A new fast SALT2-like SNIa modeling framework

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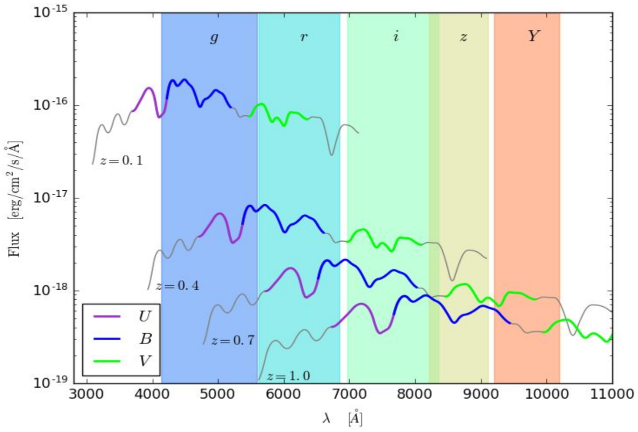
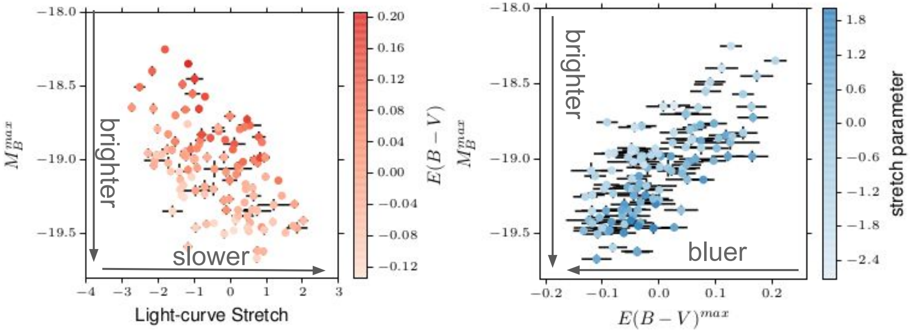
Spectrophotometric model

- To construct a Hubble Diagram, everything must be expressed in the same restframe band : band B (by convention) at peak : $\mathrm{m_B^{obs}}$

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

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





SALT 2 (Spectral Adaptive Light curve Template, Guy & al 2007)

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Parameters common to all SNe : 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 sampled SN Ia data with known redshift : called training sample

New generation of SALT2 model

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- **Strong points :**
  - low and high z;
  - empirical spectro-photometric modelization;

- **Limitations :**
  - new parameters needed;
  - stiff (minimizer and model are indivisible) ;
  - usable on O(1000) SNe ;
  - manual training ;
  - not maintained

➢ New SALT2 :
  - New tools (Sparse matrix, Python3 ...);
  - New techniques (One minimisation, updatable model, error model …);
  - Gather modern well measured SN Ia sample;

Table 9.

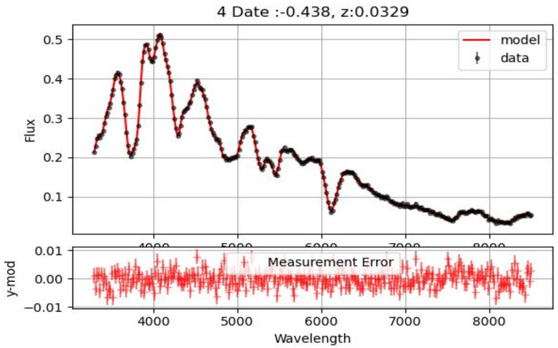
	w shift	σ_w^{syst}	Fraction of $\sigma_w^{(stat)}$
Stat. Uncertainty	+0.000	0.031	1.000
Total Sys Uncertainty	+0.031	0.025	0.814
Calibration			
SALT2 Cal	-0.002	0.014	0.457
Survey Cal	+0.006	0.009	0.285
HST Cal	-0.006	0.006	0.177
Supercal	+0.002	0.003	0.098
SN Modeling			
Selection	+0.010	0.007	0.233
Intrinsic Scatter	+0.019	0.005	0.170
β Evol.	-0.001	0.007	0.238
γ Evol.	-0.002	0.000	0.000
m_{step}Shift	-0.002	0.002	0.064
External			
MW Extinction	+0.010	0.008	0.262
Pec. Vel.	+0.000	0.003	0.103

Notes: The dominant systematic uncertainties in the Pantheon SN sample with respect to w while solving for a wCDM model. The w shift is defined relative to the statistical value and σ_w^{syst} is defined to be $\sqrt{\sigma_w^2 - \sigma_{w-stat}^2}$ when a specific systematic uncertainty is applied.

2D Hybrid Model

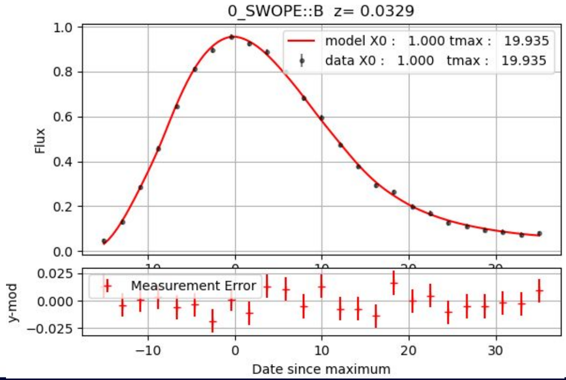
- Spectrum :

$$S_{obs}(\lambda,t) = \frac{1}{1+z} X_0 \left[M_0\left(\frac{t-t_{max}}{1+z}, \frac{\lambda}{1+z}\right) + X_1 M_1\left(\frac{t-t_{max}}{1+z}, \frac{\lambda}{1+z}\right)\right] e^{cCL(\frac{\lambda}{1+z})}$$



- Light Curve:

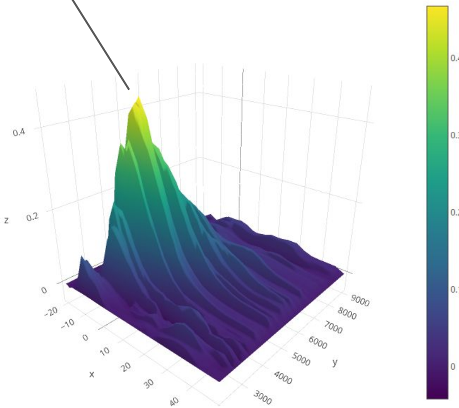
$$\phi_{band}(t) = \frac{1}{1+z}\int S(\lambda,t) T_{band}(\frac{\lambda}{1+z}) \frac{\lambda}{hc} d\lambda$$

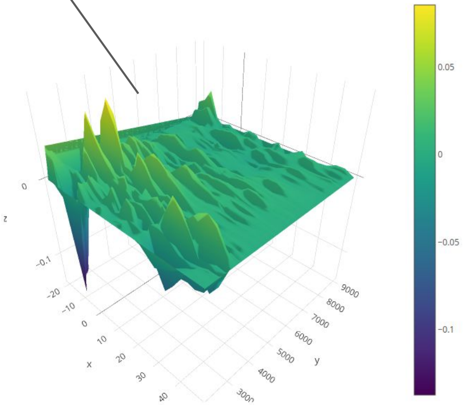


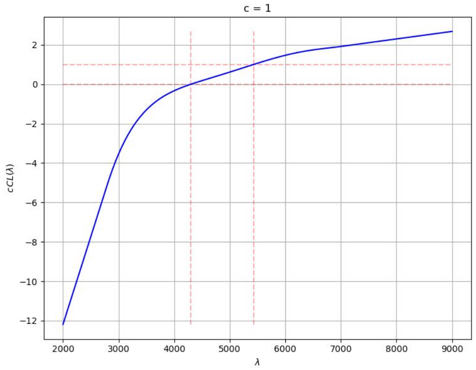
Training needs

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

- re-calibration of spectra to fix the amplitude on the photometry







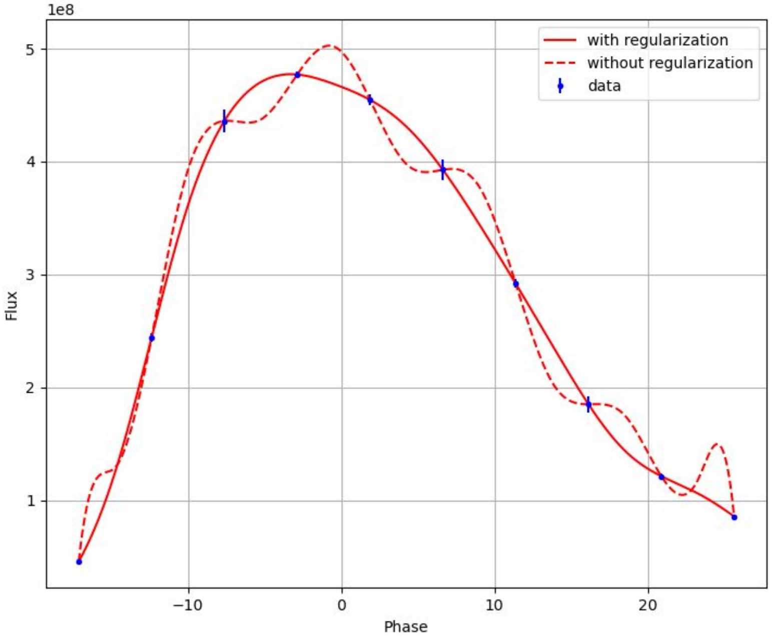
$$\chi^2(\beta) = (Y - \mathrm{Model}(\beta))^T V^{-1} (Y - \mathrm{Model}(\beta))$$

Training needs

- re-calibration of spectra to fix the amplitude on the photometry

- add regularisation to smooth the splines and constrain the model where there is no data

- Break degeneracies with constraints :



$$\chi^2(\beta) = (Y - \mathrm{Model}(\beta))^T V^{-1} (Y - \mathrm{Model}(\beta)) + \mu_{reg} \beta^T P \beta$$

Training needs

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

- re-calibration of spectra to fix the amplitude on the photometry
- add regularisation to smooth the splines and constrain the model where there is no data
- Break degeneracies with constraints :

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

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

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

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

$$< X_1 >= 0$$

$$< X_1^2 > - < X_1 >^2 = 1$$

$$< c >= 0$$

$$\chi^2(\beta) = (Y - \mathrm{Model}(\beta))^T V^{-1} (Y - \mathrm{Model}(\beta)) + \mu_{reg} \beta^T P \beta + \left[H_{lin}^T \beta - \alpha_{lin} \right] + \mu_{pen} \left[H_{pen}^T \beta - \alpha_{pen} \right]^T \left[H_{pen}^T \beta - \alpha_{pen} \right]$$

Last spring status

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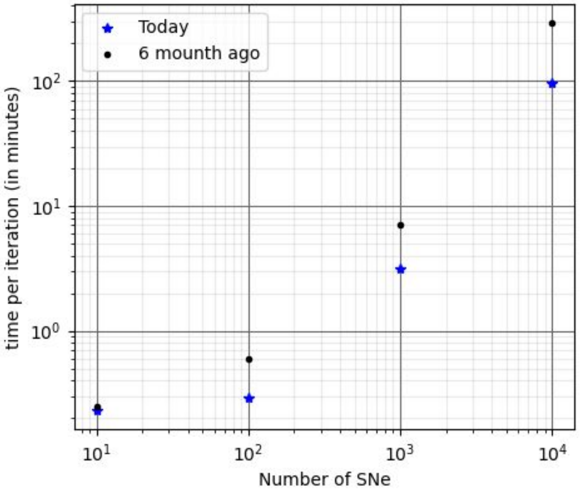
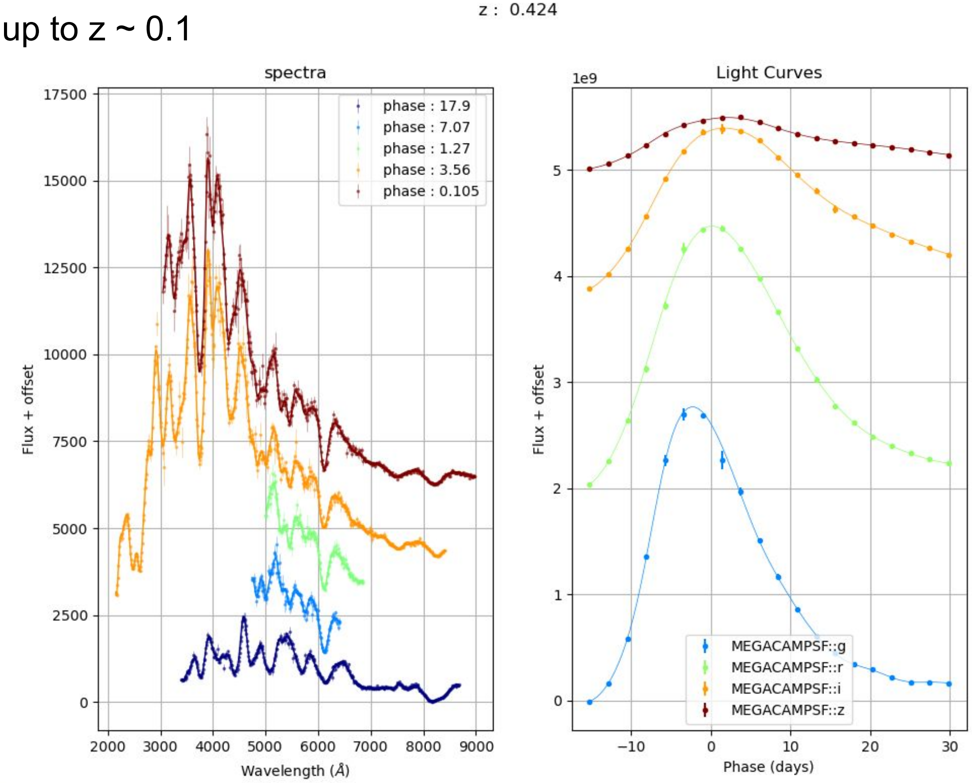
Spectrophotometric model on well sampled simulation up to z ~ 0.1

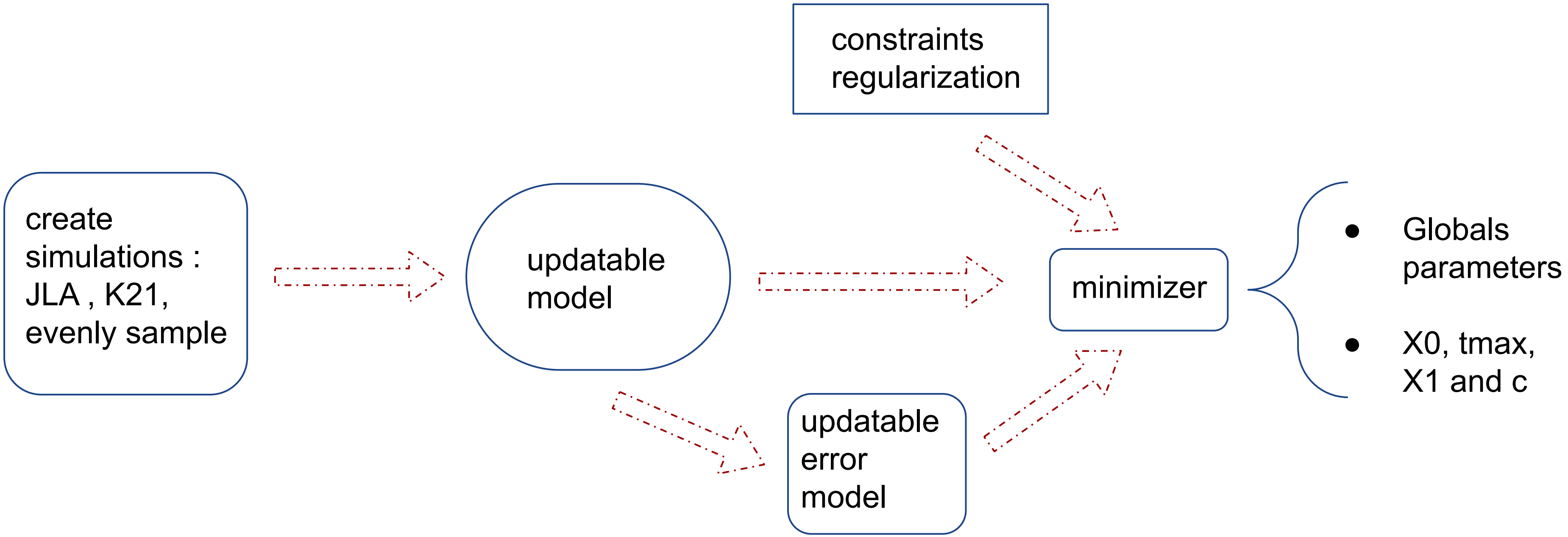
Fast training sample :

- 7 minutes for 1000 SNe (now 3 minutes)





Developed framework



2D Model : Simulations

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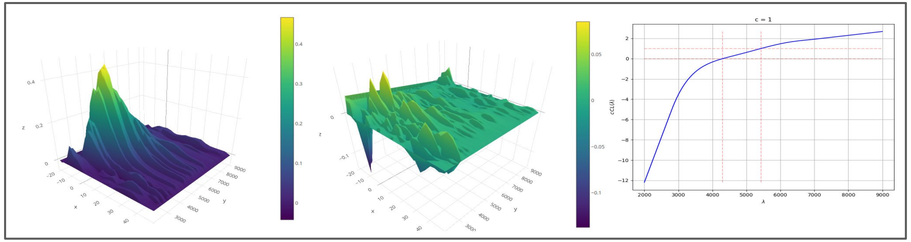
SALT2.4



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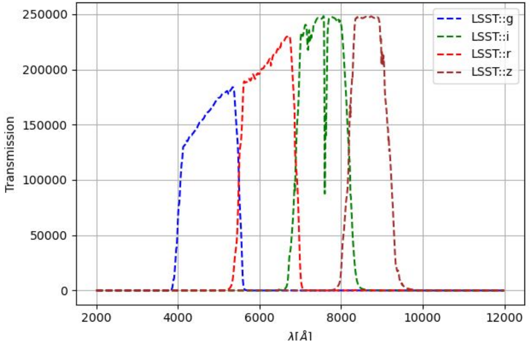

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Cadence (5 spectra & 4 lc in u, B, g and r)

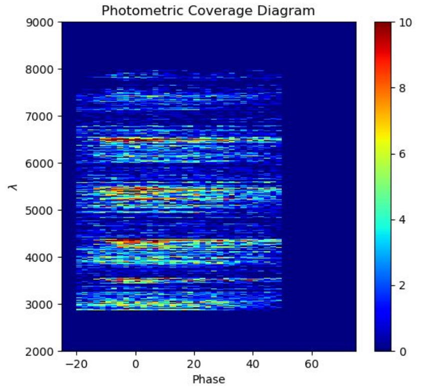
+

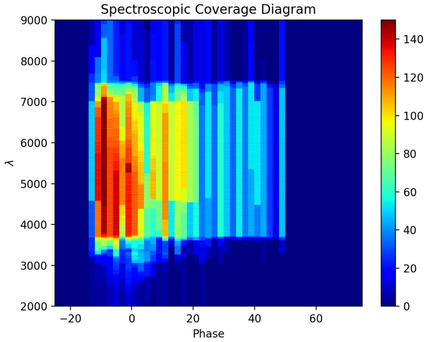
SN info (z, tmax, normalization, stretch, color)

Perfectly sampled simulation

or

Training sample : JLA or K21

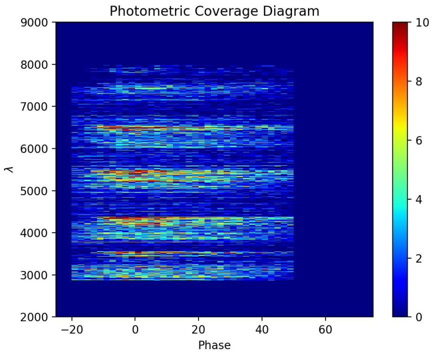


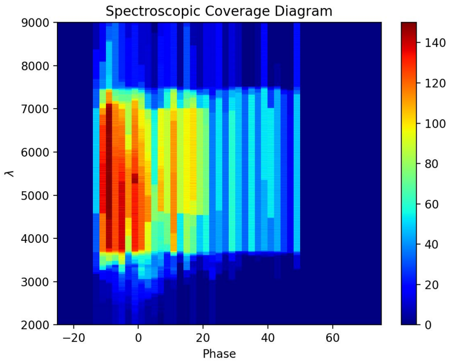


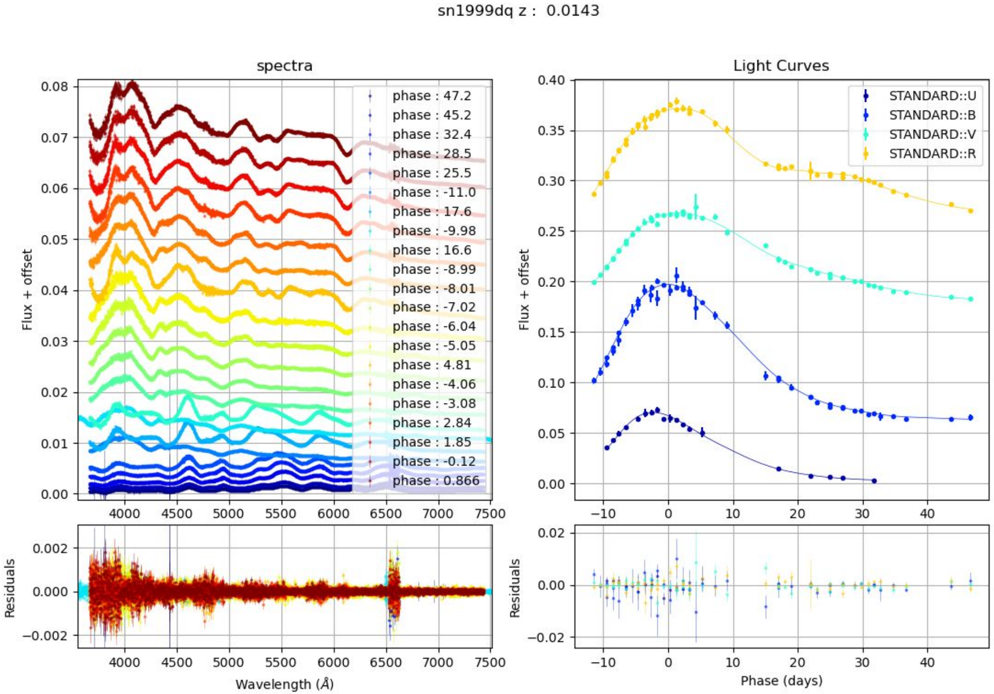
Joint Light curve Analysis (JLA : Betoule & al 2014)

Salt2 last training for JLA :

- training sample : lowz surveys, SDSS & SNLS :
- simulate : 426 SNe, 424 spectra and 1808 light curves;
- One iteration takes 1.35 minutes.







SALT3 (K21 : Kenworthy & al 2021)

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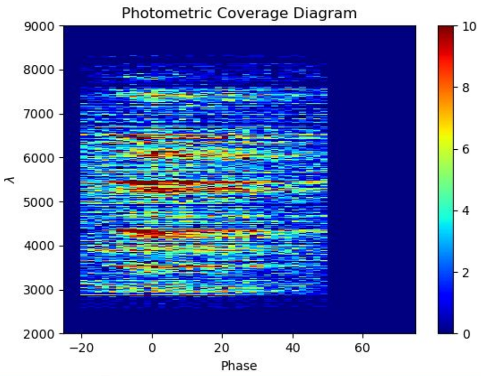
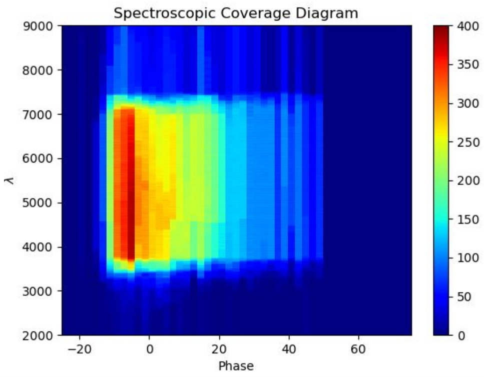
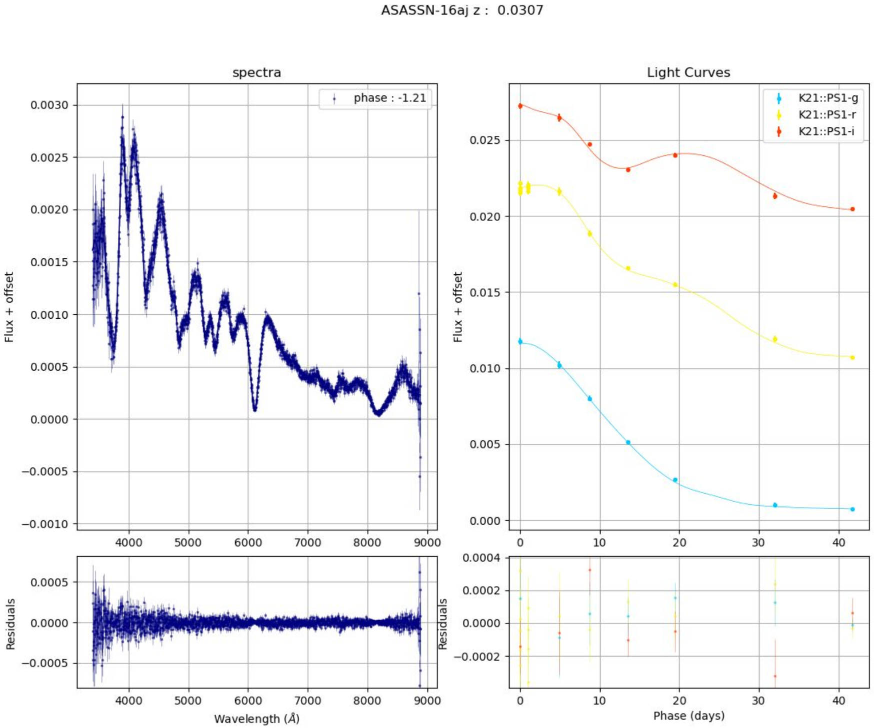
Salt3 training called K21 :

- training sample : JLA, Foundation Supernova Survey, Pan-STARRS Medium Deep Survey & DES
- simulate : 980 SNe, 1126 spectra and 4049 light curves;
- One iteration takes 3.43 minutes.







Error Model

Goal : model the residual variability in an error model

$$\sigma(p,\lambda)^2 = Err(p,\lambda)^2 + \sigma_X(p,\lambda)^2 \quad \begin{cases} \sigma_{sp} = g(p,\lambda) * S(p,\lambda) \\ \sigma_{ph} = g(p,\lambda) * \phi(p,\lambda) \end{cases}$$

$$\chi^2 = \ln|V_{\beta,g}| + R(\beta)^T V_{\beta,g}^{-1} R(\beta) + \mu_{reg}\beta^T P\beta + \left[H_{lin}^T\beta - \alpha_{lin}\right] + \mu_{pen}\left[H_{pen}^T\beta - \alpha_{pen}\right]^T \left[H_{pen}^T\beta - \alpha_{pen}\right]$$

Fit with error model

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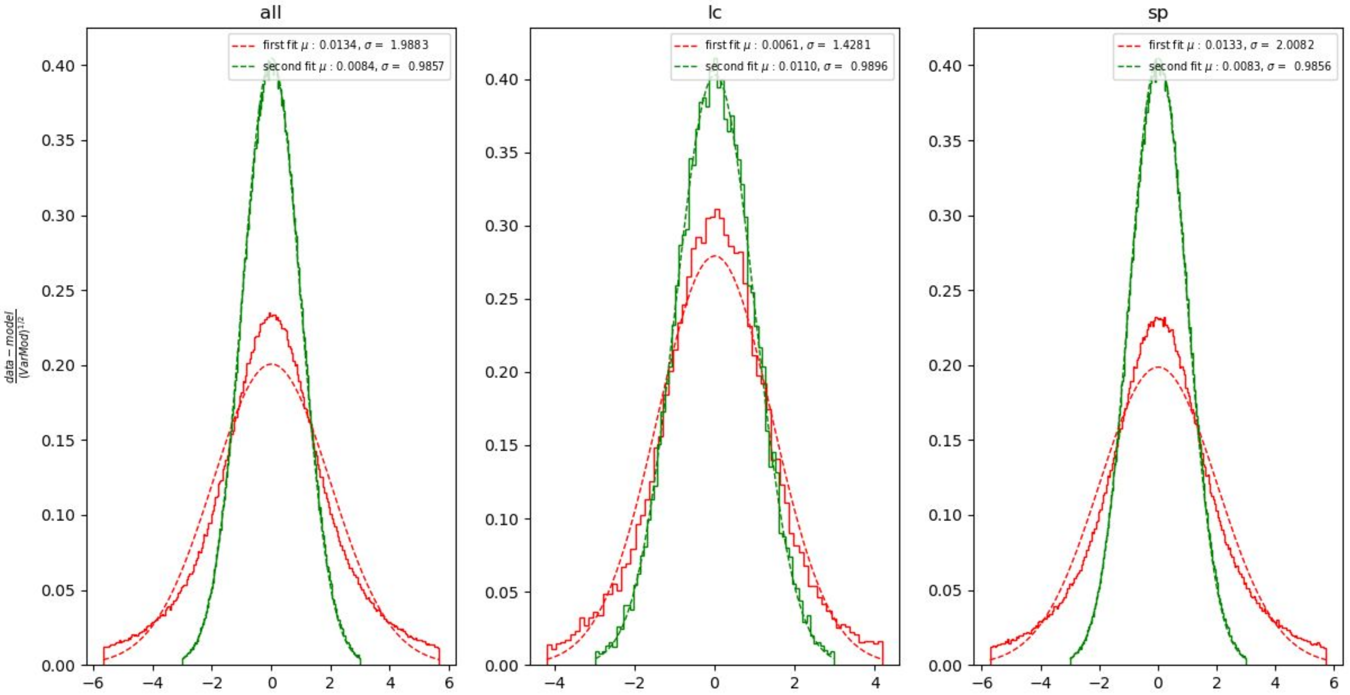
Fit procedure :

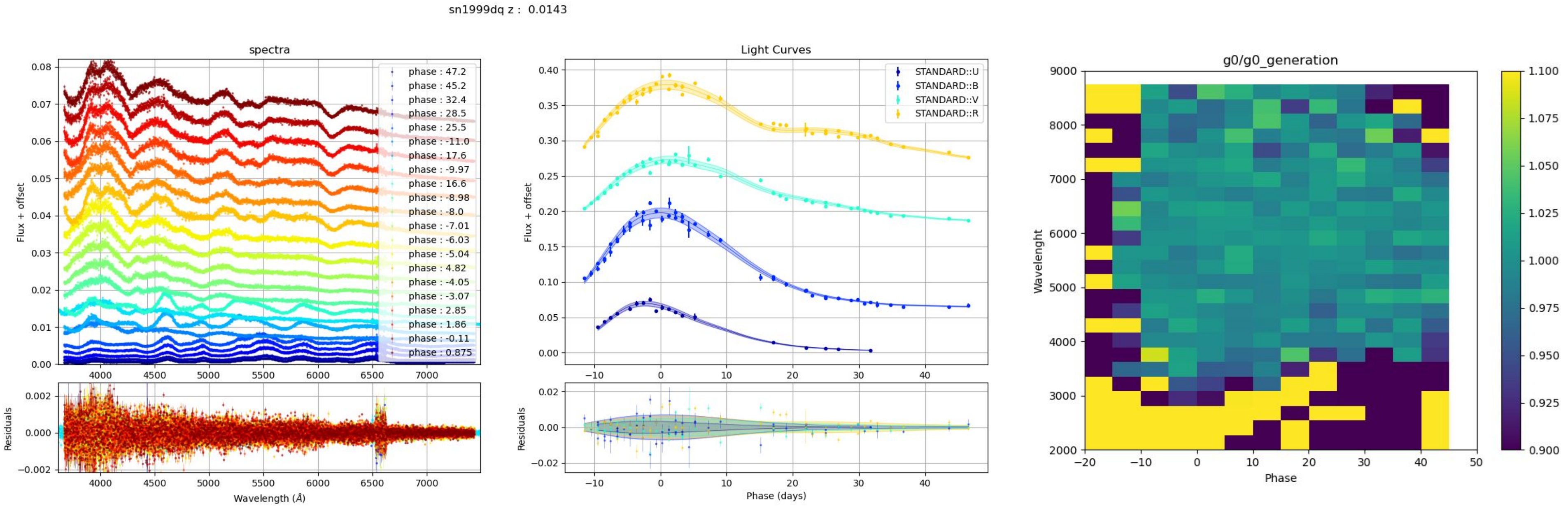
- model fit
- error model fit
- fit both together

➢ for JLA (426 SNe) in 13.9 minutes

➢ for K21 (980 SNe) in 34.4 minutes



Error model reconstruction



Conclusion & roadmap

We have constructed a fast full-fledged SALT2-like model with notable methodology enhancements :

- Fit tmax along with other parameters ;
- One single minimization ;
- Can model the SN intrinsic residuals variability in the same fit ;
- Propagation of systematic uncertainties

Ongoing:

➔ Add photometric calibration uncertainty propagation
➔ Add color scatter
➔ Extensive bias study on simulations, with the publication of our model

➔ Release of training & Cosmology on the full sample : K21 enriched with the Supernova Factory & HSC SNe.