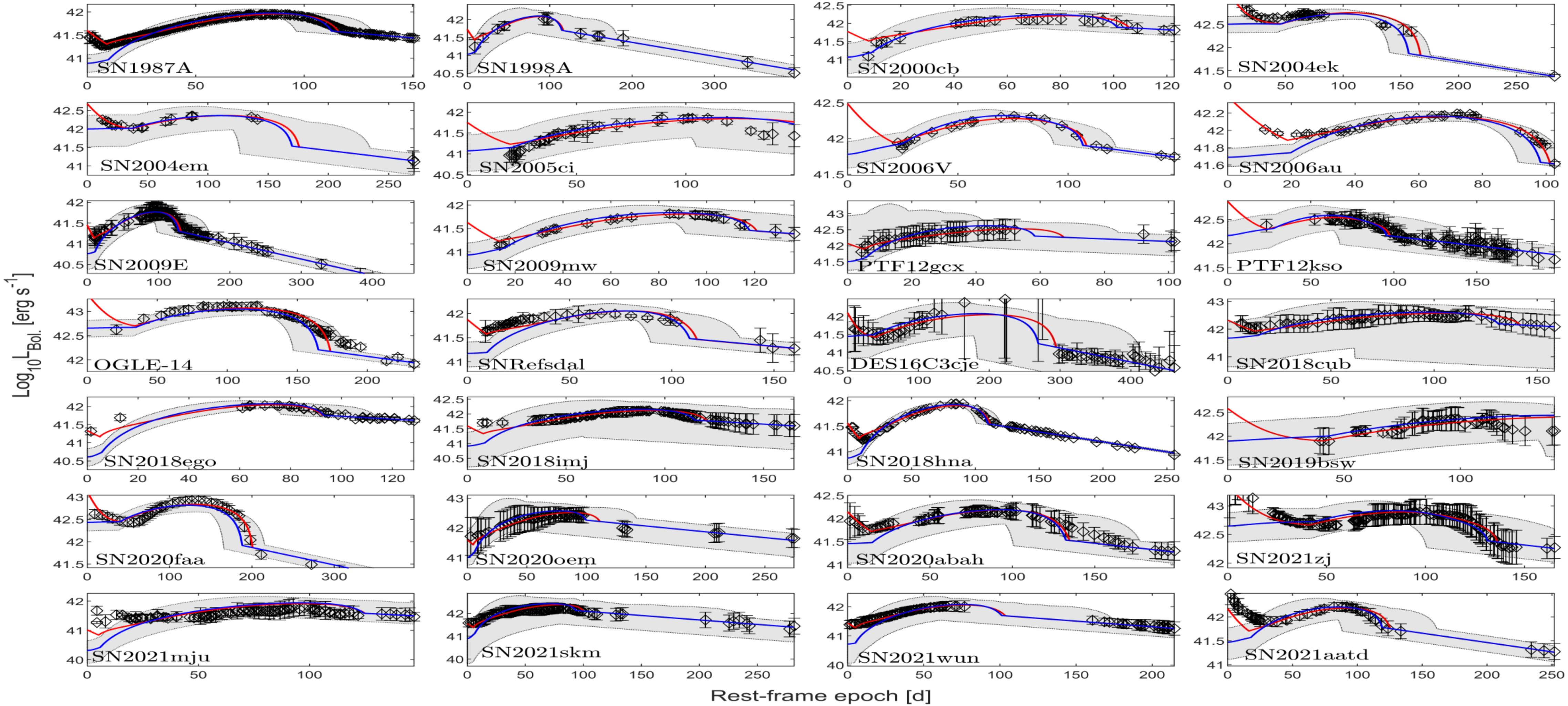
## Posterior Probability

$$P(\theta|log\bar{L}) = N_{norm}\cdot P(log\bar{L}|\theta)\cdot P(\theta)$$



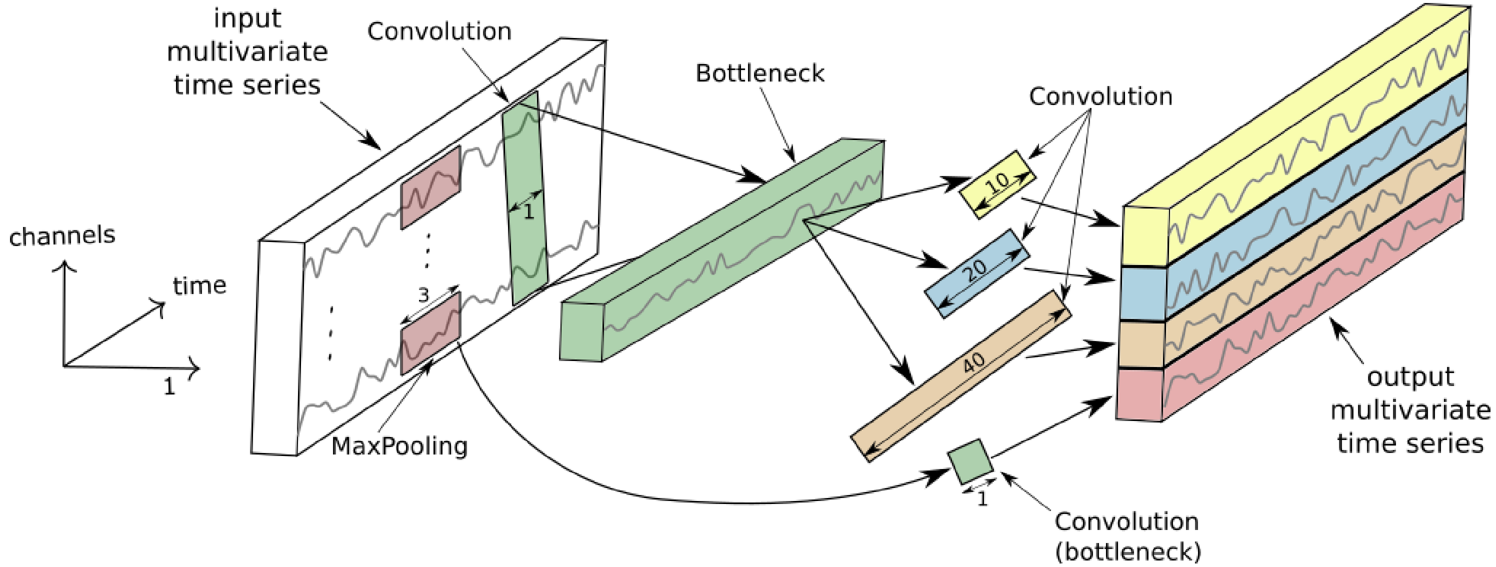
# Preliminary results for 28 long-rising SNe

S.P. Cosentino, C. Inserra, M.L. Pumo (A&A, to be submitted)



# Machine Learning application: *InceptionTime* model

- **Machine Learning** algorithms trained on **large samples of semi-analytical** models, curriculum learning using numerical hydrodynamical symulations
- **Infer ejecta parameters** with advanced ML tools to speed up the characterization of large **CC-SN sample expected from LSST survey**;




(e.g. *Grassia, S.P. Cosentino, M.L. Pumo, G. Mangioni, published in IEEE PDP2025 Conf. Proc.*)

# Accomplished Work, Results

- **Curriculum-learning** strategy**: models** are **trained starting with simpler examples and gradually increasing in complexity**, mimicking the human learning process
  - It helps models to generalize better and can lead to faster convergence during training, while also being data efficient

- **Three** learning **phases:**

1. **Training on** the **semi-analitical** data, **testing on** the **hydrodynamical** observations

2. **Training on** (a subset of) the **hydrodynamical** data**, validation and testing on** the **ones left** out the training set

3. **Training on** all the **hydrodynamical** data**, testing on the real-world observations**

# Main Results

- First vs second phase result comparison on hydrodynamical data

Major improvement in results:

| Phase | Radius | Mass | Energy | Nickel |
|---|---|---|---|---|
| 1 | 87% | 30% | 64% | 13% |
| 2 | **42%** | **10%** | **28%** | **7%** |

- Real-world data performance:

| | Radius | Mass | Energy | Nickel |
|---|---|---|---|---|
| 3 | **10%** | **18%** | **12%** | **7%** |

# Final steps and future activities

- **Occlusion tests** to highlights the importance of each observed point in **SN Light Curve (LC)** (e.g. *M. Grassia, S.P. Cosentino, M.L. Pumo, G. Mangioni, 2025, Science Advance, to be submitted*);
- Training **GenAI model** designed to capture fundamental relationships between key physical parameters and simulated **LCs for H-rich Interacting SNe** (ASTRAI project);
- Development of **new model for** different types of sourcing functions and ejecta composition, to describe **other class of optical transients** (e.g. ILRT, SLSNe, Ib\c);
- Simulations of **High-Energy neutrinos** in ejecta-CSM interaction, modeling other real SN events to **perform the observation strategies for Large Volume Neutrino Observatories**

# Thanks for your attention!

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