PETS: Pure Expansion Template for SNIa

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Type Ia Supernova in Cosmology

- Provided the first evidence of an accelerated expansion of the universe (Perlmutter et. al 1997, Riess et al. 1998);
- Key probe to cosmology;
- Not perfect standard candles -> need to undergo a **standardization** procedure;
- With next generations surveys (like Vera Rubin LSST) we will gain statistical power when constraining cosmology;
- In this project we try to access the systematics associated with the standardization procedure.

State-of-the-art Light Curve Fitters

- SALT2 (Spectral Adaptive Light Curve Template 2) (Guy et al. 2005, Guy et al. 2007, Betoule et al. 2014)

$$\phi_{SALT2}(p,\lambda;\mathbf{x}) := x_{0,SALT2}[M_{0,SALT2}(p,\lambda) + x_{1,SALT2}M_{1,SALT2}(p,\lambda) + \ldots]\exp(-cCL(\lambda)),$$

Average training set SED

Describes the main variability around the average SED (stretch-like feature)

Describes color index variations. Usually without mention to its source

According to Guy et al. 2007, the term in brackets can be understood as a **Principal Component Analysis (PCA)** of a representative training set.

At the time the model was proposed there was not a enough dense high quality data available to perform PCA.

State-of-the-art Light Curve Fitters

- SNEMO2 (SuperNova Empirical MOdels) (Saunders et al. 2018):

  Employs **Gaussian Process Regressions** (GPRs) to reconstruct SNIa SEDs (Spectral Energy Distribution) and posteriorly, applies **Factor Analysis**;

  Replaces SALT2 PCA decomposition with FA and replaces the color law by an extinction curve;

  Trained on SNFactory DR9 spectra:

  2474 spectra from **171** spectroscopically confirmed SNeIa with redshift ranging from **0.01** to **0.08**.

  Explores adding more components to the decomposition (SNEMO7, SNEMO15)

PETS rest-frame flux proposal

- We drop the exponential term and add a component with time and wavelength dependencies:

$$\phi_{PETS}(p, \lambda; \mathbf{x}) := x_0[M_0(p, \lambda) + x_1 M_1(p, \lambda) + x_2 M_2(p, \lambda) + ...].$$

Average training set SED

1st principal component/ common factor

2nd principal component/ common factor

Training set: **SNFactory DR9 spectra;**

We perform **PCA** and **FA** decompositions;

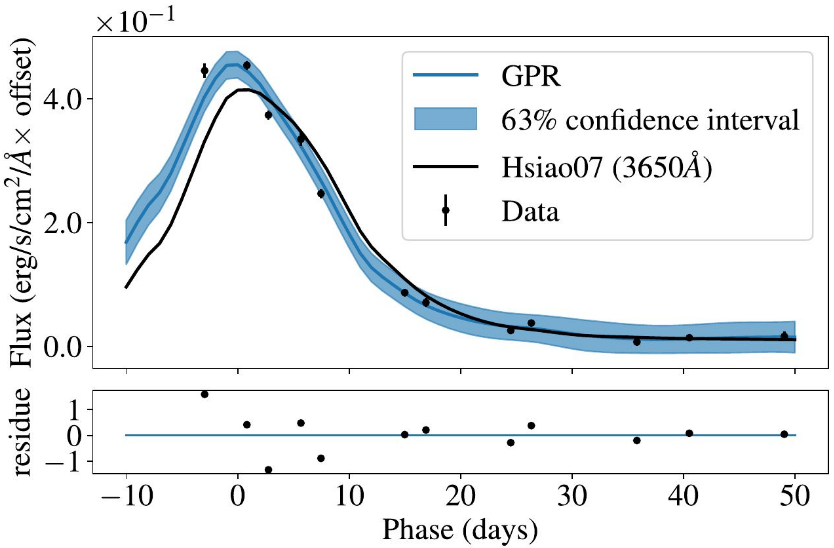
Simple 3-component linear model that does not require the assumption intrinsic color variations and dust extinction affects the flux in the same way;

Gaussian Process Regressions

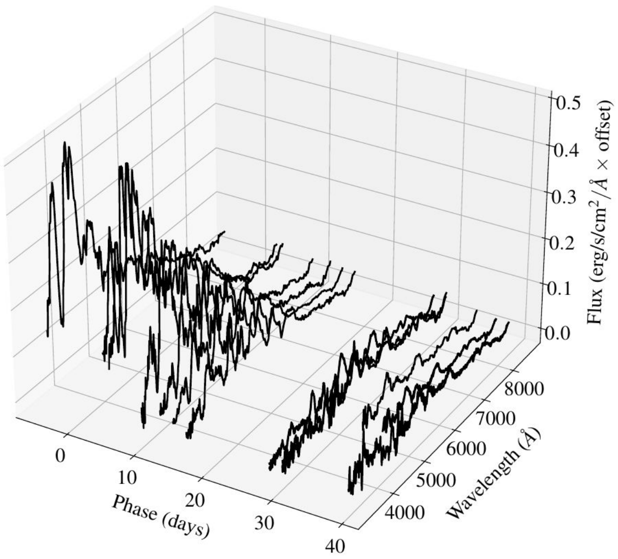
Defining a mean curve and a kernel, we can interpolate and extrapolate the original data, reconstructing monochromatic light curves.

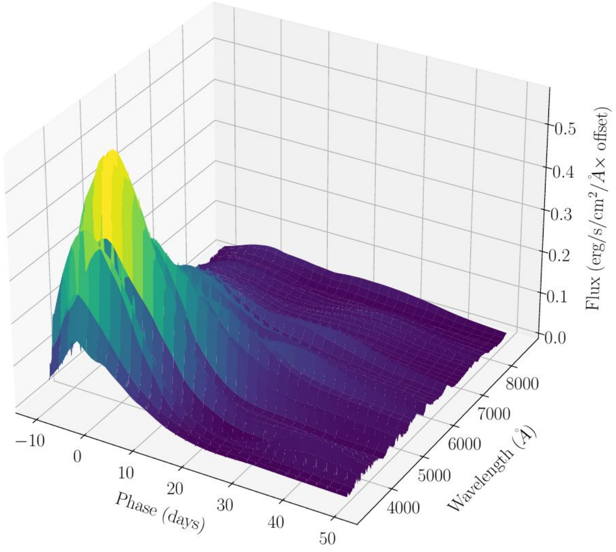
$$\begin{bmatrix} \mathbf{y} \\ \mathbf{f}_* \end{bmatrix} \sim \mathcal{N}\left(\mathbf{m}(P), \begin{bmatrix} K(P,P) + \sigma_n^2 & K(P,P_*) \\ K(P_*,P) & K(P_*,P_*) \end{bmatrix}\right),$$

$$k(p_i,p_j) = \frac{\sigma_m^2}{\Gamma(\nu)2^{\nu-1}}\left[\frac{\sqrt{2\nu}(p_i-p_j)^2}{\Delta l}\right]^{\nu} K_\nu\left[\frac{\sqrt{2\nu}}{\Delta l}(p_i-p_j)^2\right],$$



Gaussian Process Regressions





We go from a SED with several gaps to a SED evaluated in a evenly-spaced 2-d grid.

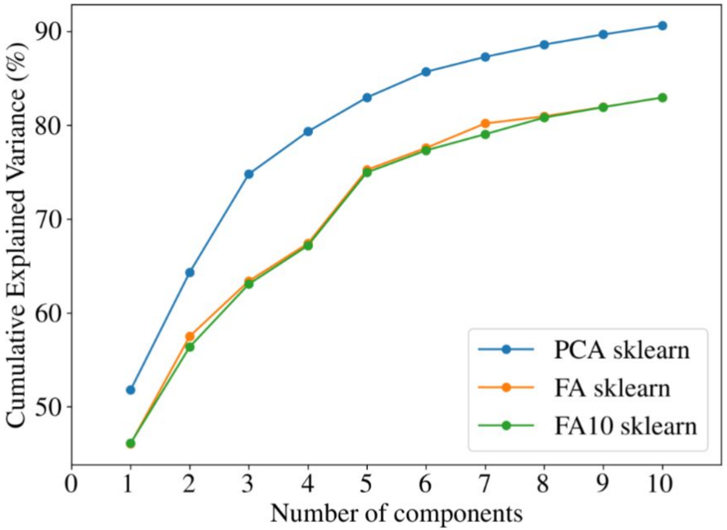
Principal Component Analysis

Underlying assumption: SNe Ia SEDs similarities allows us to describe a general SED as a linear combination of a representative set (starting with 150 SEDs/dimensions);

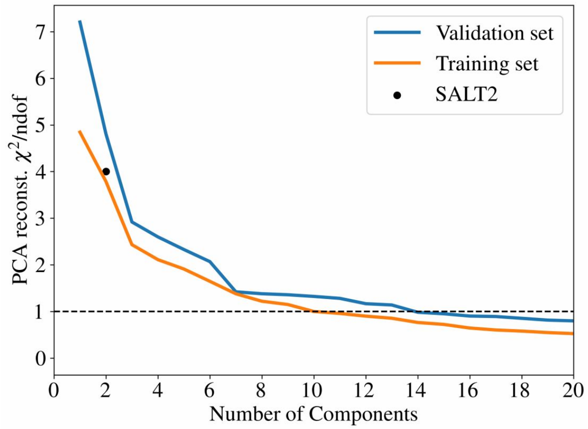
PCA find successively the directions that maximize variance in the original space (PCs);

PCs are a linear combination of the original basis;

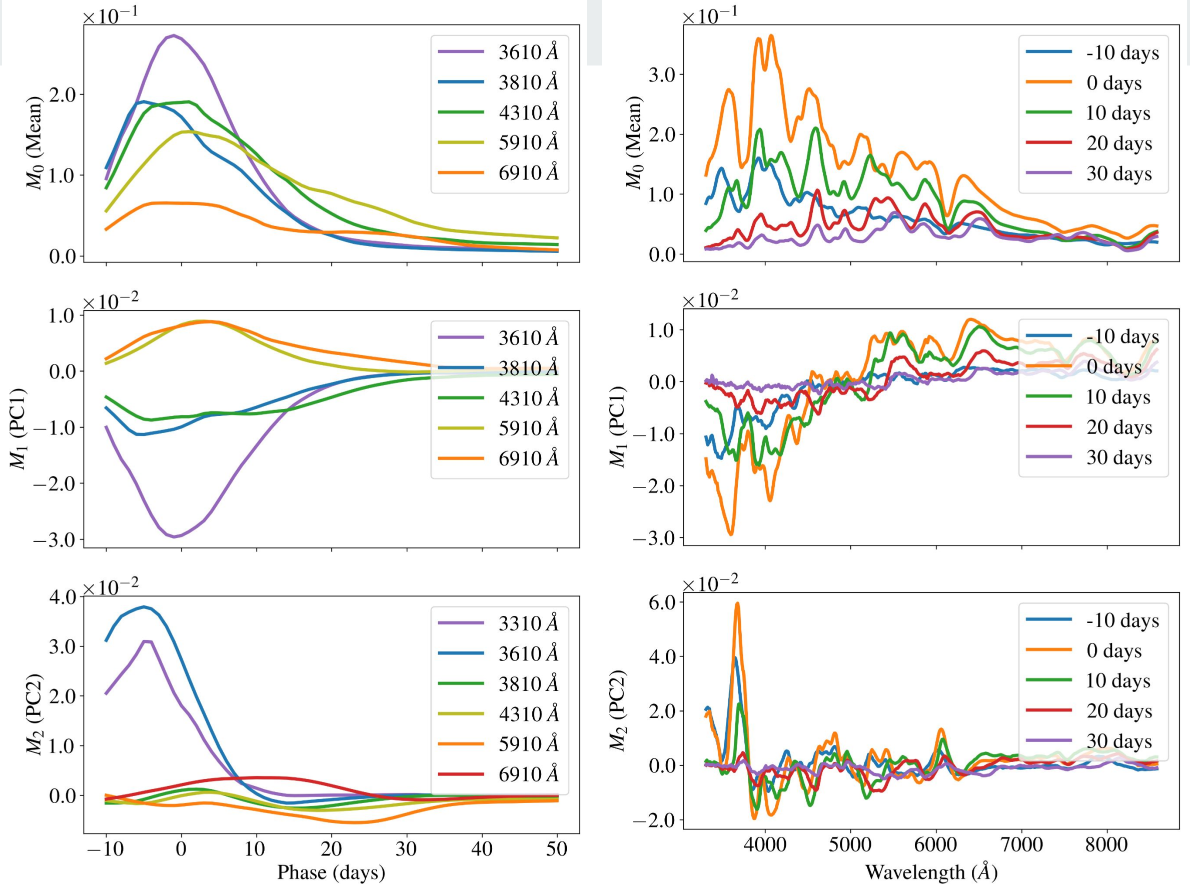
For correlated data, a **reduced** set of new basis components must explain well the original space variability -> **New lower dimension basis -> M_1, M_2 ...**



PCA components

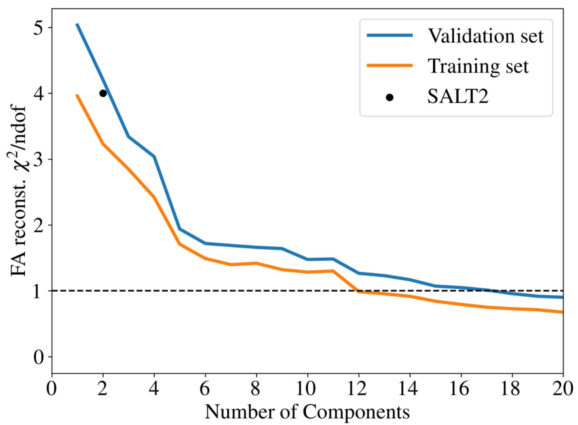


Model reconstruction performance when keeping different number of components of the new ordered basis.



PCs obtained for our set of 150 training SNIa SEDs.

Factor Analysis



FA has an explicit model and assumes the existence of **hidden variables**.

$$\mathbf{x} = \mathbf{\Lambda f} + \mathbf{e} \qquad \mathbf{e} \sim \mathcal{N}(0, \mathbf{\Psi})$$

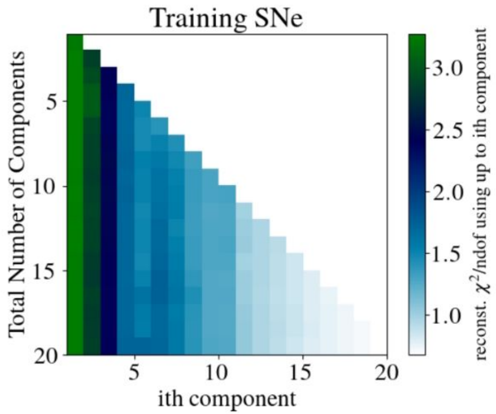
The observations are linear combinations of the **common factors** plus a **specific factor**;

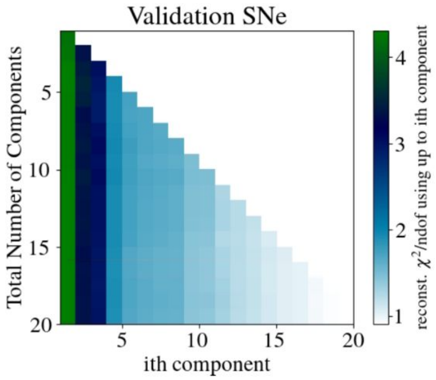
The **common factors** will be our model components **M_1, M_2** ....

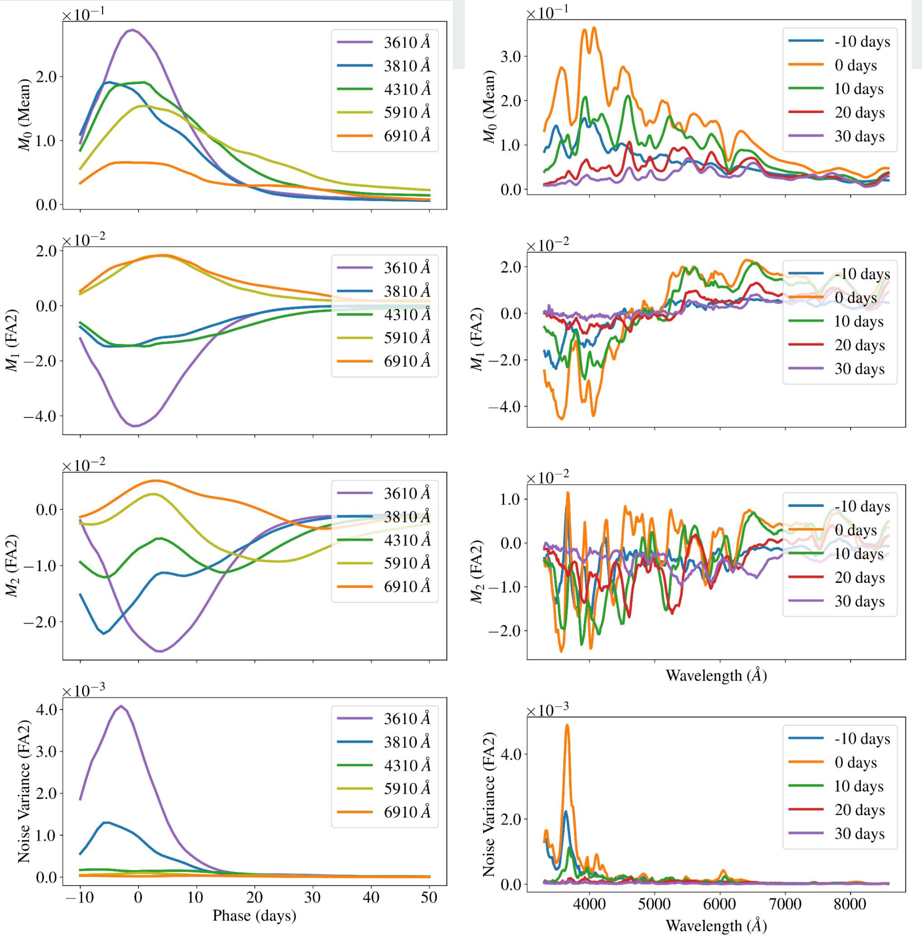
This generative model solves for the **common factors** and **noise variance** in a iterative process;

The common factors for FA considering X number of hidden variables is not a subset of the common factors of a FA considering X+Y numbers of hidden variables.

FA components

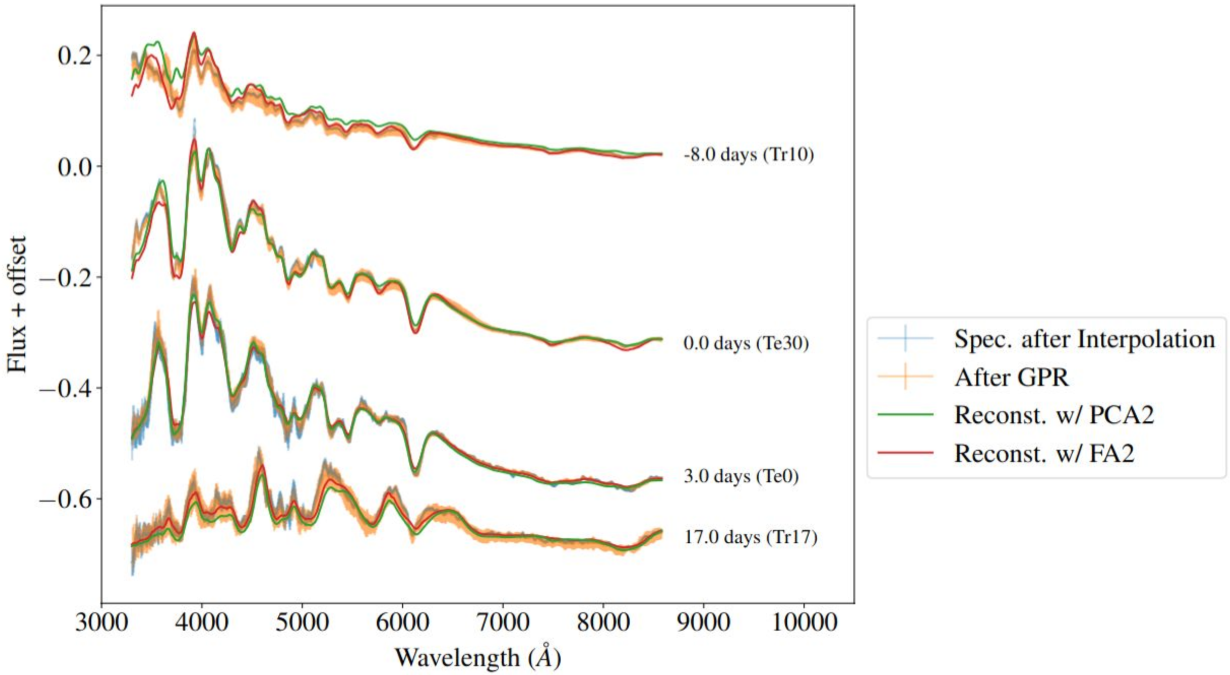






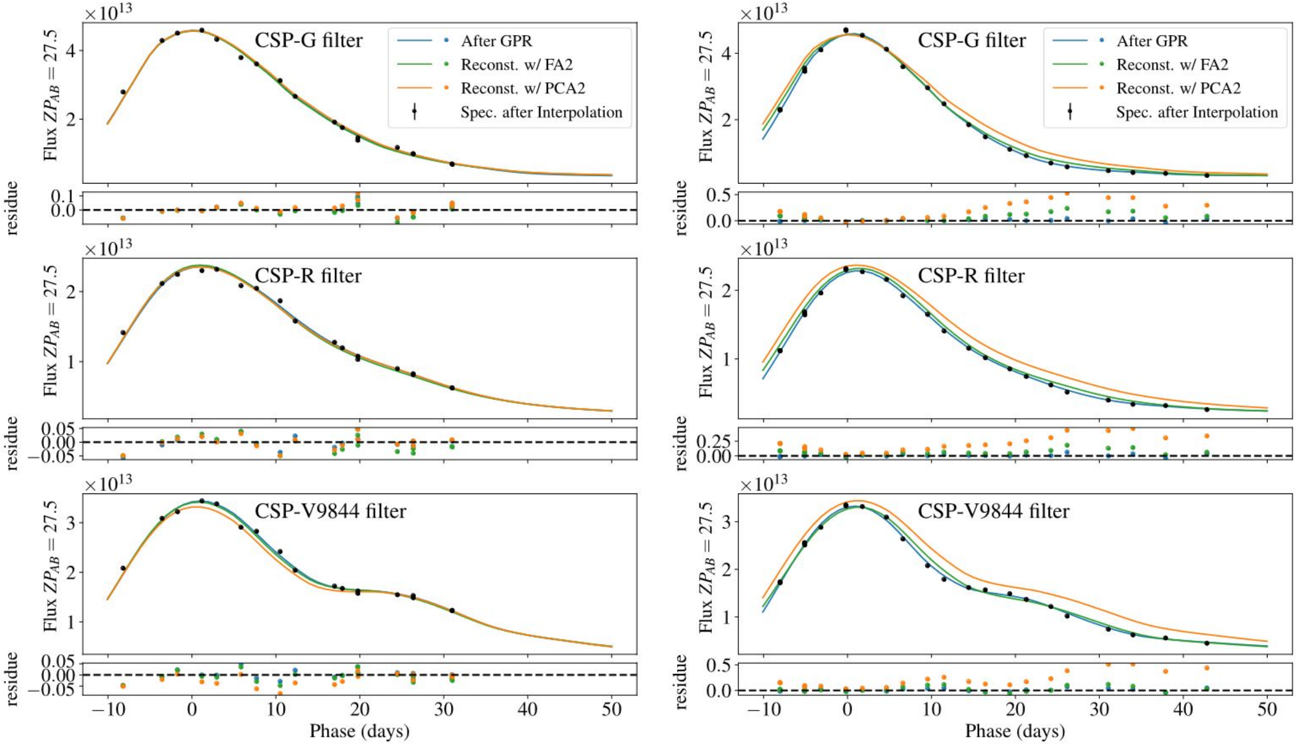
Factors obtained for our set of 150 training SNIa SEDs for N_c= 2.

Spectra Reconstructions

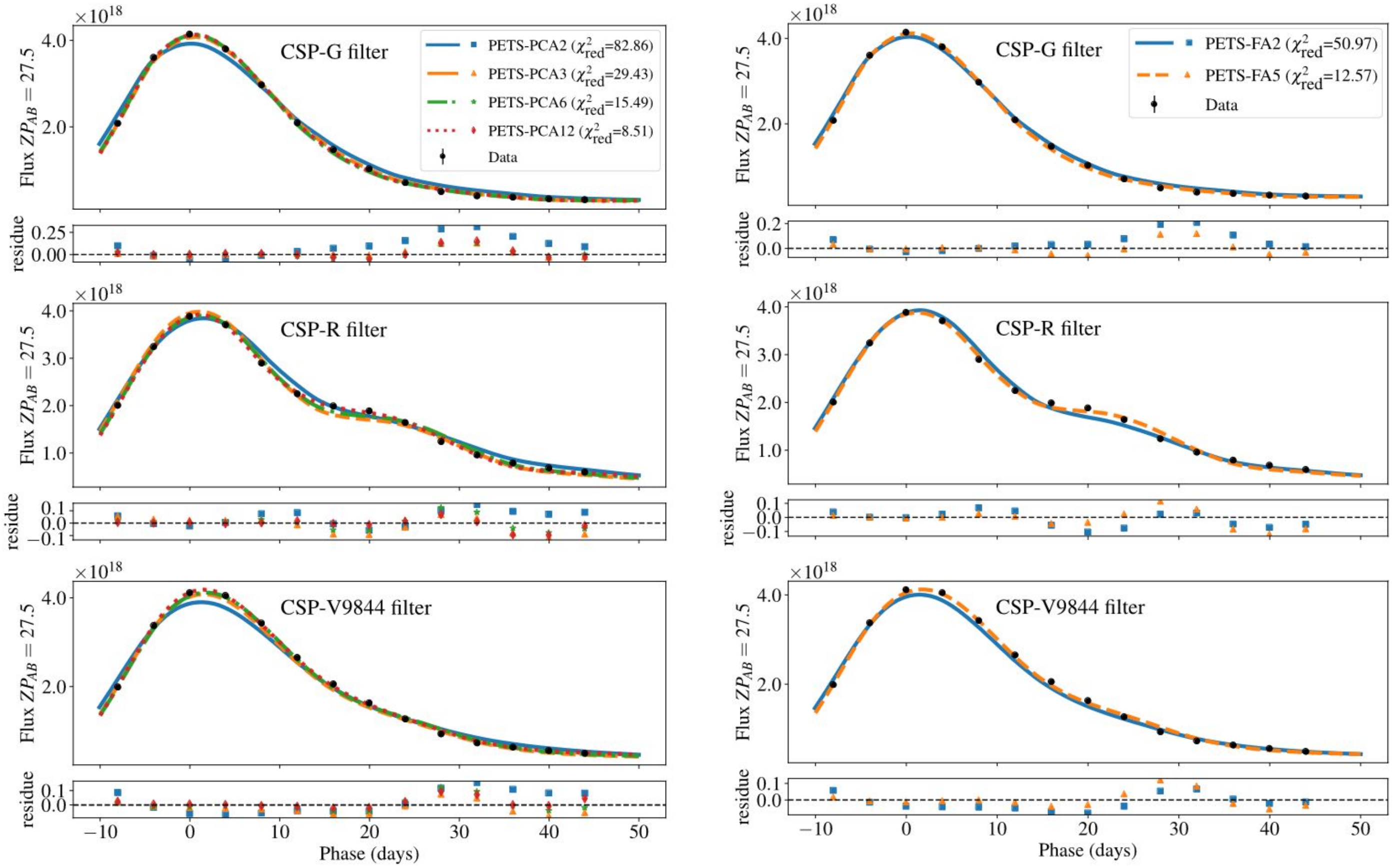


We also analyzed spectra reconstructions. FA outperforms PCA. The models struggle most to reconstruct spectra before the maximum light (where we have less training data) and for lower wavelengths.

Light Curve Reconstructions

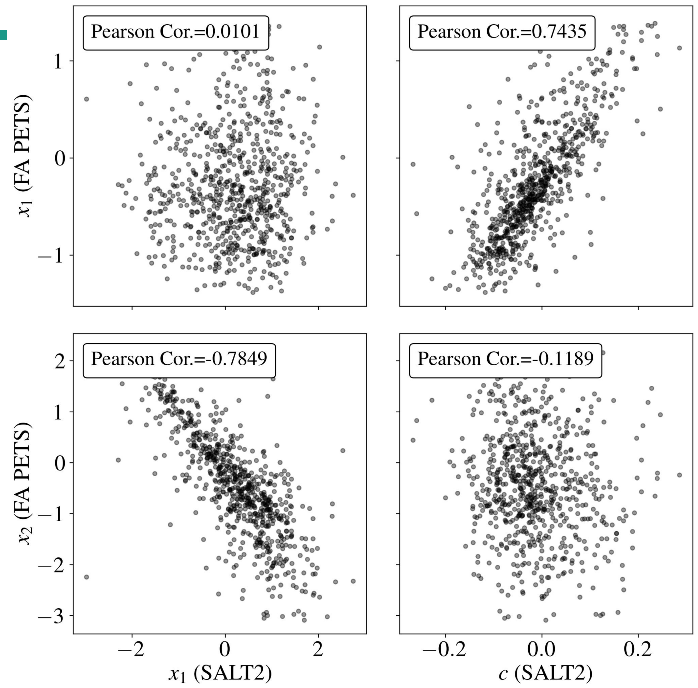


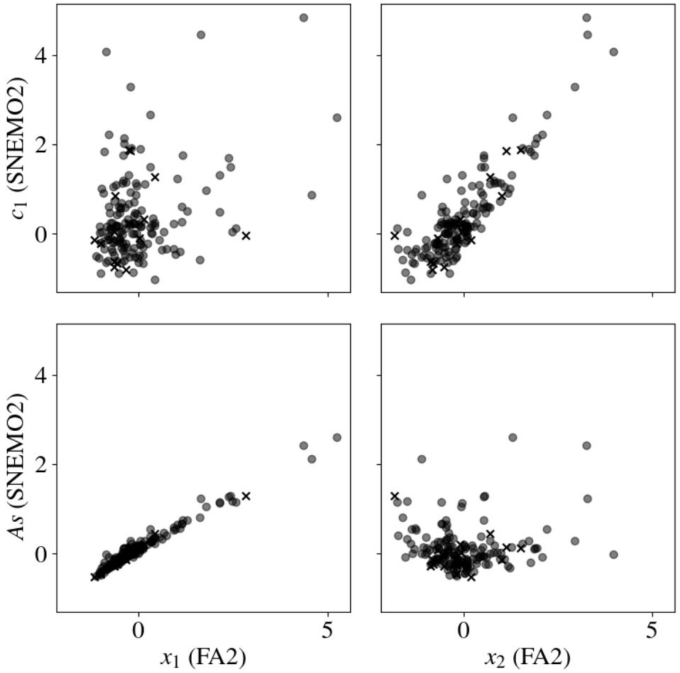
FA outperforms PCA.



We create a light-curve fitter with different number of components and evaluate the model performances.
We show light-curve fitting of a representative validation SNIa. PETS-FA outperforms PETS-PCA. The PCA model shows more significant improvement when adding model components. PETS-PCA2 struggles most to fit the maximum flux.

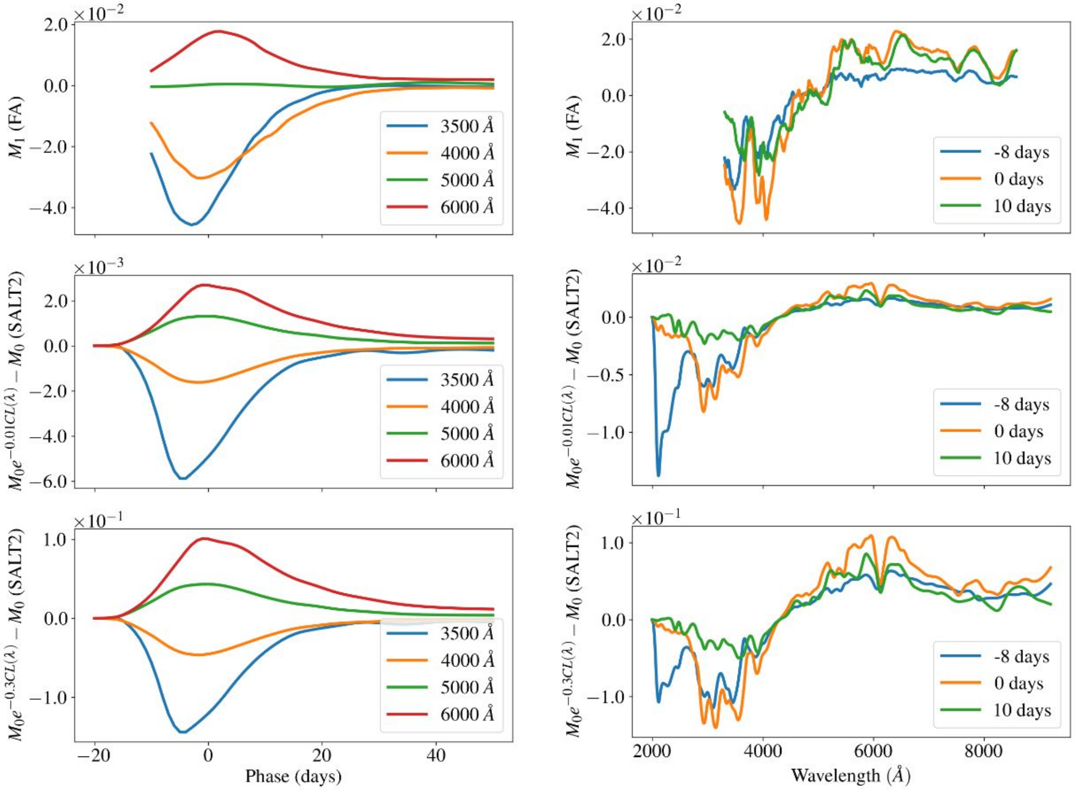
Correlation with SNEMO2 and SALT2 fit parameters



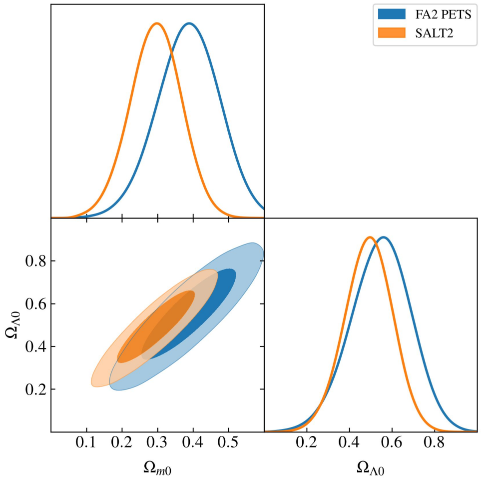


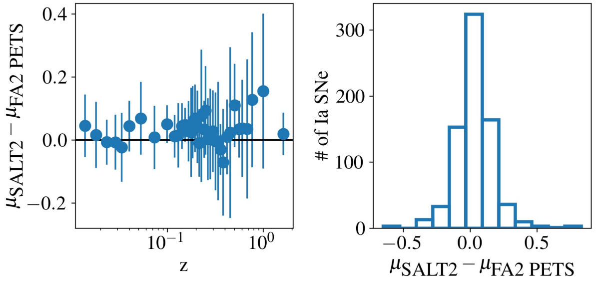
Main SNIa SEDs variation is related to color-index variations. Our M1 surface mainly addresses the color index variations.

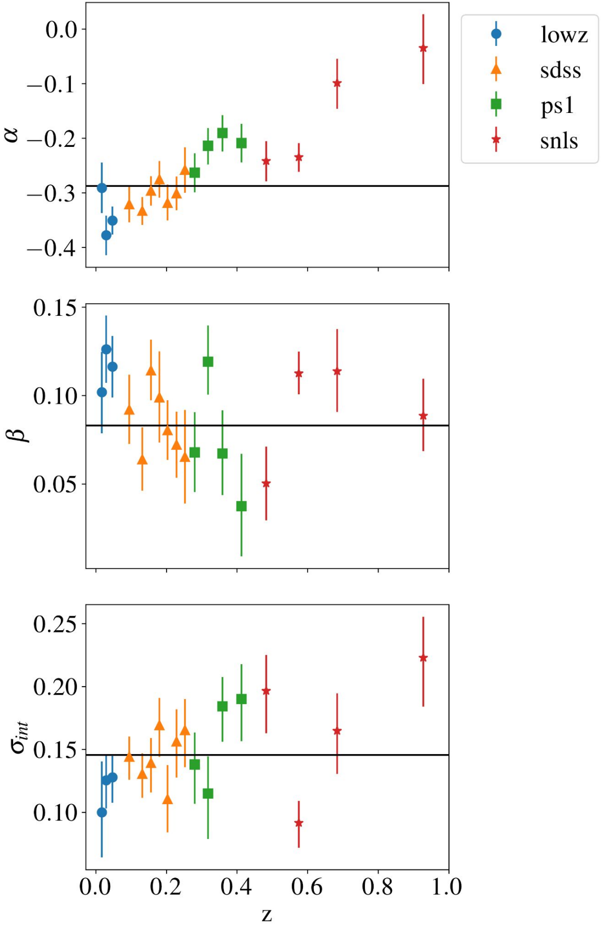
Comparison with SALT2 color component



Initial cosmology evaluation







Conclusions and Future works

The main feature responsible for SNIa SEDs variations is as expected related to the color-index variations;

Our simple 3-component model succeeded in constraining cosmological parameters in accordance to SALT2. But it still lacks model covariance and has poor UV coverage;

Our model does not reduce the systematics associated with the standardization procedure but shows promising results;

We will explore FA oblique rotations since they can offer insight on common factors physical interpretations.

Thank you!