

Spectro-standardisation of ZTF Sne Ia

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Twins Embedding

ZTF spectra calibration

Standardisation



January 2024





Summary

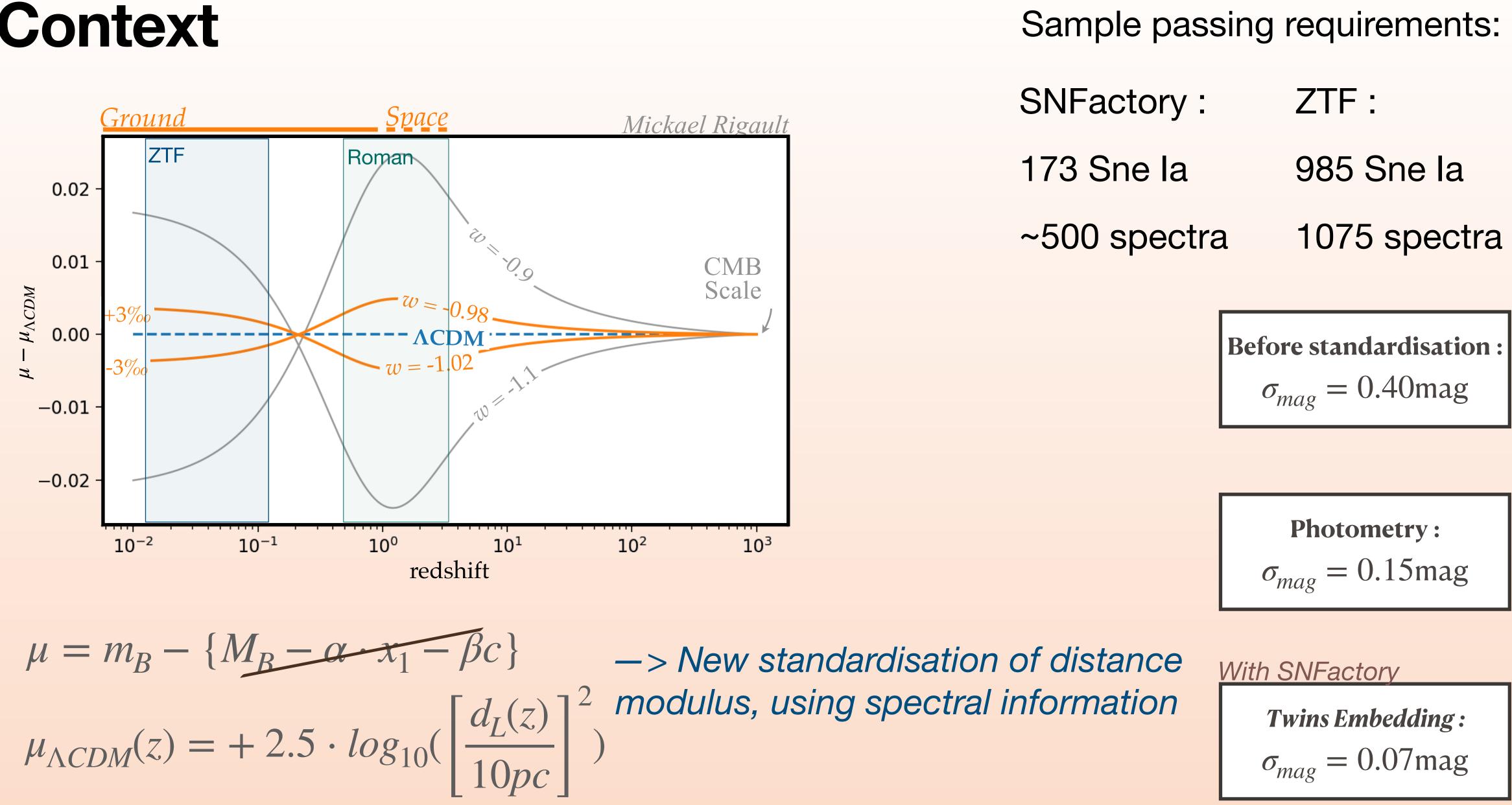
Part I

- Twins
- Twins Embedding

Part II

- Flux calibration of ZTF spectra
- Standardisation with SALT on ZTF spectra

Context

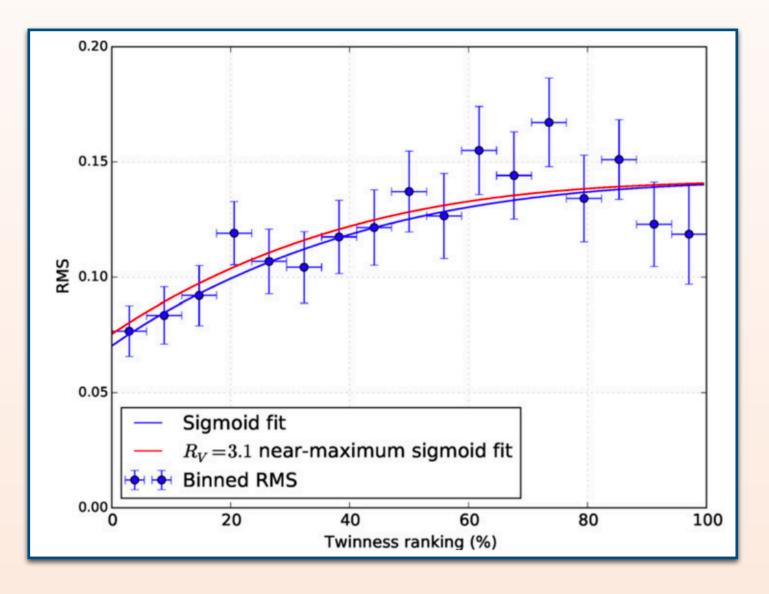


Twins

SNF20070531-011 SNF20071003-016 0.5 days Flux + offset 3.4 days 2 days .9 davs 6000 5000 4000 7000 8000 Wavelength (λ) in AA

Spectral time-series of two 'Twins' Sne Figure from Fakhouri 2015

Twins supernovae have matching spectral time-series



Twins have lower dispersion in luminosity than spectroscopically dissimilar Sne - Figure from Fakhouri 2015

-> magnitude dispersion is smaller for the lowest 'twiness' parameters

-> Only one spectrum at maximum per SN la is sufficient to have the variation information

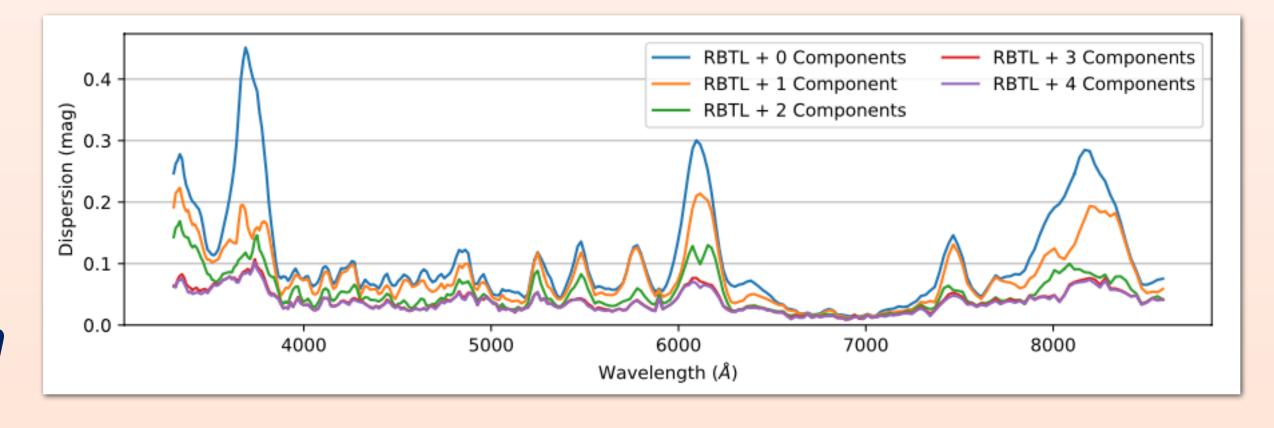


Spectrophotometric standardisation method Using Machine Learning

Twins Embedding - Boone et al. 2021

1. Differential time evolution model 2. RBTL - remove grey scatter and extinction **3.** Manifold Learning - parameters reduction

Pre-processing data : Adjust relative brighness of the Sne to a common redshift



From K.Boone et al. 2021. SN Factory spectra fluxes STD, in function of wavelengths, for different numbers of Manifold Learning components (parameters reduction)





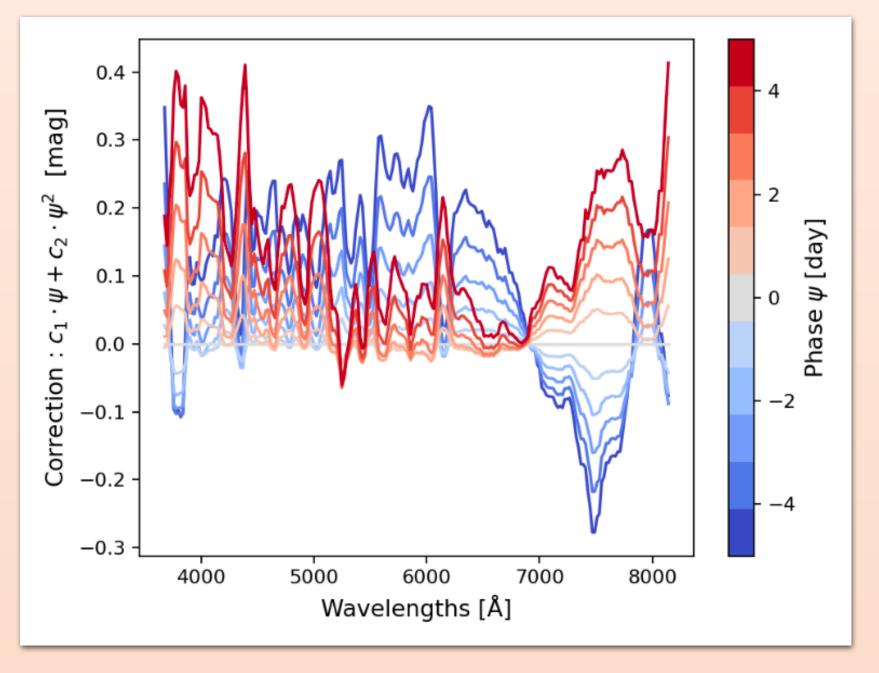
Differential time evolution model => Spectra @ max

Formula of quadratic evolution in phase :

$$m_i(p;\lambda_k) - m_i(0;\lambda_k) = p \cdot c_1(\lambda_k) + p^2 \cdot c_2(\lambda_k)$$

with *p* the phase, $c_{1,2}(\lambda_k)$ the coefficients common to all Sne

 $m_i(p, \lambda_k)$ the magnitude of the SN *i*



Quadratic evolution in phase of SN Ia spectra

$$f_{\text{meas., s}}(p; \lambda_k) \sim N(f_s(p; \lambda_k); \sigma_{\text{tot., s}}^2 \ (p; \lambda_k))$$

$$f_s(p;\lambda_k) = 10^{-0.4(m_i(p;\lambda_k) + m_{\text{gray},s})}$$

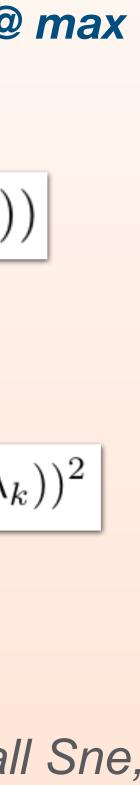
$$\sigma^2_{tot.,s}(p;\lambda_k) = \sigma^2_{\text{meas.},s}(\lambda_k) + (\epsilon(p;\lambda_k) \cdot f_s(p;\lambda_k))$$

<u>Fitted parameters :</u> $f_s(p, \lambda_k)$ the model flux of spectrum s $\epsilon(p, \lambda_k)$ the model uncertainties common to all Sne, $m_{gray,s}$ the gray offset of the spectrum s $c_{1,2}(\lambda_k)$ the coefficients common to all Sne

Known:

 $f_{obs}(p, \lambda_k)$ the observed flux of spectrum s

Capture 84.6% of the spectral evolution variance common to every Sne between -5 and 5 days





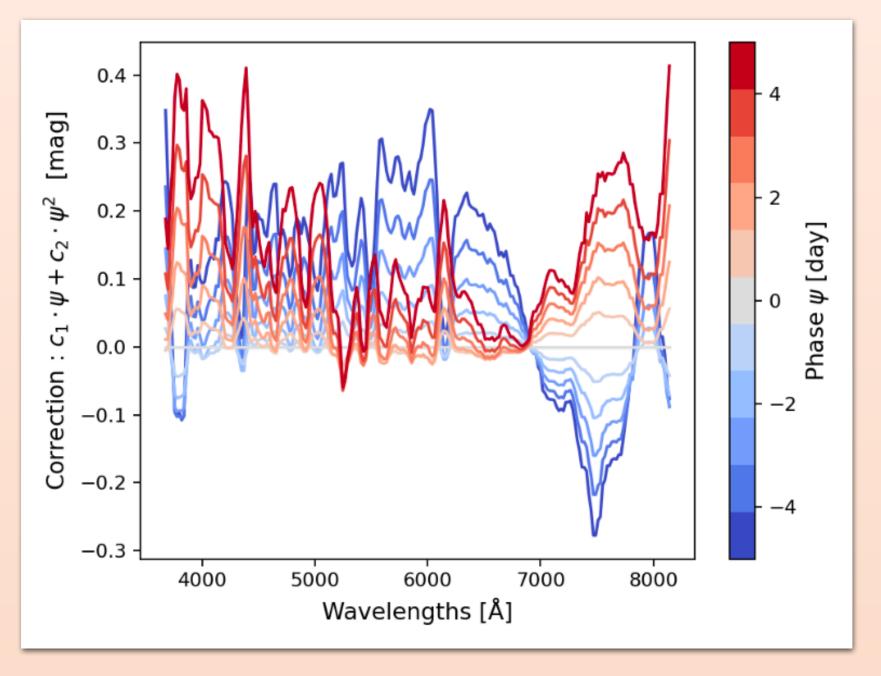
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 $f_{meas.,s}(p, \lambda_k)$ the observed flux of spectrum s $\sigma_{meas.,s}(\lambda_k)$ the measured uncertainty of sp. s

Capture 84.6% of the spectral evolution variance common to every Sne between -5 and 5 days





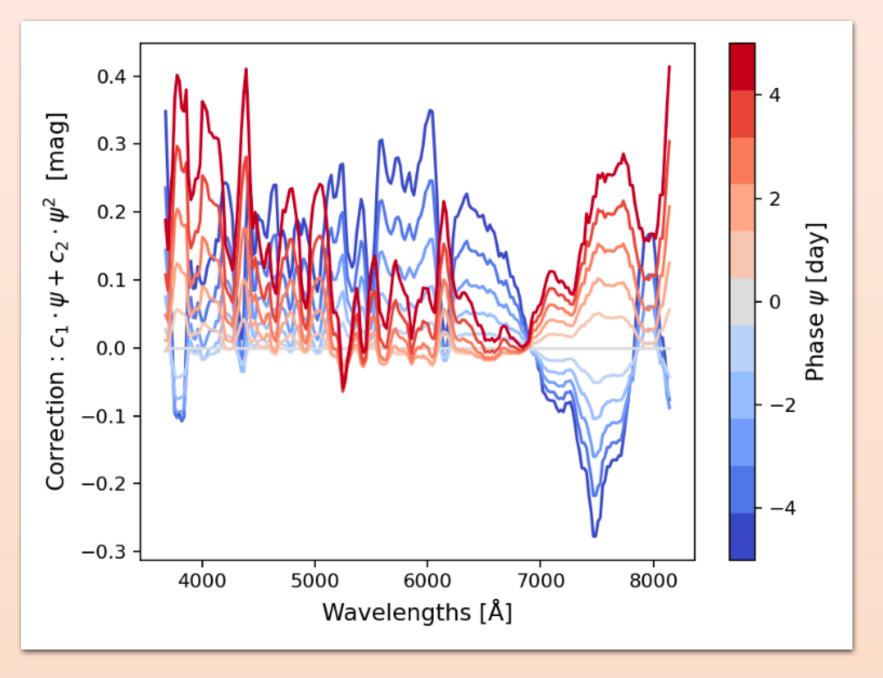
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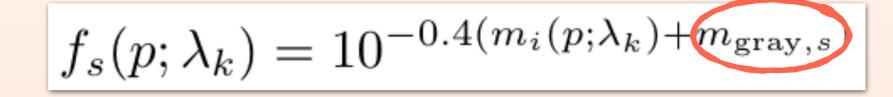
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 $c_{1,2}(\lambda_k)$ the coefficients common to all Sne $m_i(p, \lambda_k)$ the magnitude of the SN *i*



Quadratic evolution in phase of SN Ia spectra

 $f_{\text{meas., s}}(p; \lambda_k) \sim N(f_s(p; \lambda_k); \sigma_{\text{tot., s}}^2 \ (p; \lambda_k))$



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Fitted parameters : $\epsilon(p, \lambda_k)$ the model uncertainties common to all Sne, $m_{gray,s}$ the gray offset of the spectrum s $c_{1,2}(\lambda_k)$ the coefficients common to all Sne

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Capture 84.6% of the spectral evolution variance common to every Sne between -5 and 5 days





Read between the lines (RBTL)

Remove variability:

- Magnitude offset (e.g peculiar velocity of host)
- Extinction (e.g Dust in the host)

Fitted parameters : Δm_i the offset with mean for SN i $\Delta \tilde{A}_{V,i}$ the extinction coefficient for SN i $\eta(\lambda_k)$ the intrinsic dispersion (common to all)

Known: $f_{max,i}(\lambda_k)/\sigma_{f_{max},i}^2(\lambda_k)$ the spectrum flux/uncertainty at max for SN i $f_{mean}(\lambda_k)$ the mean spectrum at max $C(\lambda_k)$ the extinction law (Fitzpatrick 99)

=> Explain Scatter **Between the lines**

Capture Grey scatter + Extinction

Fit all together with bayesian inference :

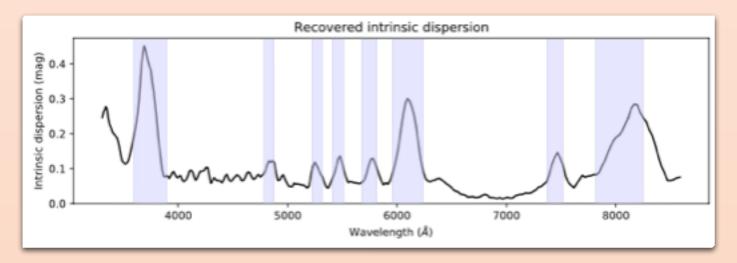


$$f_{\text{model},i}(\lambda_k) = f_{\text{mean}}(\lambda_k) \times 10^{-0.4} (\Delta m_i + \Delta \tilde{A}_{V,i})$$

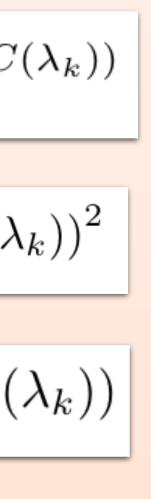
$$\sigma_{\text{total},i}^2(\lambda_k) = \sigma_{f_{\max,i}}^2(\lambda_k) + (\eta(\lambda_k)f_{\text{model},i}(\lambda_k))$$

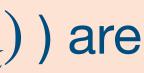
$$f_{\max.,i}(\lambda_k) \sim N(f_{\text{model},i}(\lambda_k); \sigma^2_{\text{total},i}(\lambda_k))$$

Areas with large intrinsic dispersion ($\eta(\lambda_k)$) are deweight during the fit :











Read between the lines (RBTL)

Remove variability:

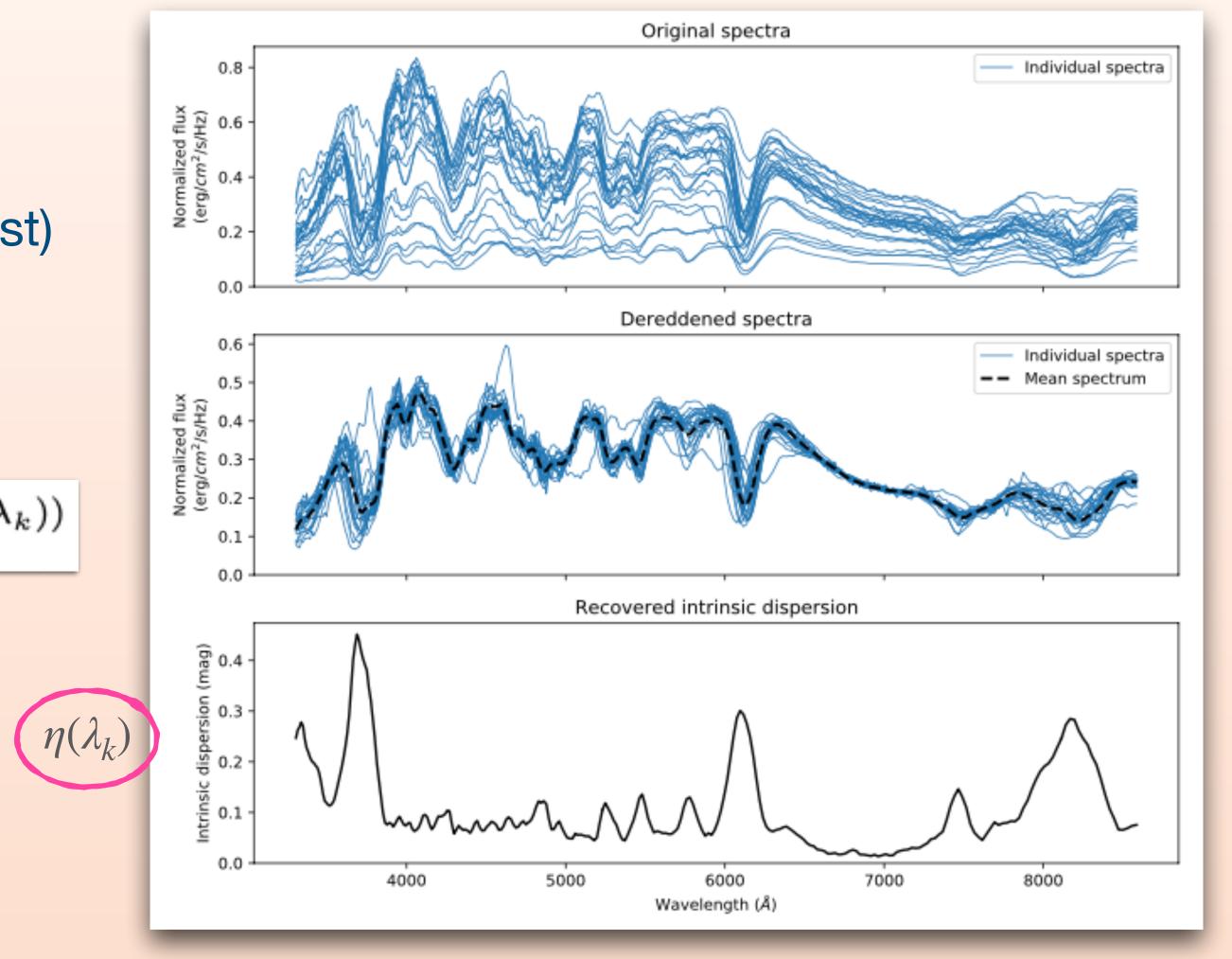
- Magnitude offset (e.g peculiar velocity of host)
- Extinction (e.g Dust in the host)

$$f_{\text{dered.},i}(\lambda_k) = f_{\max.,i}(\lambda_k) \times 10^{+0.4(\Delta m_i + \Delta \tilde{A}_{V,i}C(\lambda_k))}$$

Areas with large intrinsic dispersion ($\eta(\lambda_k)$) are deweight during the fit

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SNFactory spectra before/after dereddening, and residual intrinsic dispersion (std) - from Boone 2021





Read between the lines (RBTL)

Remove variability:

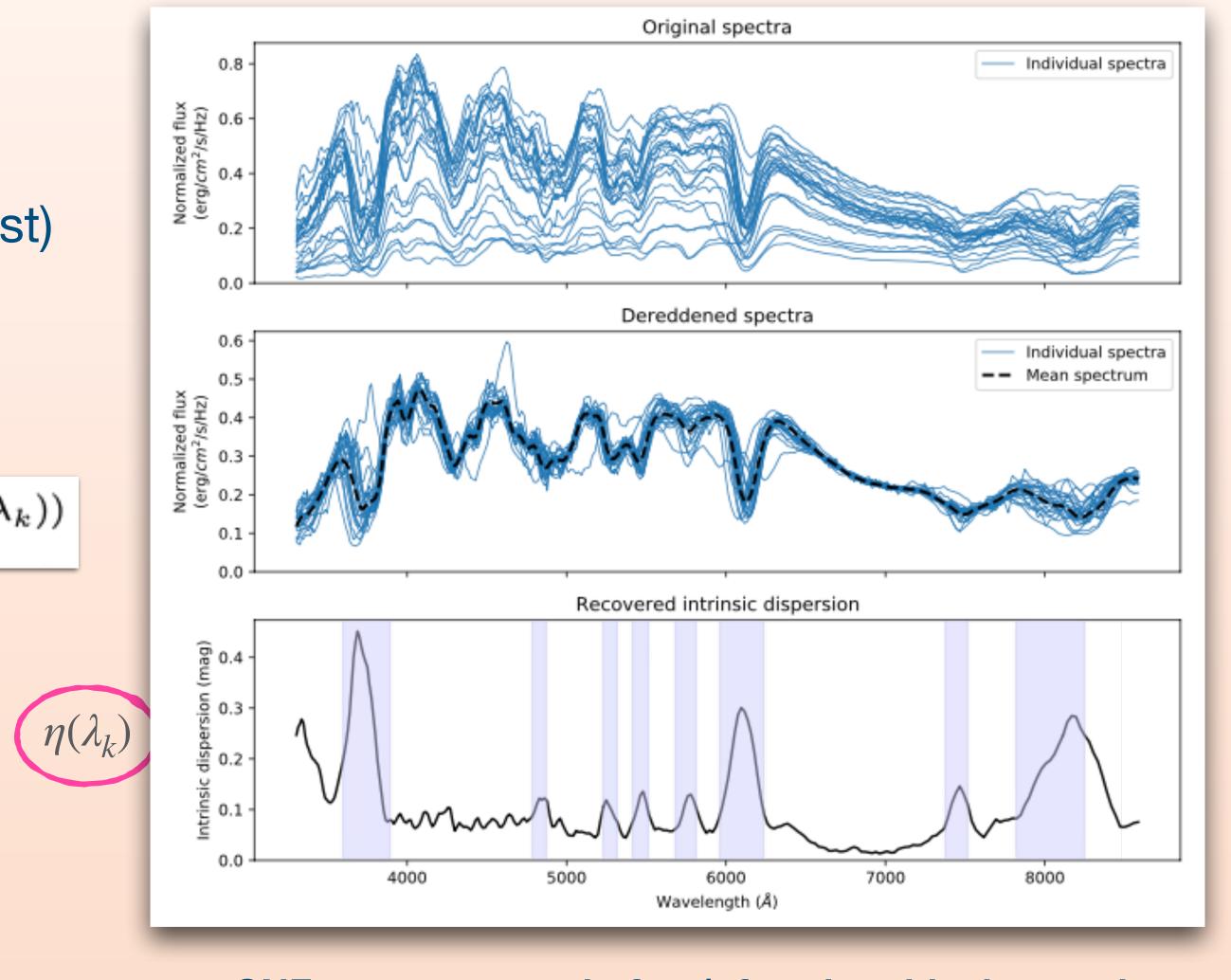
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SNFactory spectra before/after dereddening, and residual intrinsic dispersion (std) - from Boone 2021



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The Twins Embedding parameters space => Explain

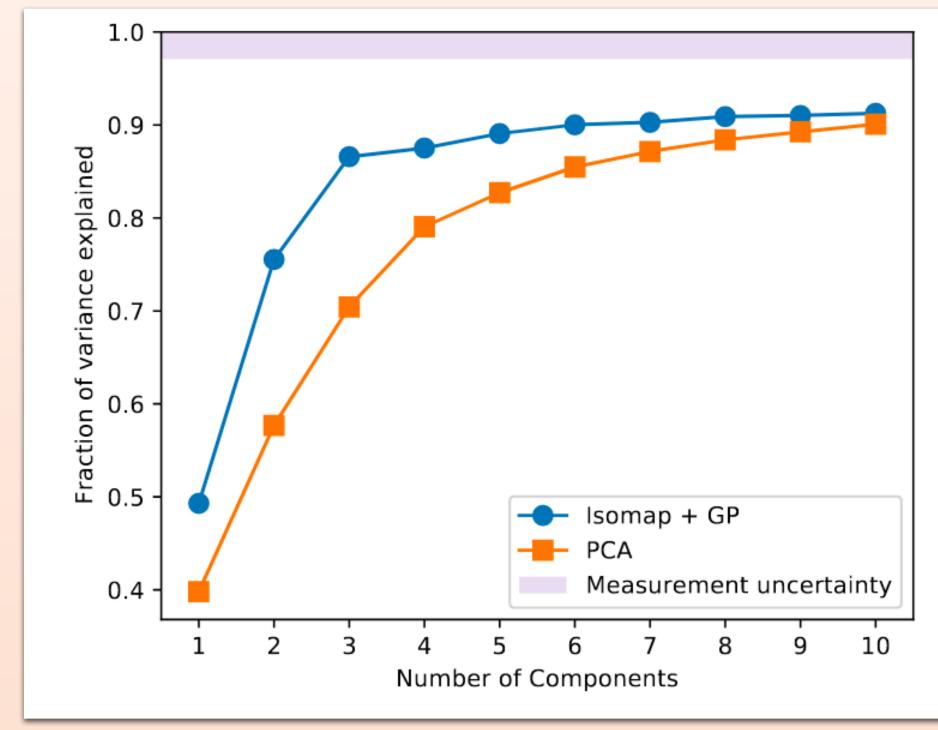
Spectral distance between two Sne I and j :

$$\gamma_{ij} = \sqrt{\sum_{k} \left(\frac{f_{\text{dered.},i}(\lambda_k) - f_{\text{dered.},j}(\lambda_k)}{f_{\text{mean}}(\lambda_k)} \right)^2}$$

Isomap algorithm embed high-dimensional space to low-dimentional while preserving distances

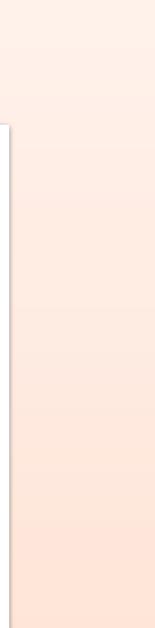
But it does not provide a model of a spectrum given its coordinates in the embedding : for that they use Gaussian Process

86.6% of variance explained with 3 components



Fraction of the variance explained for different models from Boone 2021







TWINS EMBEDDING I



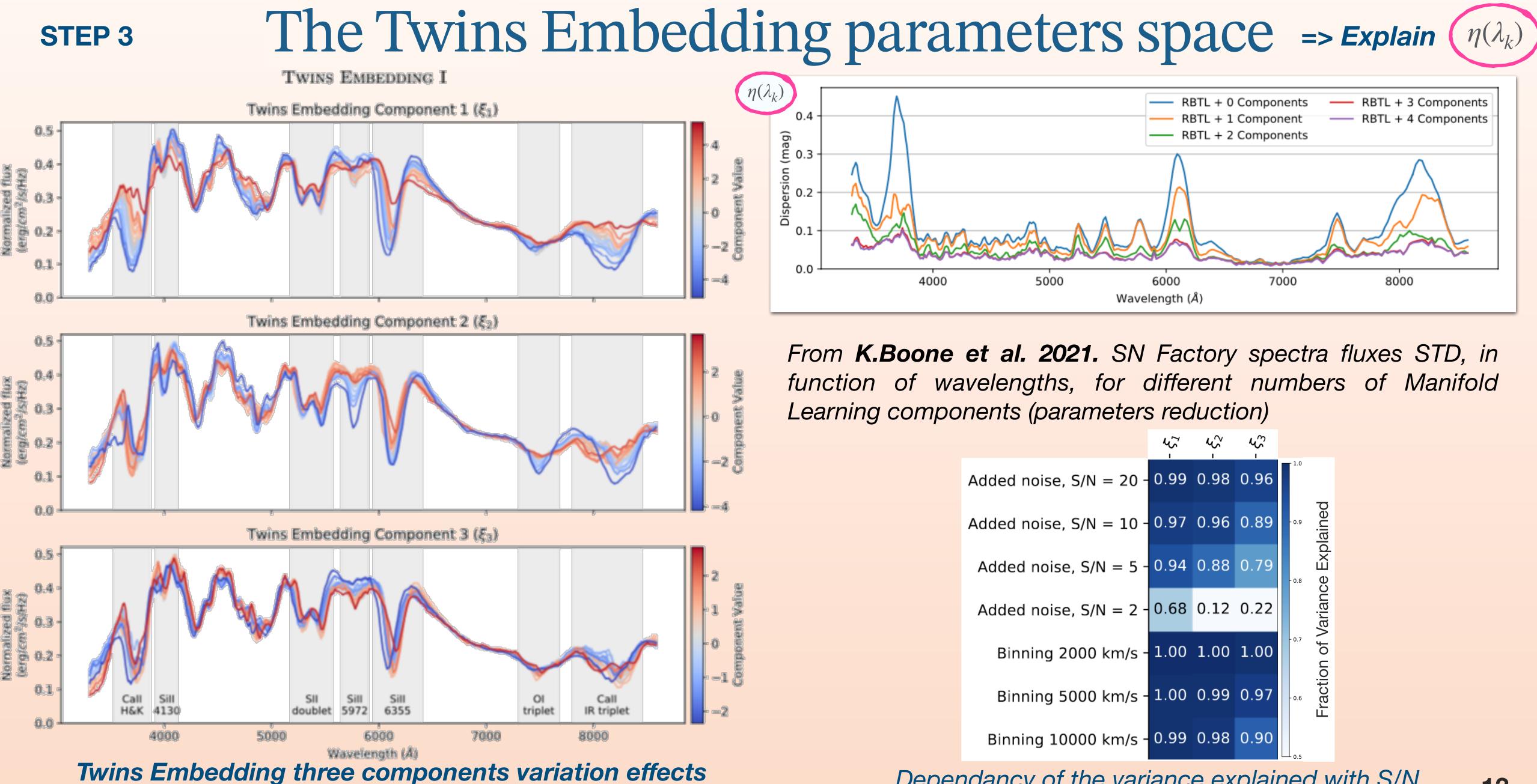


Figure from Boone 2021

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Added noise, S/N = 20 -	0.99	0.98	0.96	1.0	
Added noise, S/N = 10 -	0.97	0.96	0.89	- 0.9	lained
Added noise, S/N = 5 -	0.94	0.88	0.79	- 0.8	e Explair
Added noise, S/N = 2 -	0.68	0.12	0.22		of Variance
Binning 2000 km/s -	1.00	1.00	1.00	- 0.7	
Binning 5000 km/s -	1.00	0.99	0.97	- 0.6	Fraction
Binning 10000 km/s -	0.99	0.98	0.90	0.5	

Dependancy of the variance explained with S/N and binning



With ZTF Spectra

Steps :

- Flux calibration of the spectra
- Correct from the Milky Way
- **Put each spectrum at same z**
- Convert the flux in magnitude and put to phase=0

 $m_i(p;\lambda_k) - m_i(0;\lambda_k) = p \cdot c_1(\lambda_k) + p^2 \cdot c_2(\lambda_k)$

Correction of RBTL variability by fitting the Δm_i and $\Delta \tilde{A}_{V,i}$

 $f_{\text{dered.},i}(\lambda_k) = f_{\max.,i}(\lambda_k) \times 10^{+0.4(\Delta m_i + \Delta \tilde{A}_{V,i}C(\lambda_k))}$

Projection on the 3 components space to get ξ

□ Standardisation of the magnitude residuals ...







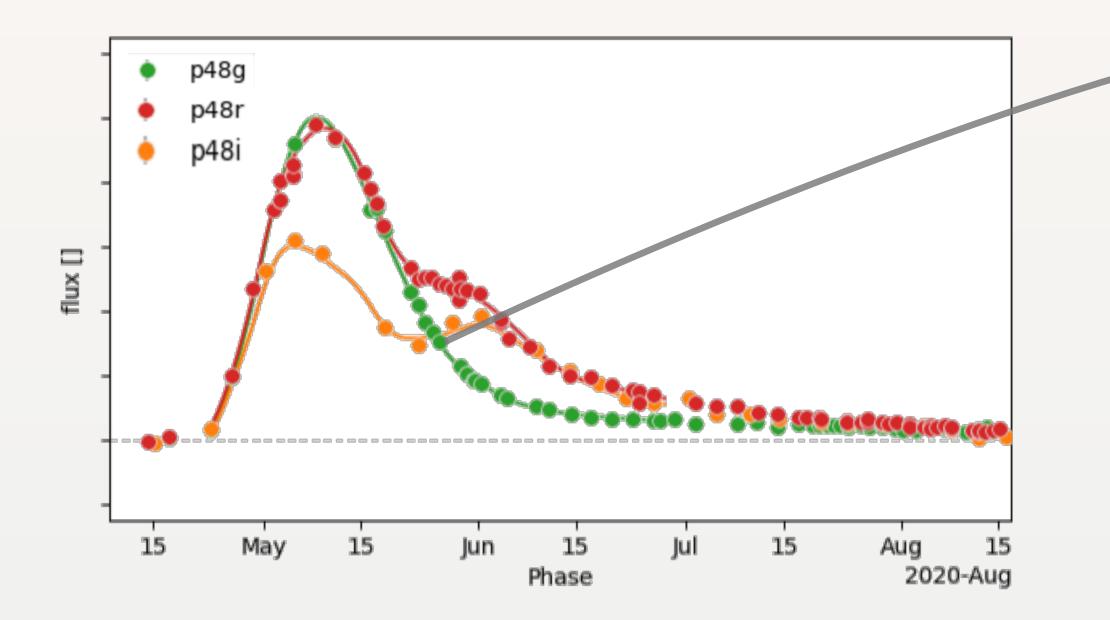
ZTF Data - Plan

- Flux calibration of ZTF spectra
- Correction of the MW and the redshift
- Standardisation of the spectra with SALT

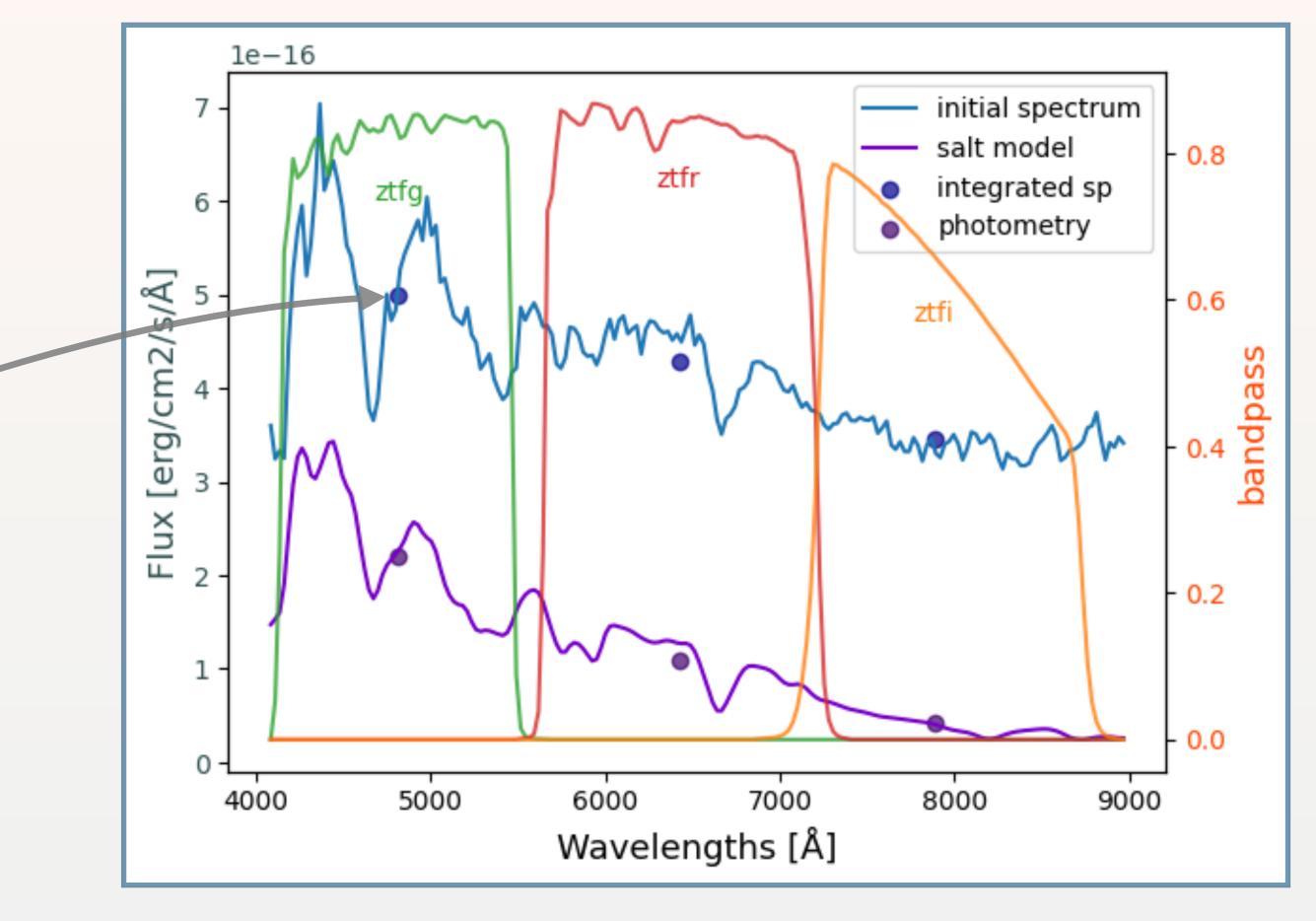
dshift th SALT

Synthetic Photometry

A point on the lightcurve corresponds to the spectrum integrated on the band



Lightcurves of ZTF20abxzrqw In ztf-g, ztf-r, ztf-i filters



Synthetic photometry with ZTF filters For ZTF18abjijwk at phase 0.45





Spectrophotometric Calibration

2nd order polynomial :

 $poly \sim c_2 \cdot \lambda_{norm}^2 + c_1 \cdot \lambda_{norm} + c_0$

Legendre Polynomials :

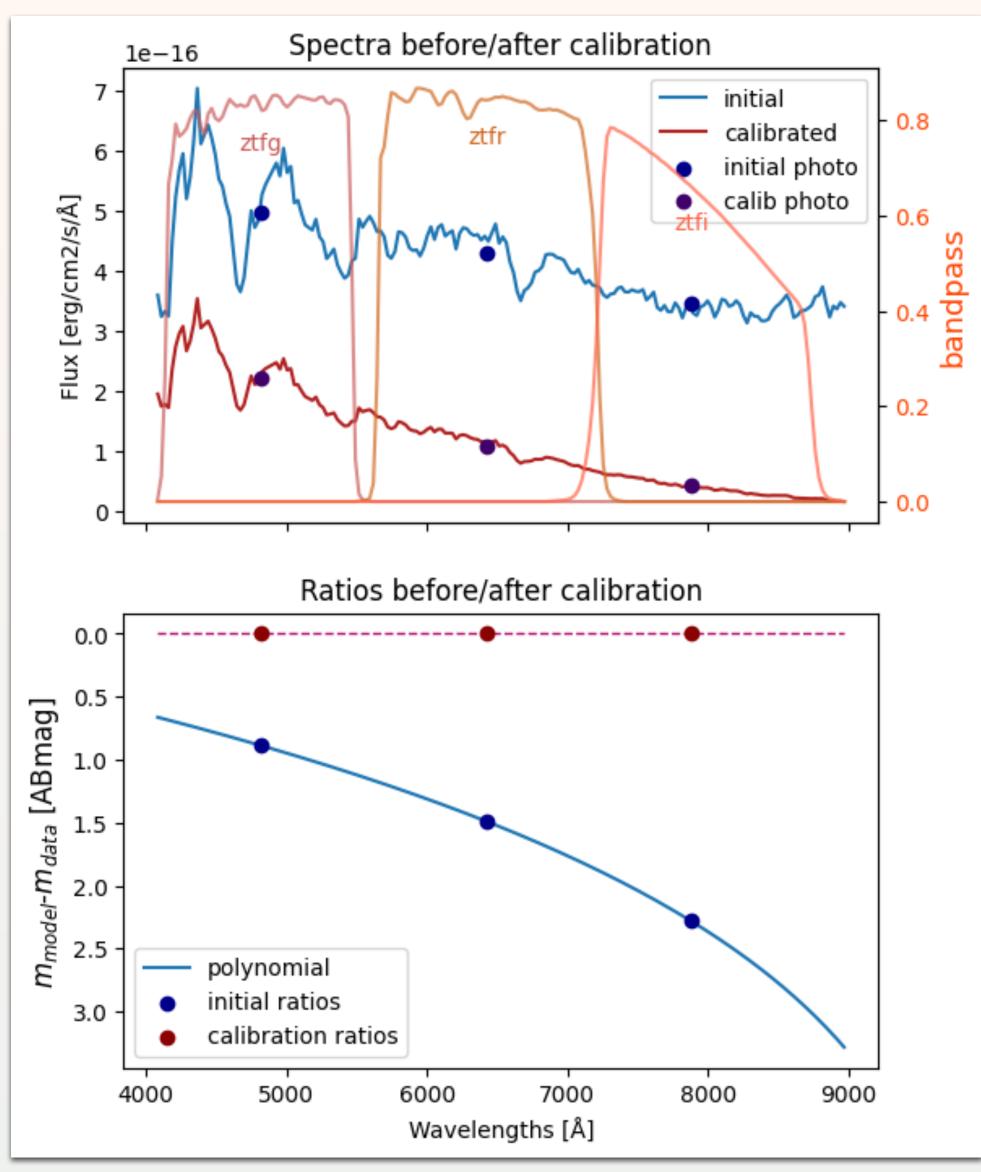
We normalise wavelengths between -1 and 1 $\lambda_{norm} = 2 \cdot \frac{\lambda - \lambda_{min}}{\lambda_{max} - \lambda_{min}} - 1$

Minimisation function :

$$\chi^{2} = \sum_{N} \left(\int_{3 \text{filters}} f_{obs}(\lambda) \cdot poly(\lambda) \cdot d\lambda - F_{photo}^{g,r,i} \right)^{2}$$

Polynomial converted in magnitude :

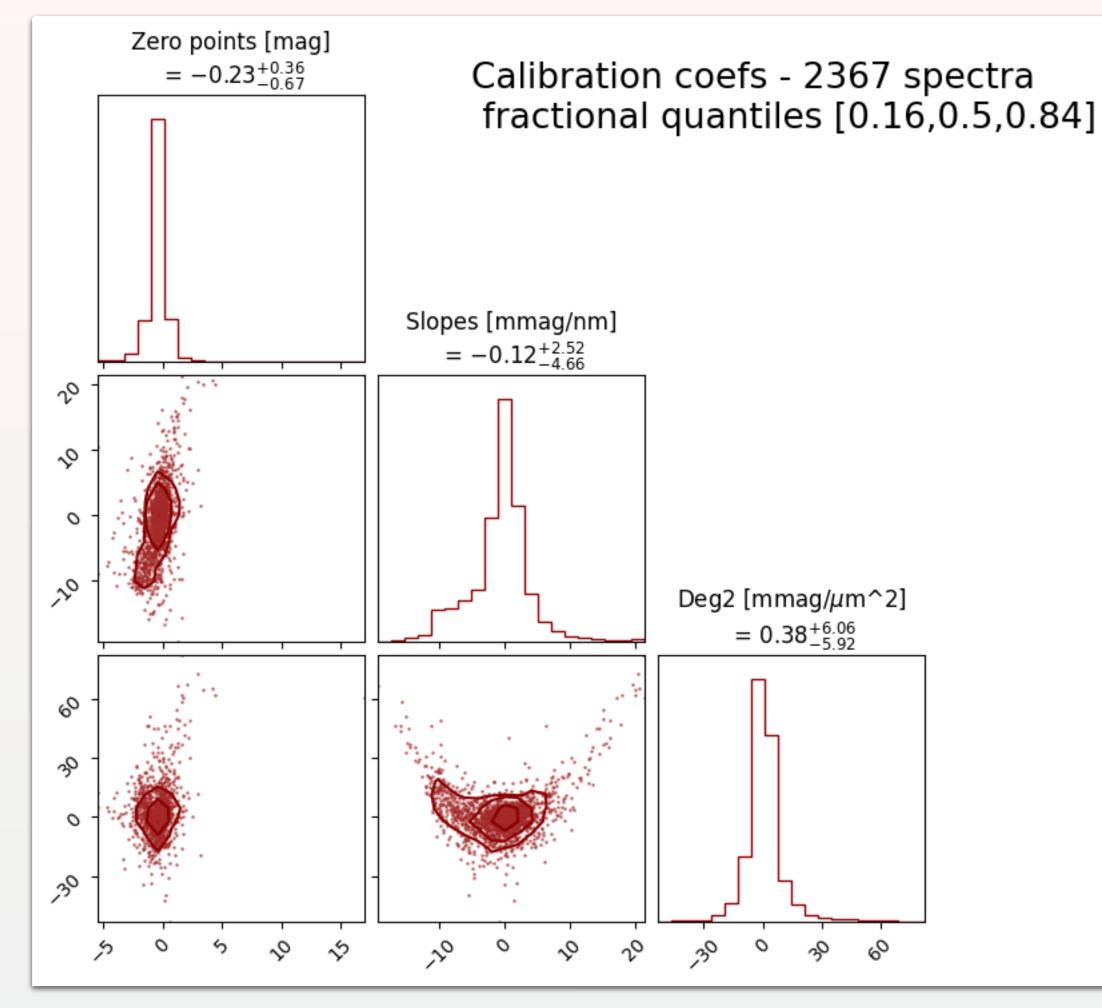
$$m_{model} - m_{init} = -2.5 \cdot \log_{10} \left(\frac{f_{model}}{f_{init}} \right)$$

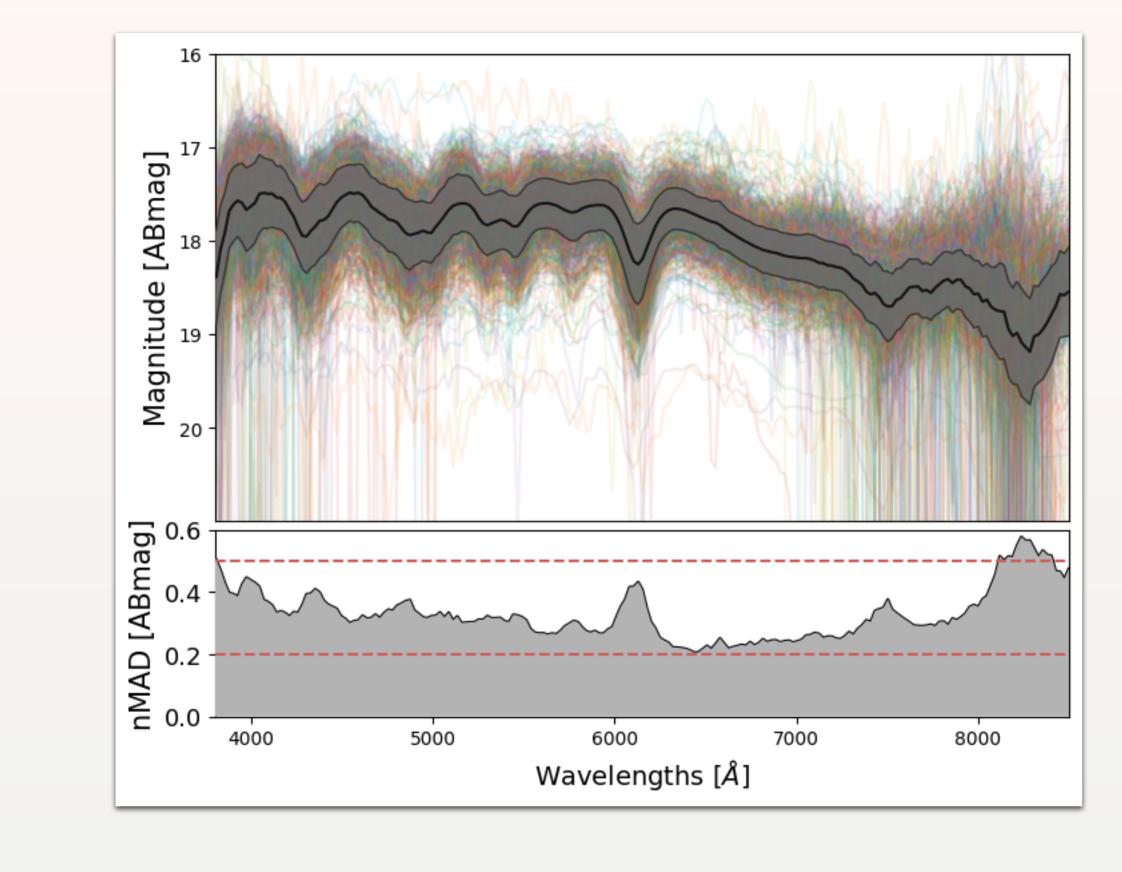


Example of calibration with ZTF18abjijwk

Spectrophotometric Flux Calibration

For 2367 spectra





Calibrated, corrected of MW and redshift at 0.05, for 1075 spectra of 985 Sne Ia (cosmology cuts + phase bewteen +/-5 days)



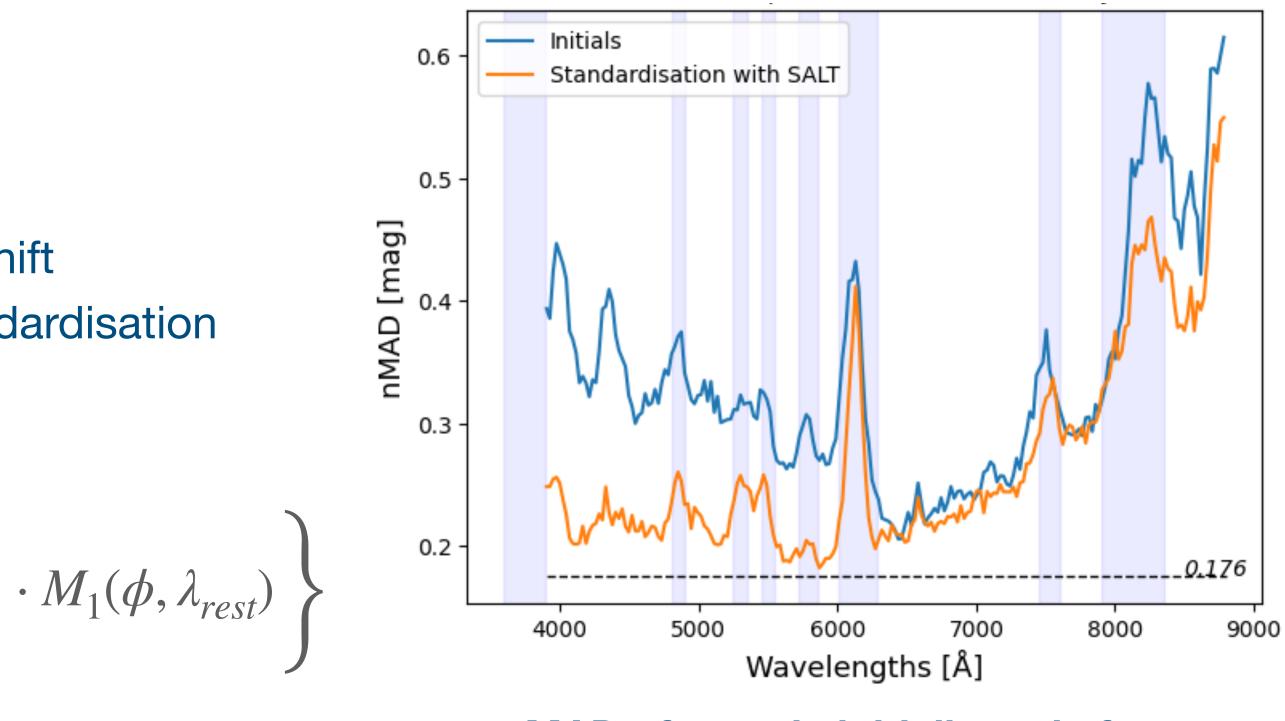
Standardisation with SALT - applied to ZTF spectra

Method :

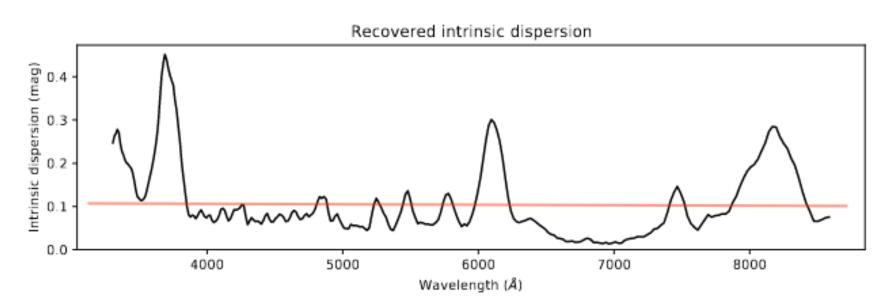
Correct the fluxes from SALT parameters and redshift Convert the fluxes in ABmag, and apply Tripp standardisation

$$f_{corrected}(\lambda) = \begin{cases} \frac{f_{init}(\lambda) \cdot (1+z) \cdot d_L(z)^2}{10^{-0.4 \cdot CL(\lambda_{rest}) \cdot c}} - x0 \cdot x1 \\ \times \frac{M_0(\lambda_{rest}, 0)}{M_0(\lambda_{rest}, \phi)} \cdot \frac{1}{(1+z_{ref}) \cdot d_L(z_{ref})^2} \end{cases}$$

$$\Delta \mu(\lambda) = m_{corrected}(\lambda) - (M_B - \alpha \cdot x_1 - \beta c)$$



nMAD of sample initially and after SALT correction+standardisation



Intrinsic variability after RBTL - from Boone 2021



GFlux calibration of the spectra

Preparation of the sample : correction of the MW and redshift

SALT standardisation, SNEMO

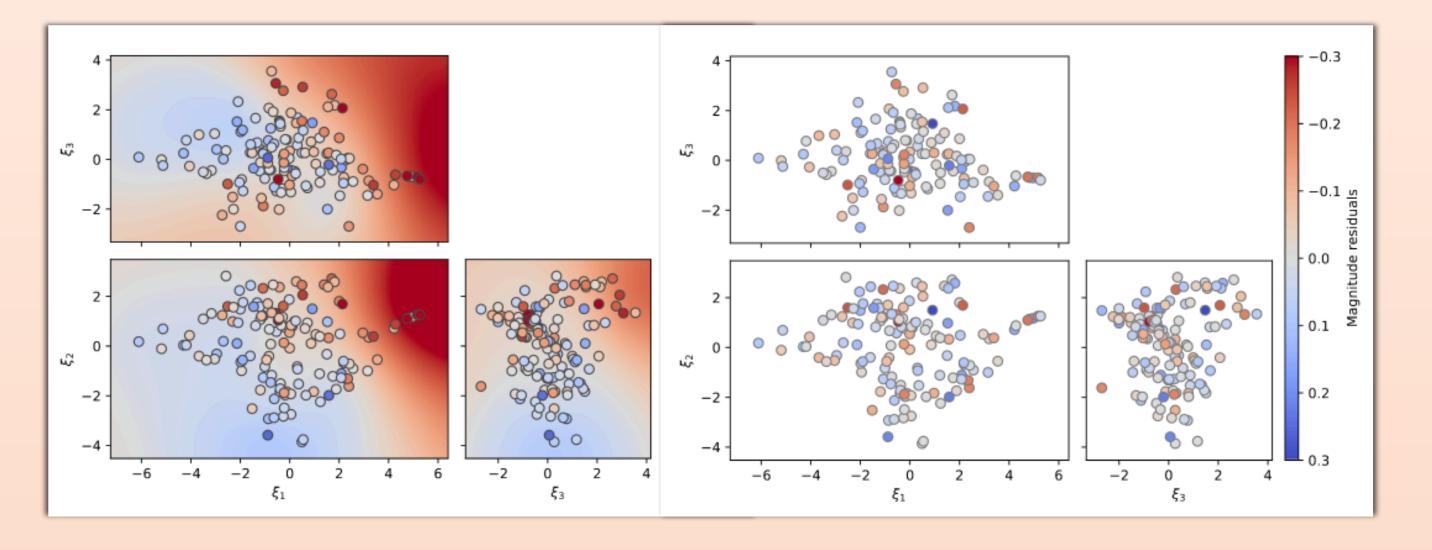
Test the Twins Embedding method with ZTF spectra

□ More methods can be tested, like PAE by G.Stein

BACK-UP SLIDE The standardisation using Twins Embedding

To map the magnitude residuals through the TE space : linear standardisation not sufficient, instead Gaussian Process regression :

$$\vec{m}_{\text{RBTL}} \sim \mathcal{GP}\Big(m_{\text{ref}} + \omega \Delta \vec{\tilde{A}}_V, \\ \mathbf{I} \cdot (\vec{\sigma}_{\text{p.v.}}^2 + \sigma_u^2) + K_{3/2}(\vec{\xi}, \vec{\xi}; A, l)\Big)$$



Before/after correction of magnitude residuals with GP from Boone 2021b

George GP regression python package is used for the fit

Fitted parameters :

m_{ref} a common reference magnitude ω a linear correction term σ_{μ} the unexplained residual dispersion A, *l* the GP kernel parameters

Known :

 $\overrightarrow{m}_{RBTL}$ the magnitudes residuals of the RBTL, $\Delta \overrightarrow{A}_V$ the reddening coefficients ,

 ξ the coordinates in the TE space,

 $\overrightarrow{\sigma}_{p,v}^2$ the host galaxy peculiar velocity variance







BACK-UP SLIDE Standardisation with SALT - applied to ZTF spectra

Flux modelled with SALT, in observed wavelengths :

$$F(\lambda,\phi) = x_0 \cdot \left[M_0(\lambda_{rest},\phi) + x_1 \cdot M_1(\lambda_{rest},\phi) \right] \cdot 10^{-0.4 \cdot c \cdot CL(\lambda_{rest})} / (1+z)$$

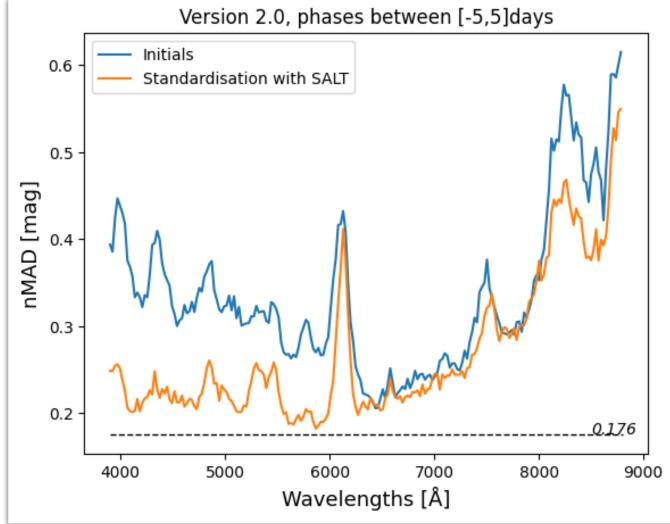
Method : Correct the fluxes from SALT parameters, convert the fluxes in ABmag, and apply Tripp standardisation

$$f_{Initials}(\lambda) = f_{meas}(\lambda) \cdot \frac{(1+z) \cdot d_L(z)^2}{(1+z_{ref}) \cdot d_L(z_{ref})^2}$$

$$\Delta \mu_{Initials}(\lambda) = F_{to}M\left(f_{Initials}(\lambda)\right)$$

$$f_{corrected}(\lambda) = \left\{\frac{f_{init}(\lambda) \cdot (1+z) \cdot d_L(z)^2}{10^{-0.4 \cdot CL(\lambda_{rest}) \cdot c}} - x0 \cdot x1 \cdot M_1(\phi, \lambda_{rest})\right\} \cdot \frac{M_0(\lambda_{rest}, 0)}{M_0(\lambda_{rest}, \phi)} \cdot \frac{1}{(1+z_{ref}) \cdot d_L(z_{ref})^2}$$

 $\Delta \mu_{stand}(\lambda) = F_{to} M \left(f_{corrected}(\lambda) \right) - (M_B - \alpha \cdot x_1 - \beta c)$



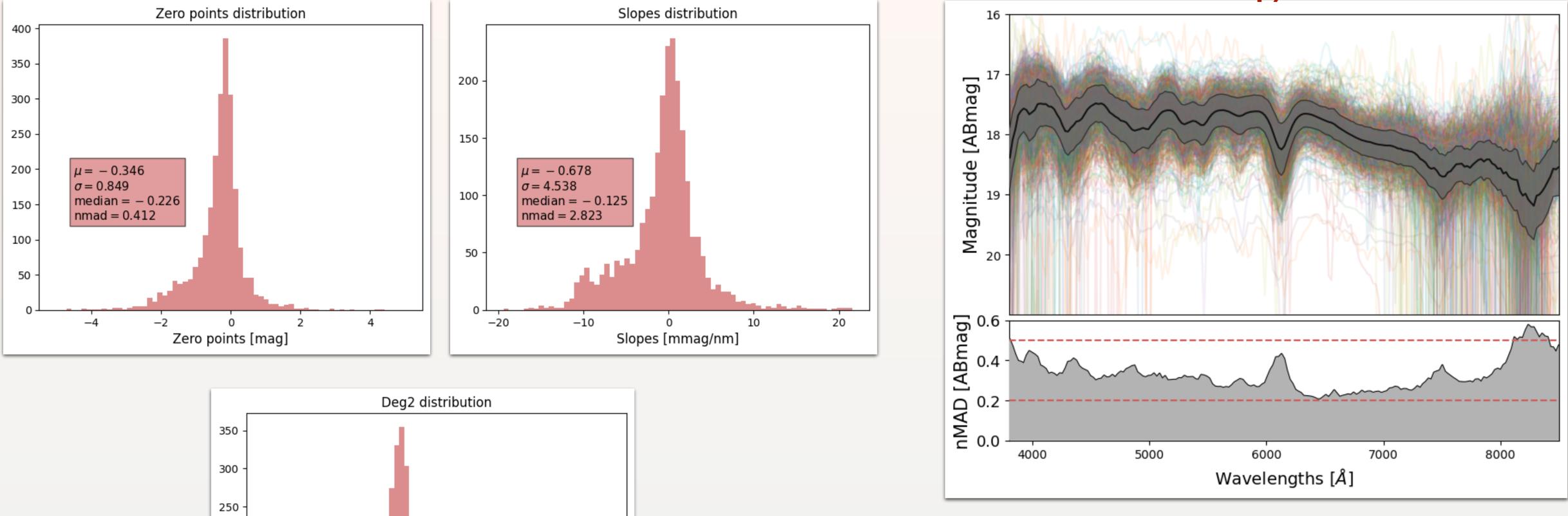
nMAD of sample initially and after SALT correction+standardisation

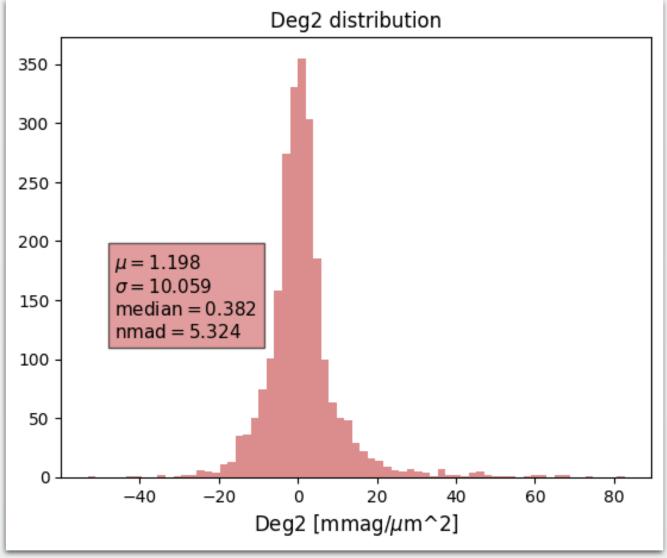
Hubble diagram
analogy:
$$\mu = m_B - (M_B - \alpha \cdot x_1 - \beta c)$$
$$\mu(z) = +2.5 \cdot \log_{10}(\left[\frac{d_L(z)}{10pc}\right]$$



Spectrophotometric Flux Calibration Corner plot des 3 histogrammes (dire le nbr de sp, mettre tableau en backup)

For 2367 spectra





Calibrated, corrected of MW and redshift at 0.05, for 1075 spectra of 985 Sne Ia (cosmology cuts + phase bewteen +/-5 days)

