Empirical spectrophotometric modelization of SN Ia

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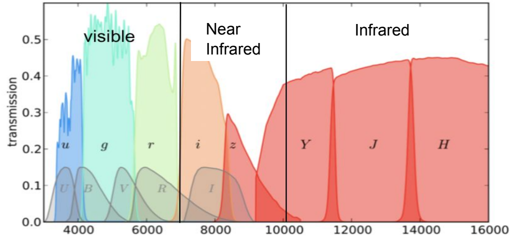
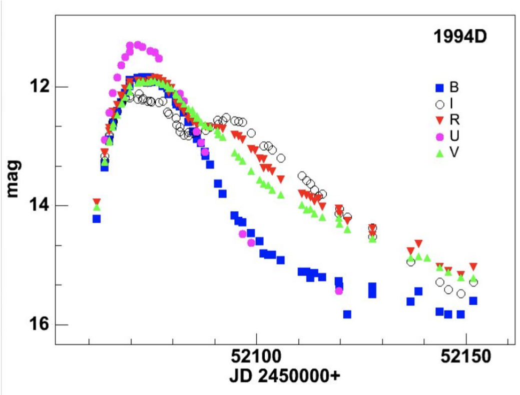
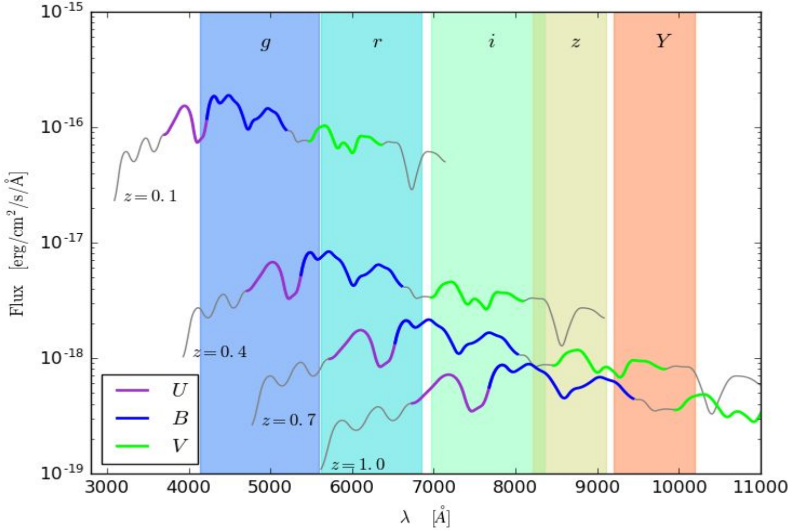
Observation method

- To constrain cosmological parameters, we measure luminosity distance from flux observation.
- Observations in differents filters (wavelength range)
- The integral of blue spectrum emitted in SN restframe is observed :
    - in band g for z = 0.1
    - in bands z, i and Y for z = 1.0





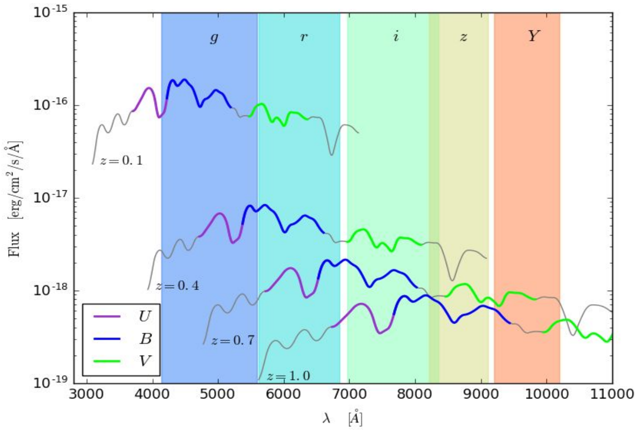


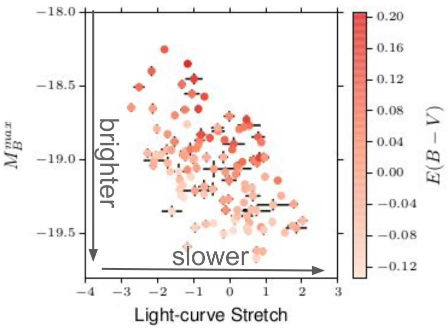
Spectrophotometric model

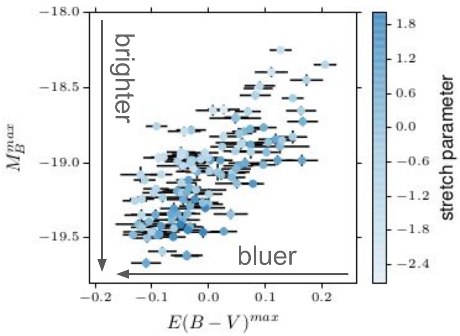
- To construct a Hubble Diagram, all must be express in the same restfram band : band B (by convention) at the maximum de luminosity : $\mathrm{m_B^{obs}}$

- To minimize the dispersion the hubble diagram residuals : extraction of SN Ia stretch, s, and color, c.

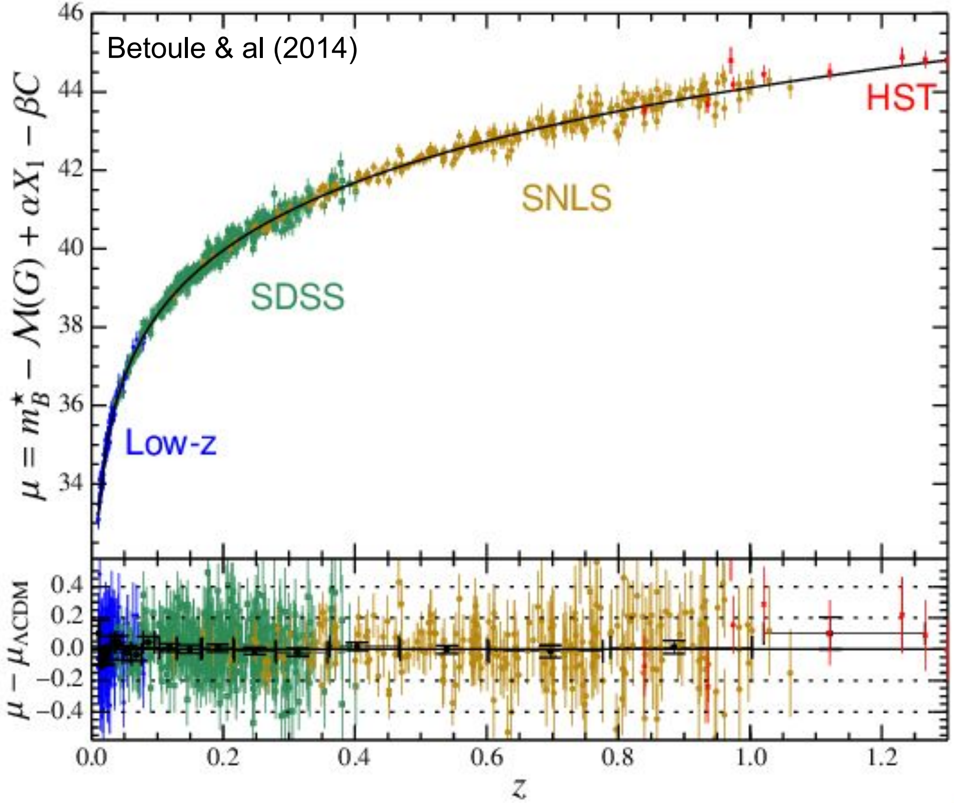
$$m_B^{obs} = \mu + M_B + \alpha s - \beta c \pm 15\%$$







Hubble diagram residuals



Uncertainty sources	$\sigma_x(\Omega_m)$	% of $\sigma^2(\Omega_m)$
Calibration	0.0203	36.7
Milky Way extinction	0.0072	4.6
Light-curve model	0.0069	4.3
Bias corrections	0.0040	1.4
Host relation[a]	0.0038	1.3
Contamination	0.0008	0.1
Peculiar velocity	0.0007	0.0
Stat	0.0241	51.6

SALT 2 (Spectral Adaptive Light curve Template)

Parameters common to all SN : proper to the model

Mean spectrum of all SNe Ia

Principal variation of the spectrum

Color law correction

$$S(SN, p, \lambda) = X_0[M_0(p, \lambda) + X_1 M_1(p, \lambda)]exp(cCL(\lambda))$$

Parameters specific to each SN

Normalization factor

link to stretch parameter

color parameter

To constraint common parameters, need to train the model on well sample SN Ia data with known redshift : called <u>training sample</u>

Other models

LPNHE PARIS

- 2nd generation : photometric model (SIFTO, Conley & al 2008, SNLS)
    - trained on low-z SNe photometric data;
    - modelization of light curve with 2 standardization parameters;
    - spectrum modelization add with a template of low-z.

- 3rd generation : spectro-photometric model (SALT2, Guy & al 2007, 2010; Betoule & al 2014, SNLS)
    - trained on light curves and spectra, low & high z;
    - but only 2 standardization parameters.

- 4th gen (SUGAR & SNEMO, Léget & al 2019; Saunders & al 2018, The Nearby Supernova Factory)
    - 3 standardisation parameter;
    - trained only on low-z SNe data, missed UV for high-z description;
    - Spectrophotometric time series only not hybrid.

Thesis goals

- Create a hybrid salt2-like model
- Gather a modern & larger training sample
- Usable for cosmology study
- Enhance systematic uncertainty propagation (especially calibration uncertainty)

The french SN community is working on the pre-LSST Hubble Diagram (with the addition of HSC & ZTF) : A new model is needed !

New generation of SALT2 model

LPNHE PARIS

- Strong points :
  - low and high z;
  - UV data;
  - empirical spectro-photometric modelization;
- Limitations :
  - old training sample (last training 2014) ;
  - maybe more parameter to describe SN variability ;
  - stiff (minimizer and model are indivisible) ;
  - usable on O(1000) SNe ;
  - manual training ;
  - not maintained

➢ New SALT2 training framework:
  - New tools (Sparse matrix, Python3 ...);
  - New techniques for simple training (One minimisation, updatable model, error model, fast algorithm …).

➢ Gather well measured SN Ia sample & addition in UV space;

➢ New component to standardization (host galaxy dependency, redshift dependency...)

SALT3

- Light curve fitter for DES Survey,
- Publish public SALT2 training code,
- New SALT2 trained model,
- Modern training sample:
    - Larger
    - Better UV coverage

SALT3: An Improved Type Ia Supernova Model for Measuring Cosmic Distances

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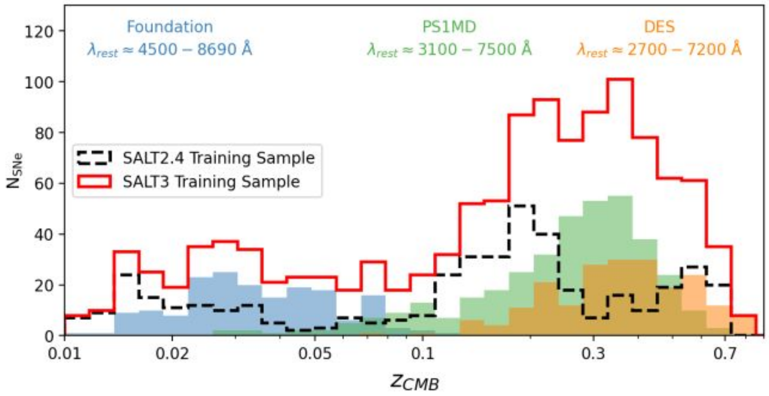
Training sample : Kenworthy & al 2021 : SALT3

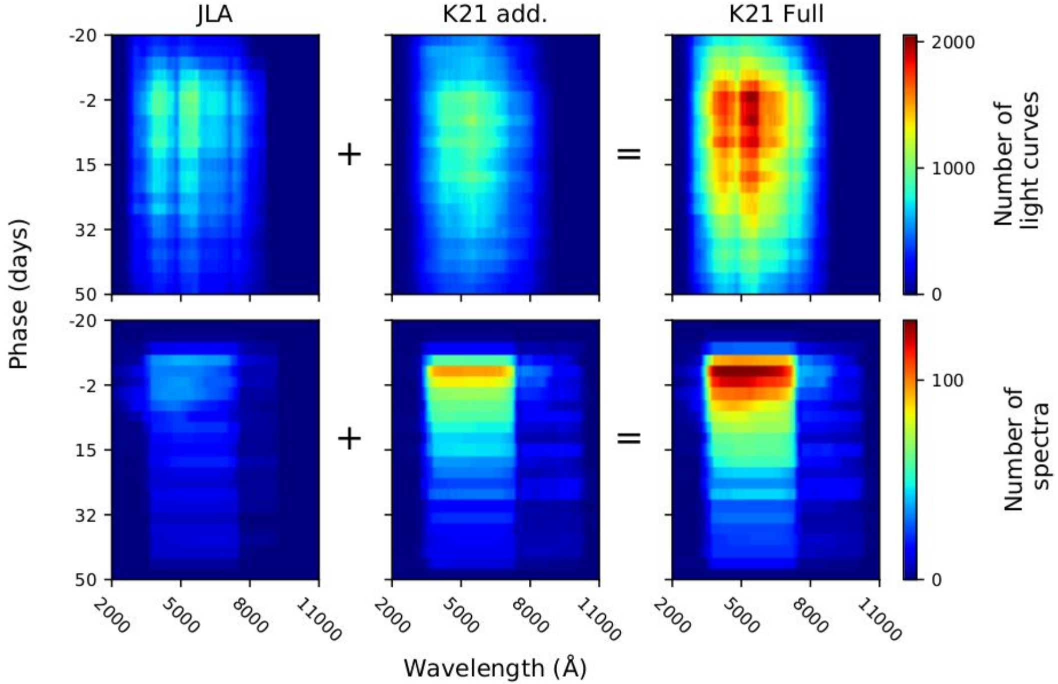
- JLA :
  - low-z; SDSS; SNLS;
- K21 :
  - + Foundation Supernova Survey;

    Pan-STARRS Medium Deep Survey; DES
- 1083 SNe

Kenworthy & al 2021



Kenworthy & al 2021



Program

- Simplified flux model:
    - fit a toy model to construct our tools ;
    - fit a error model;
- Study on data : CSP;
- 2D SALT2-like model;
- Add new standardisation component.

Model & fit present difficulties

LPNHE PARIS

- Large fit => sparse matrices;
- Empirical nonlinear model :
  - 1st a priori : all Sne same LC shape
  - 2nd a priori: there is a max
  - 3rd a priori : smooth evolution with time

  } spline with regularization shared by all SN

  - amplitude, date of maximum and stretch for each SN => simultaneous fit
    - Degeneracies (splines and SNe parameters) => constraints
- Model residual variability (error model);
  - intrinsic SN variability

➢ Creation of a toy model to built all the tools needed for the 2D model.

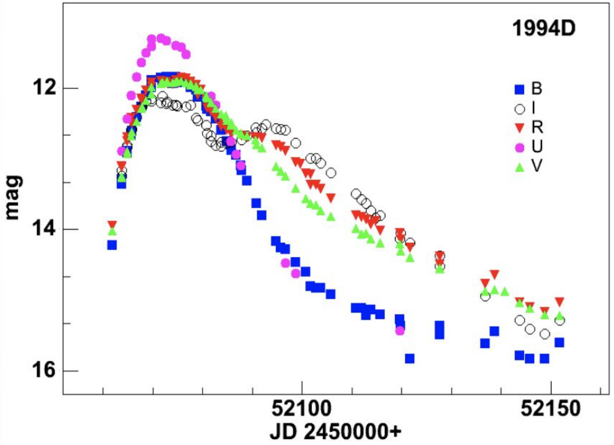
1D toy model

LPNHE PARIS

3 parameters per SN

$$f(t, sn) = f_{sn} \Sigma_i \theta_i B_i \left(\frac{t - t_{sn}}{(1 + s_{sn})(1 + z)} \right)$$

Global parameter of the model



$$\Sigma_i \theta_i B_i(0) = 1$$

$$\Sigma_i \theta_i B_i^{'}(0) = 0$$

$$\Sigma_i s_i = 0$$

Regularization

$$\mu(\Sigma_{i=0}^{N} \theta_i^2 + \Sigma_{i=1}^{N} (\theta_{i-1} - \theta_i)^2)$$

Minimizer

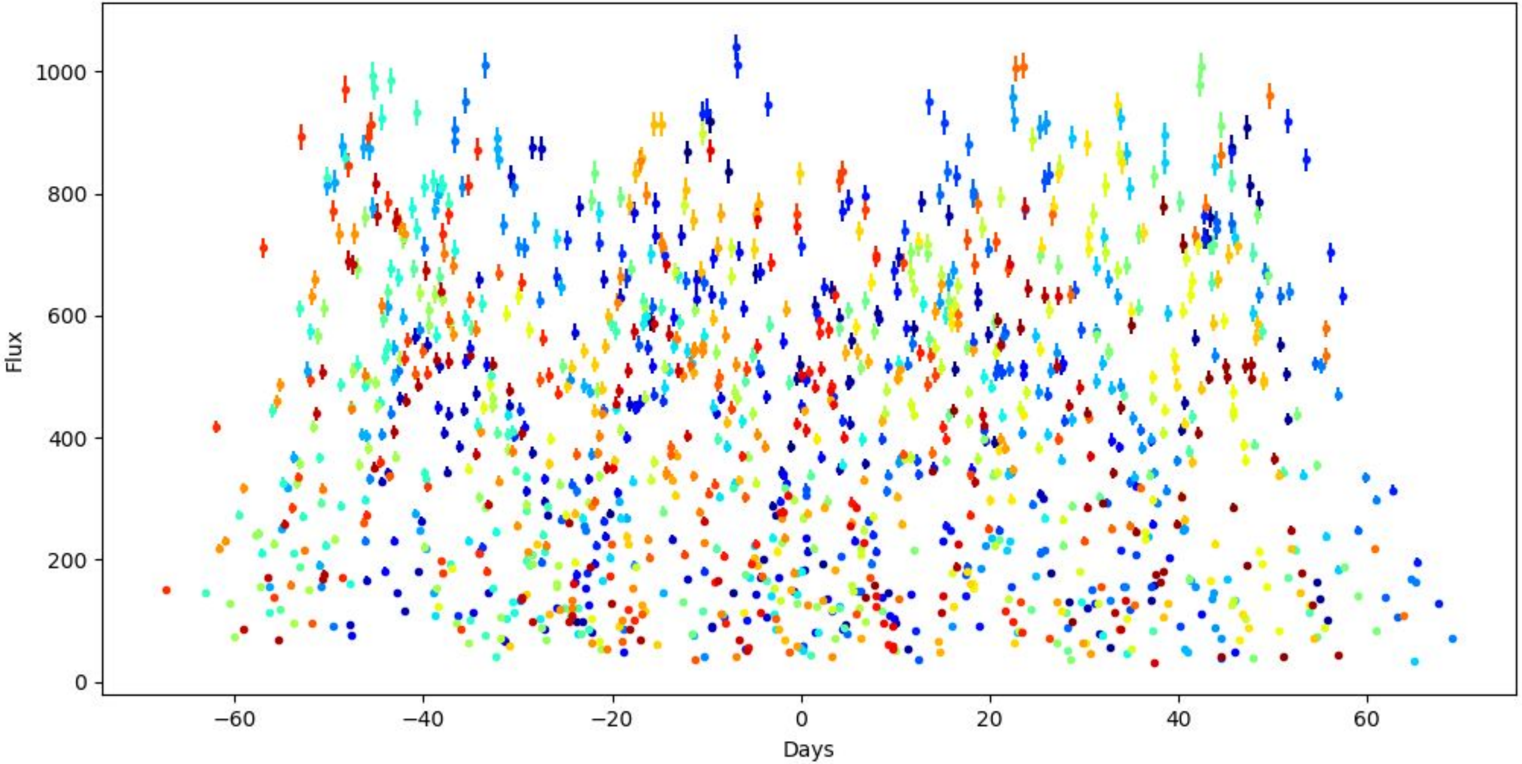
Use of a Newton Raphson algorithm :

$$L = \underbrace{R^T W R}_{\text{model fit}} + \underbrace{\mu \beta^T P \beta}_{\text{regularization}} + \underbrace{\lambda (H^T \beta - \alpha)}_{\text{linear constraints Lagrange parameter}} + \underbrace{\lambda' (H^T \beta' - \alpha')^2}_{\text{non linear constraints quadratic penalty}}$$

$$\mathrm{R} = \mathrm{data} - \mathrm{model}$$

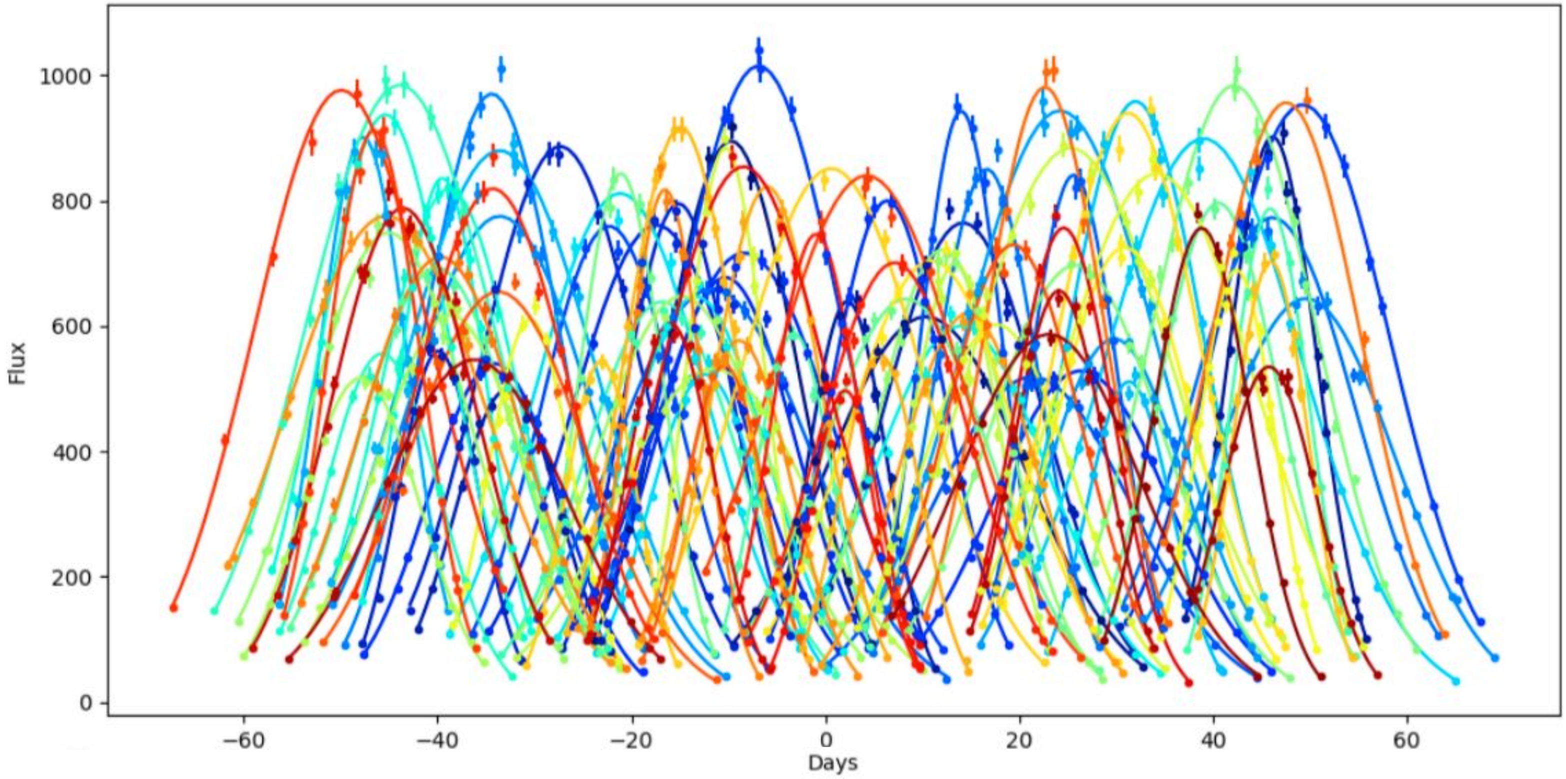
Models converge in few iterations (~5).

Simulation : gaussian reconstruction



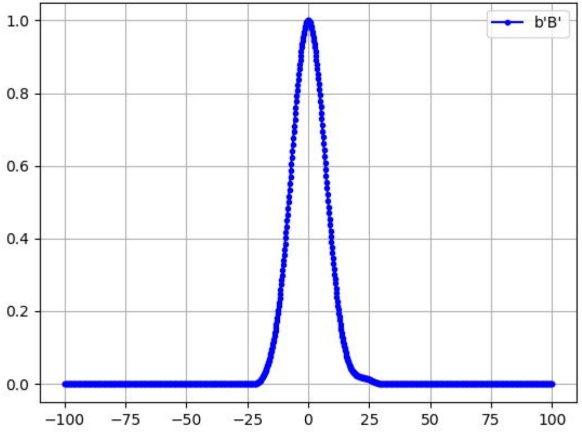
Simulation : gaussian reconstruction

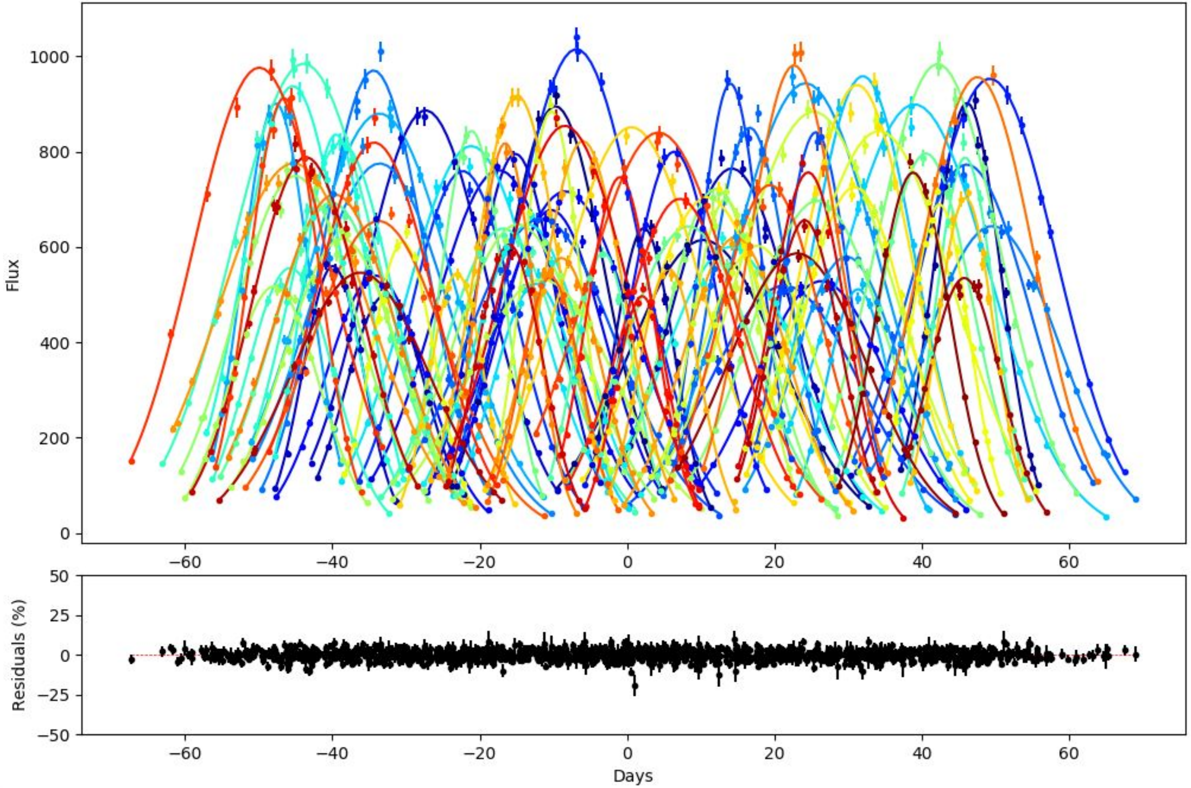
LPNHE
PARIS



Simulation : gaussian reconstruction

- Reconstruction :
  - model shape
  - tmax
  - amplitude
  - stretch





Program

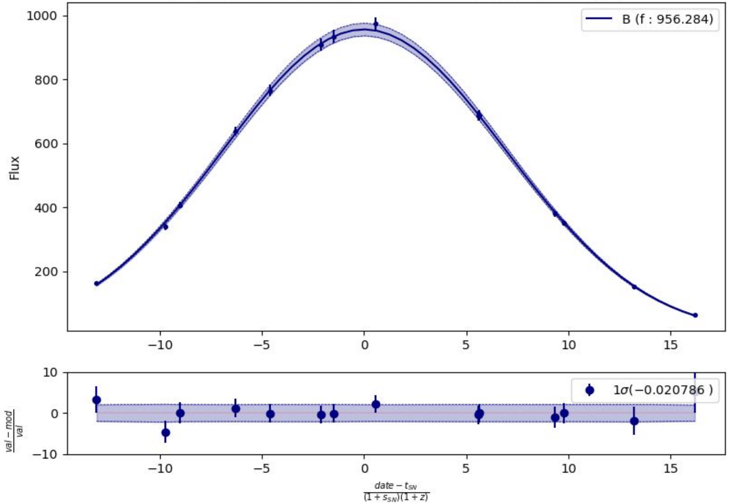
- Simplified flux model:
  - fit a toy model under constraints;
  - fit a error model;
- Study on data : CSP;
- 2D salt2-like model;
- Add new standardisation component.

Error model

Goal : Capture residual diversity

$$Variance(t, SN) = Err(t, SN)^2 + V(t, SN)$$
$$= Err(t, SN)^2 + (\gamma_{SN} * f(t, SN))^2$$

Adding a parameter by SN



Training time

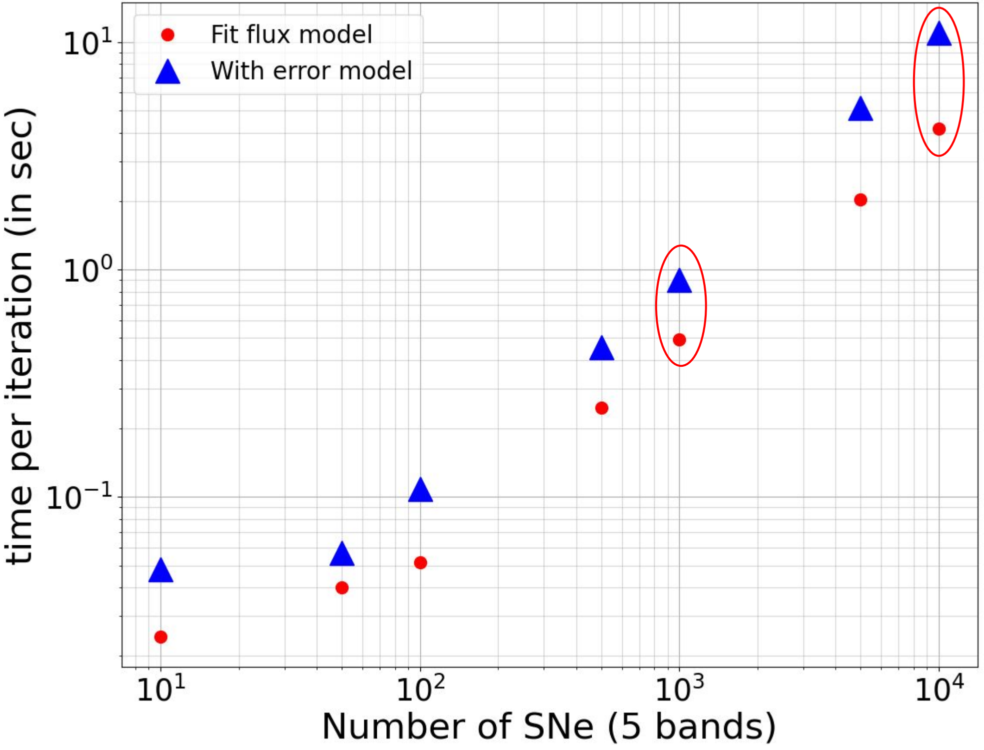
- Number of parameters :
  - 1 amplitude per SN and per band
  - 1 tmax per SN
  - 1 stretch per SN and per band
  - 50 parameter per band
  - 1 error parameter per SN and per band

For 1 000 SNe in 5 bands :

- 16 250 parameters

For 10 000 SNe in 5 bands :

- 160 250 parameters



Program

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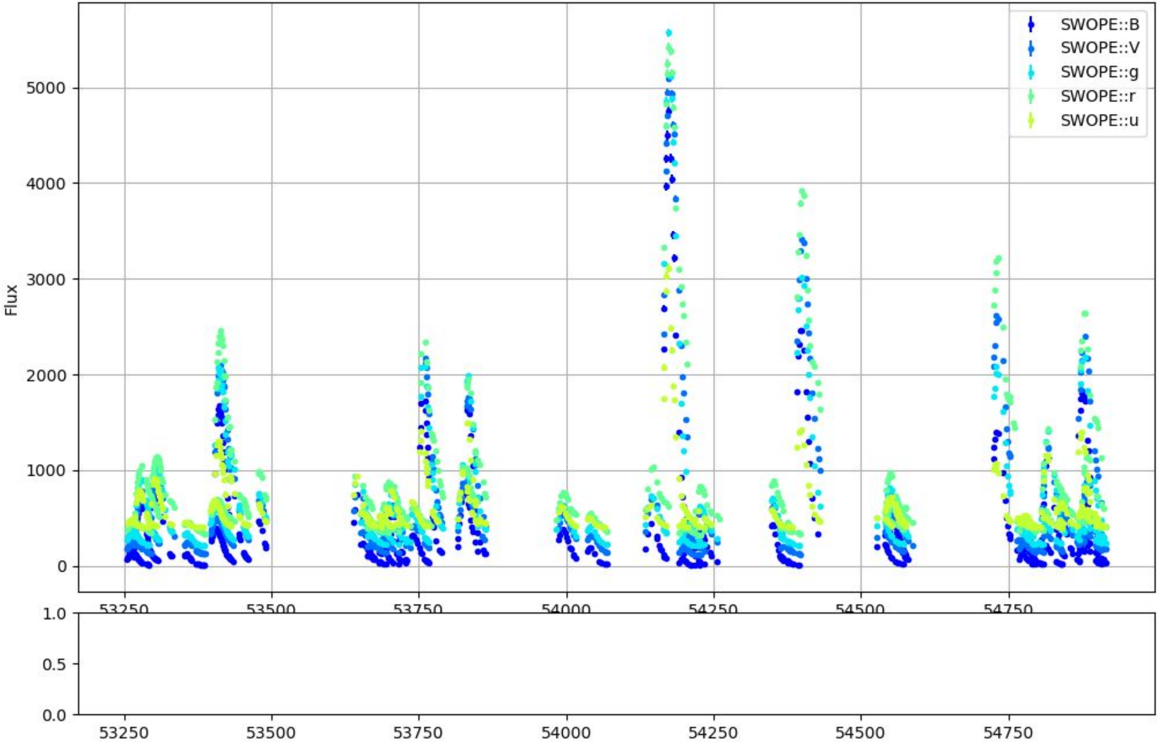
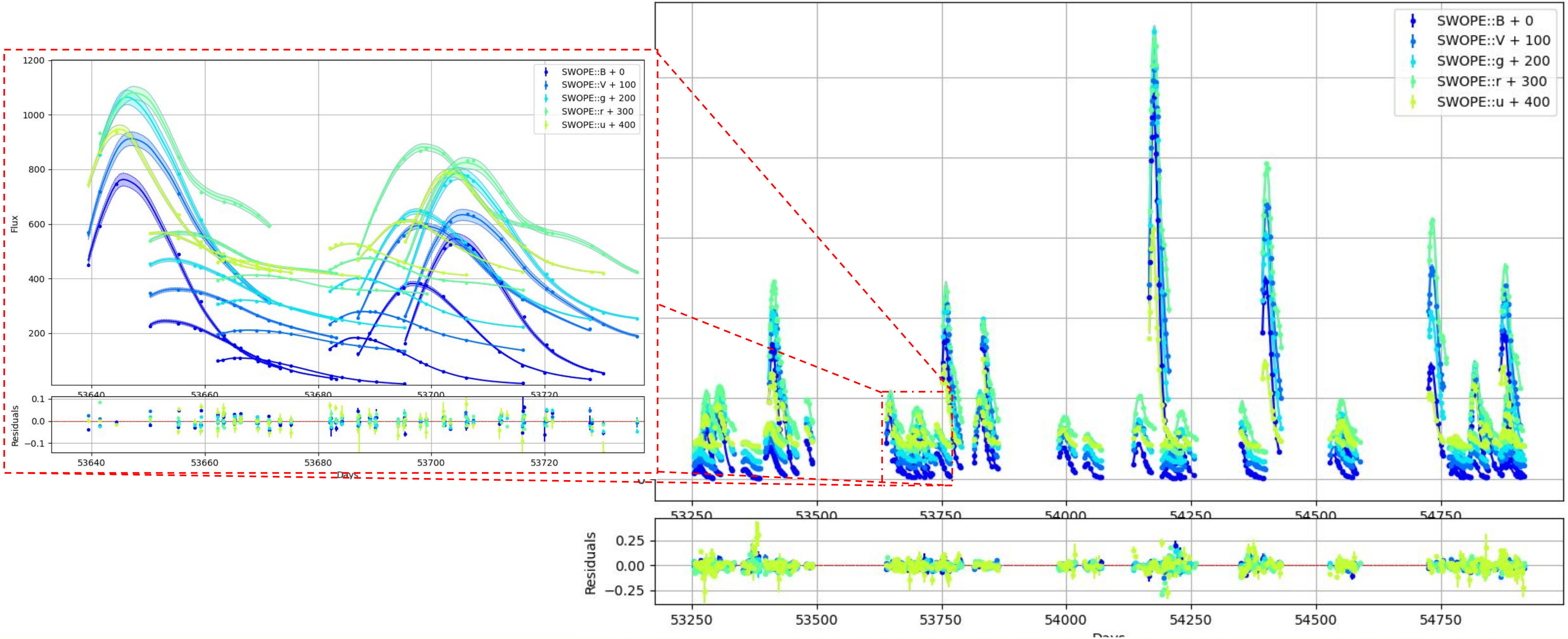
Carnegie Supernova Project

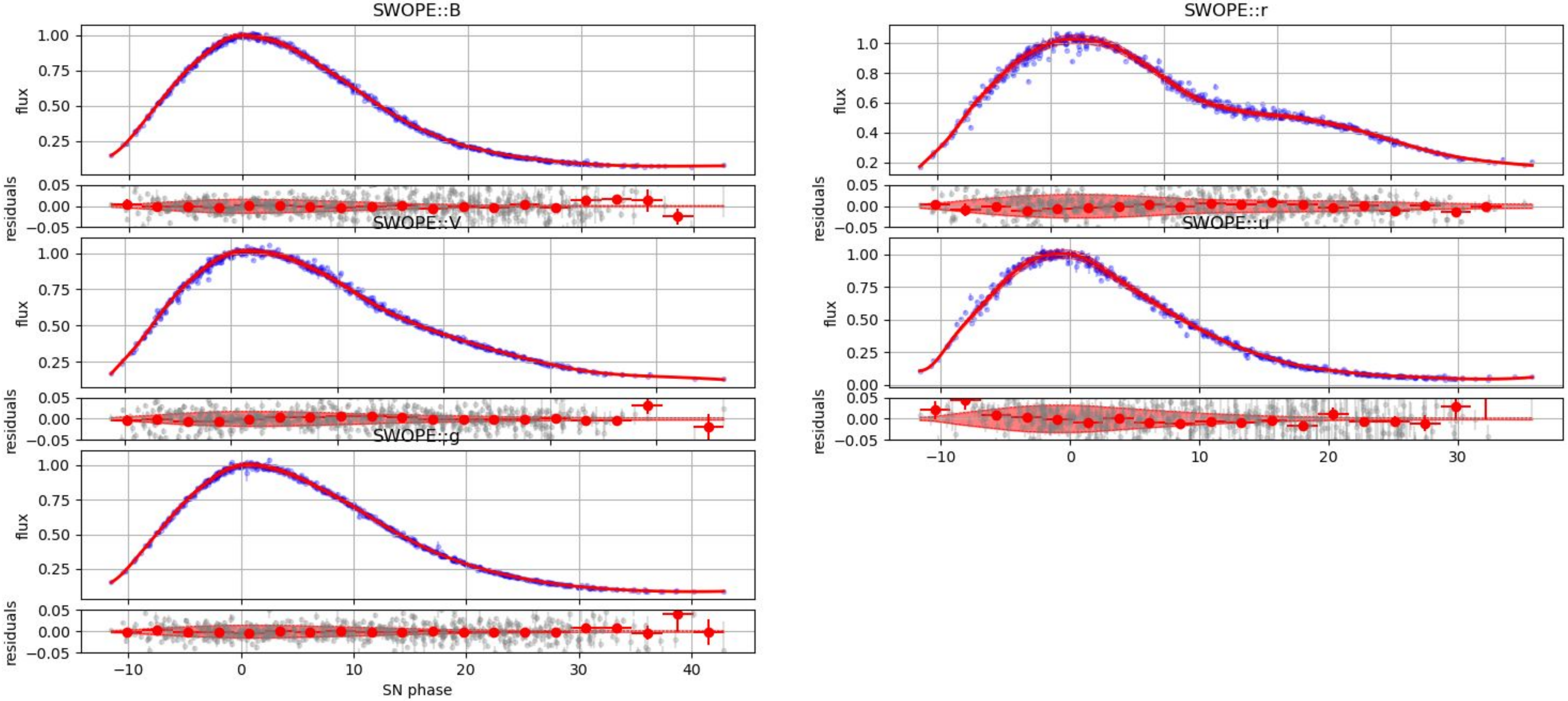
- Las Campanas Observatory in Atacama, Chile
- From 2004 to 2009
- high precision light curves in 10 bands
- optical spectrophotometry
- ~ 250 supernovae of $0<z<0.1$



Carnegie Supernova Project SNe



CSP band standardization



Program

- Simplified flux model:
  - fit a toy model under constraints;
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- Study on data : CSP;
- 2D salt2-like model;
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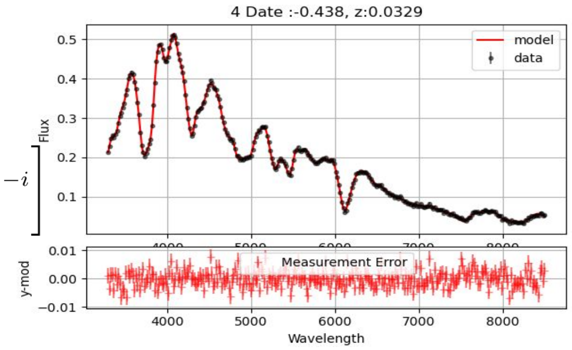
2D Hybrid Model

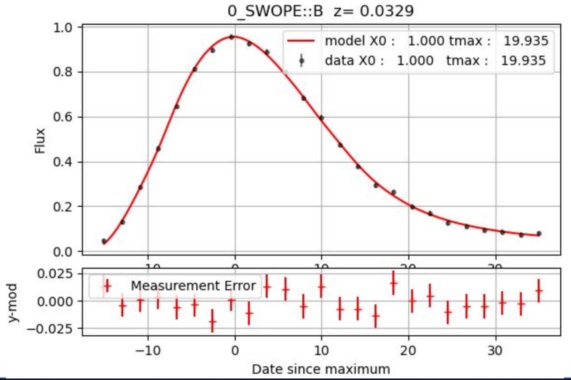
- Spectrum :

$$S_{obs}(\lambda, t) = \frac{1}{1+z} X_0 \left[M_0 \left(\frac{t - t_{max}}{1+z}, \frac{\lambda}{1+z} \right) + X_1 M_1 \left(\frac{t - t_{max}}{1+z}, \frac{\lambda}{1+z} \right) \right] e^{c\,CL(\frac{\lambda}{1+z})} \left[\sum_{i=0}^{N_s} s_i^{sp} \cdot \lambda^{N_s - i} \right]$$



- Light Curve:

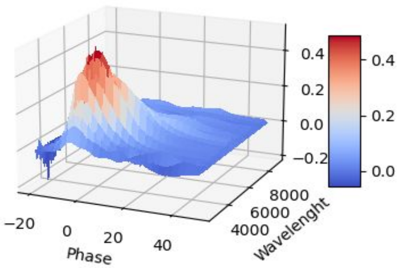
$$\phi_{band}(t) = \frac{1}{1+z} \int S(\lambda, t) T_{band}\left(\frac{\lambda}{1+z}\right) \frac{\lambda}{hc} d\lambda$$



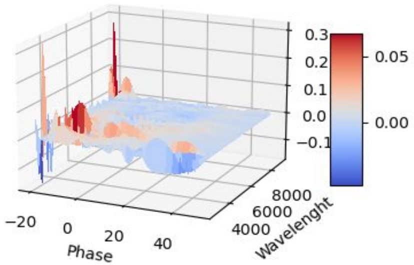
Model description

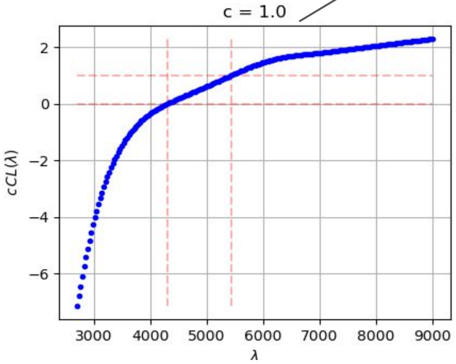
$$S_{obs}(\lambda, t) = \frac{1}{1+z} X_0 \left[M_0\left(\frac{t - t_{max}}{1+z}, \frac{\lambda}{1+z}\right) + X_1 M_1\left(\frac{t - t_{max}}{1+z}, \frac{\lambda}{1+z}\right)\right] e^{c\,CL\left(\frac{\lambda}{1+z}\right)} \left[\sum_{i=0}^{N_s} s_i^{sp} \cdot \lambda^{N_s - i}\right]$$

mean spectral surface



first variability surface





$$\int M_0(phase = 0, \lambda) T_B(\lambda) \frac{\lambda}{hc} d\lambda = 1$$

$$\int M_0'(phase = 0, \lambda) T_B(\lambda) \frac{\lambda}{hc} d\lambda = 0$$

$$\int M_1(phase = 0, \lambda) T_B(\lambda) \frac{\lambda}{hc} d\lambda = 0$$

$$\int M_1'(phase = 0, \lambda) T_B(\lambda) \frac{\lambda}{hc} d\lambda = 0$$

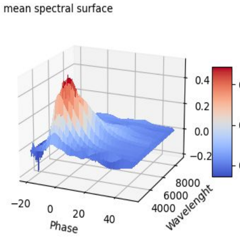
$$< X_1 >= 0$$

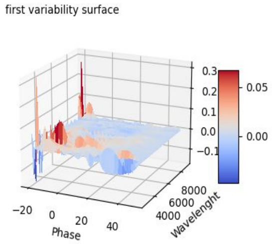
$$str(X_1) = 1$$

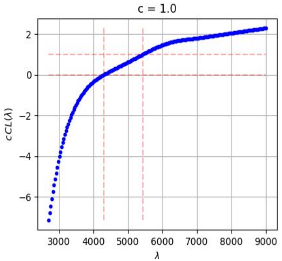
$$< c >= 0$$

2D Model : Simulation

- easier way to develop a model
- construct the framework to study bias







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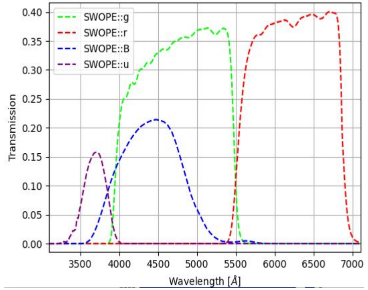

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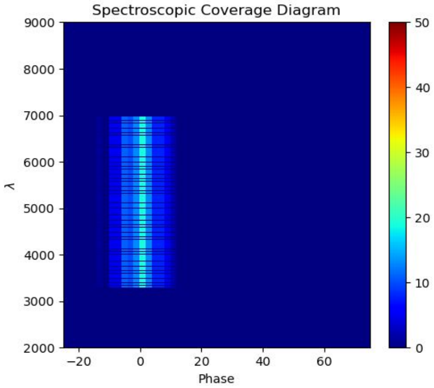
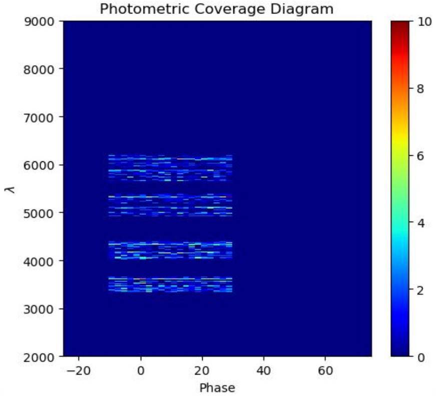
Cadence (2 spectra & 4 lc in u, B, g and r)

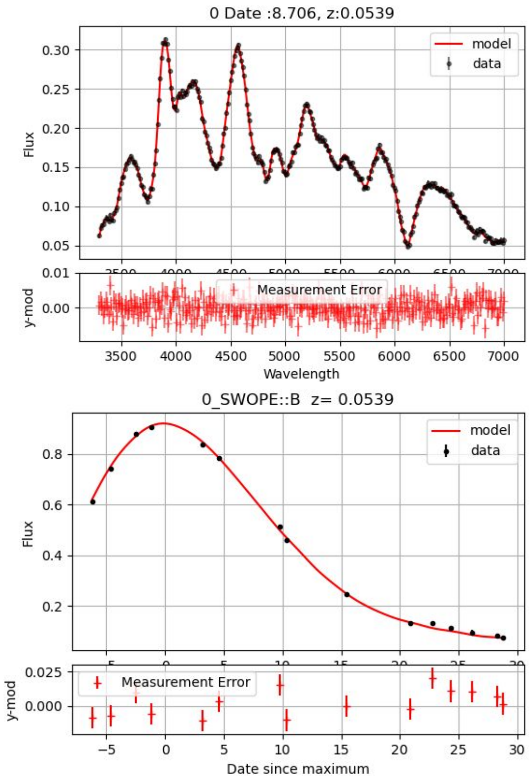
+

SN info (z, tmax, normalization, stretch, color)





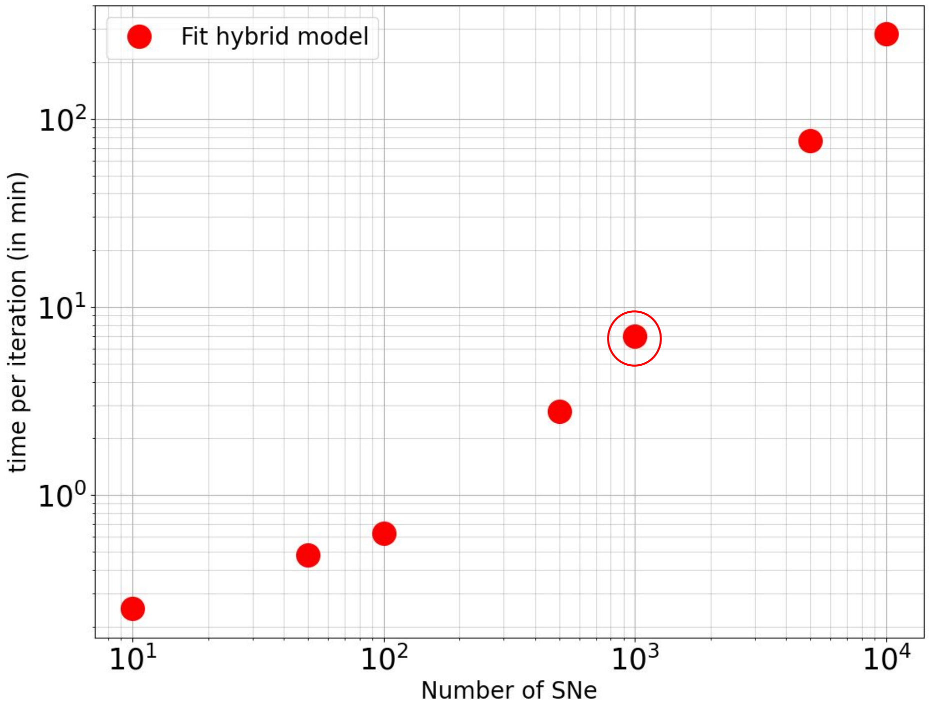
2D Model : Reconstruction



For 1 000 SNe :

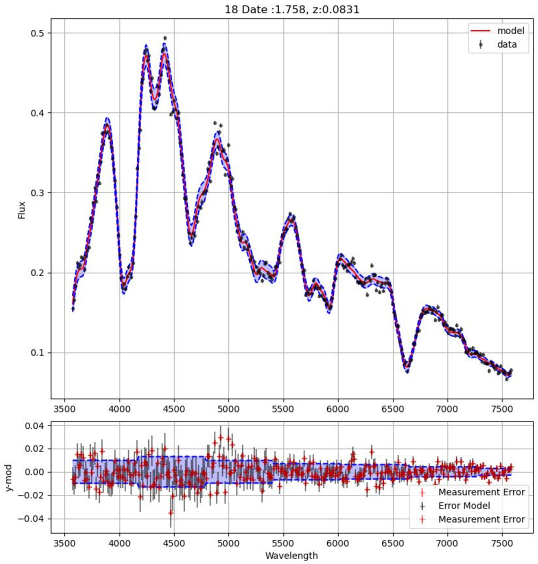
- 1 X0 per SN
- 1 X1 per SN
- 1 tmax per SN
- 1 c per SN
- 1 surface M0
- 1 surface M1
- 1 Color law
- 2 re-calibration parameter per spectra

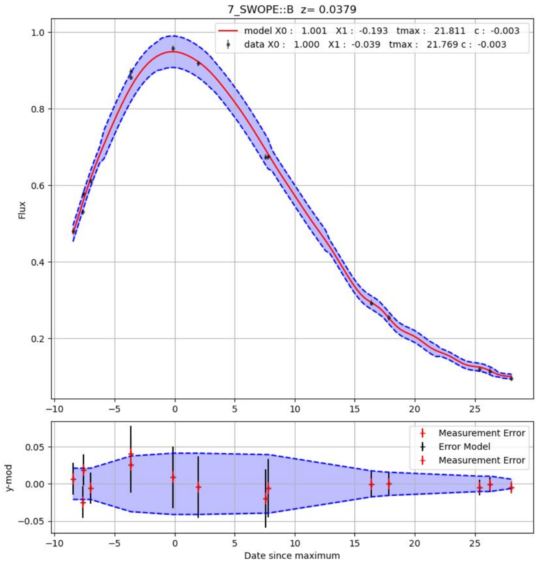
29 012 parameters



2D Model : Error Model

$$\sigma(p,\lambda)^2 = Err(p,\lambda)^2 + \sigma_X(p,\lambda)^2 \quad \begin{cases} \sigma_{sp}(p,\lambda) = \left[X_0 \exp(\mathrm{c\,CL}(\lambda)) * s(\lambda)\right]^2 {\sigma_{M_0}}^2(p,\lambda) \\ \sigma_{ph}(p,\lambda_c) = \left[X_0 \exp(\mathrm{c\,CL}(\lambda_c)) \int T\left(\frac{\lambda}{1+z}\right) \lambda d\lambda\right]^2 {\sigma_{M_0}}^2(p,\lambda_c) \end{cases}$$





Conclusion

- Training code with notable methodologic enhancement :
  - Fit tmax along with other parameters
  - One single minimization
  - Propagation of systematic uncertainties
- Fast full-fledged SALT2-like model :
  - Extensive training systematic study
  - Training & Cosmology on the full sample
- Flexible framework to explore :
  - new SN models
  - new standardization techniques

Thank you very much !