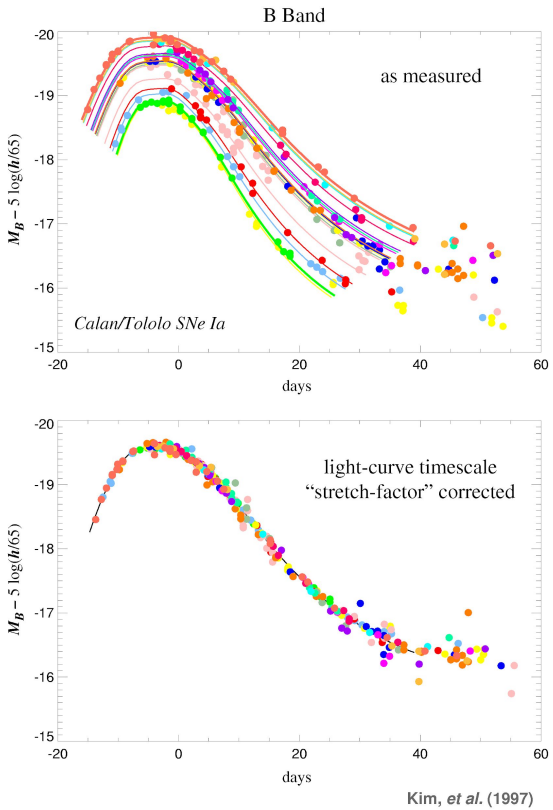
Review: Type Ia Supernovae Standardization

LPC Particules pLasmas Univers applicationS
Laboratoire de Physique de Clermont

cnrs IN2P3
Les deux infinis

Why we need standardization ?



Kim, *et al.* (1997)

Examples of variabilities :

- Intrinsic variability : Stretch
- Extrinsic variability : Color (one part of SALT2 color are intrinsic)

SALT2 standardization

State of the art: SALT2 SED model (Guy et al. 2007)

$$F(p,\lambda) = X_0 \times (S_0(p,\lambda) + X_1 S_1(p,\lambda)) \times \exp(C \times CL(\lambda))$$

Model in flux

Stretch

Color

SALT2 color law

Limit of SALT2 standardization

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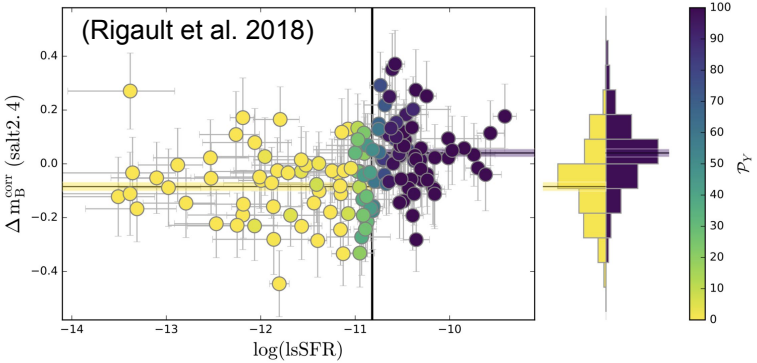
Correlation between host galaxies properties and Hubble residuals



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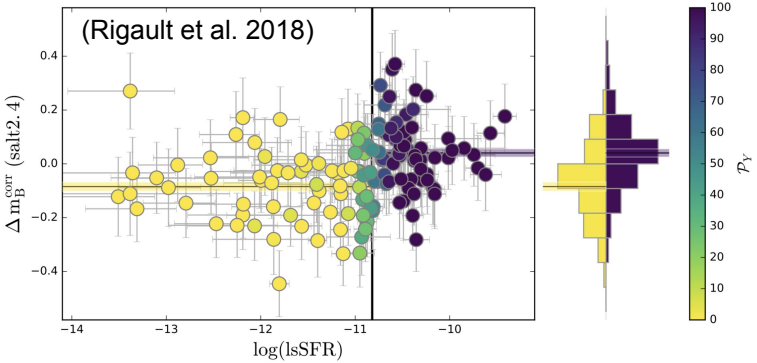
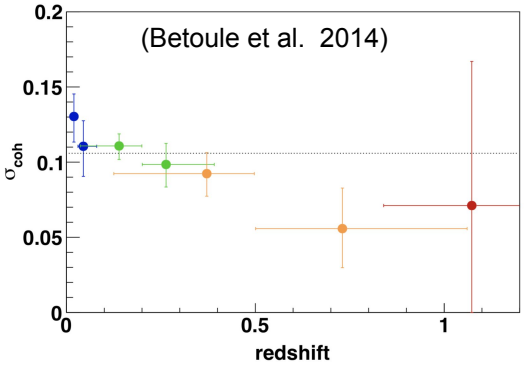


Intrinsic dispersion of Hubble residuals



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Model in flux

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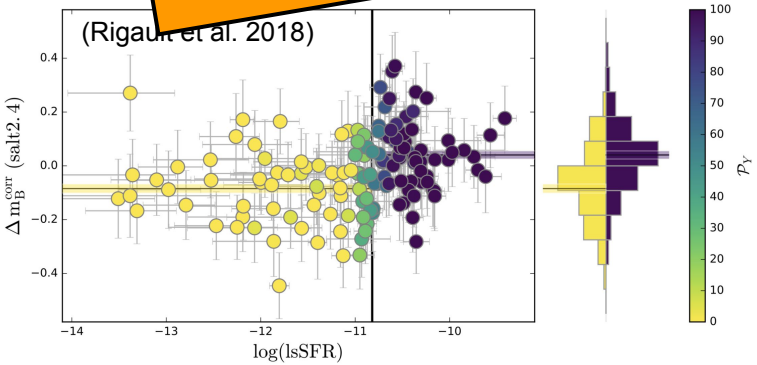
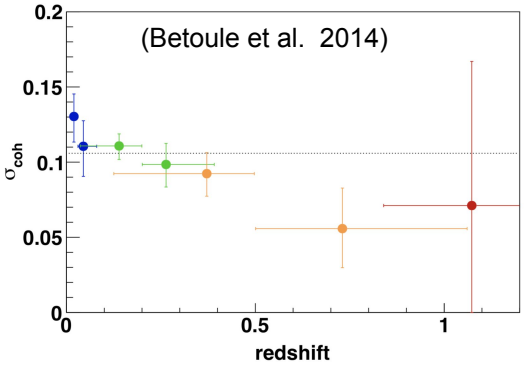
ALT2 color law

Correlation betw… proper…

…ntrinsic dispersion of Hubble residuals

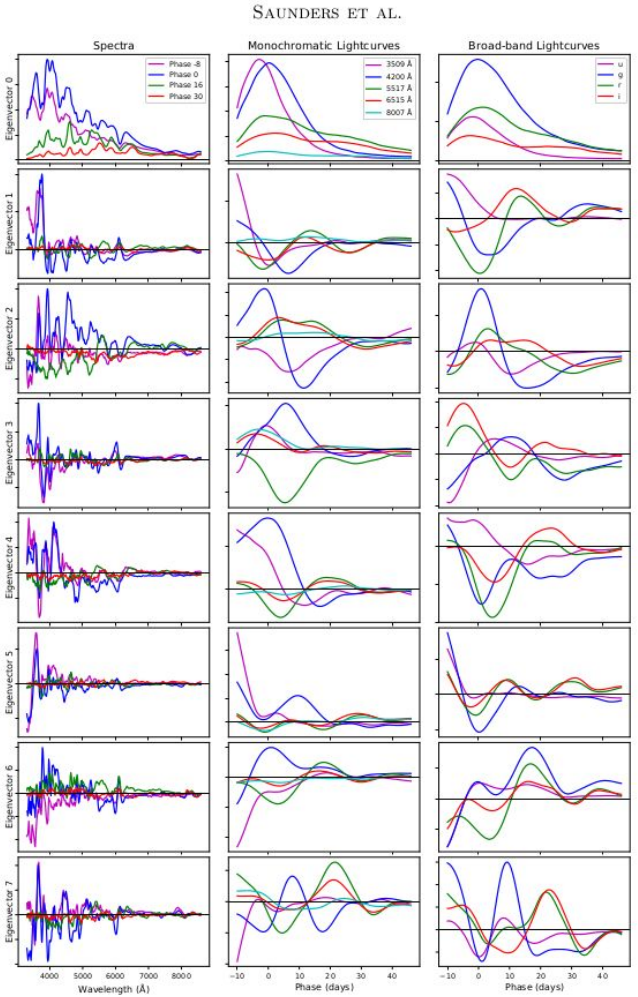
How to improve this standardization ?





SNEMO (Saunders et al)

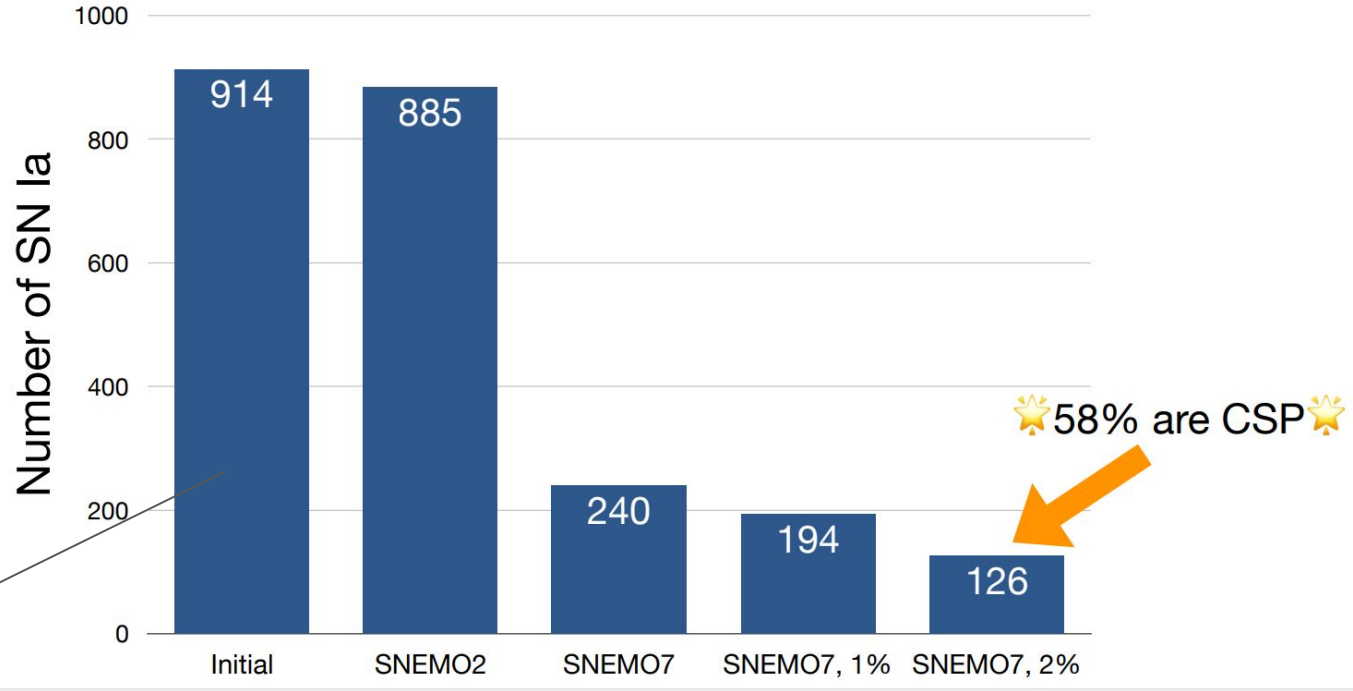
- Model based on Factor analysis on spectral times series from SNFactory
- Snemo family are models with N-component
- **SNEMO7** are the model where the unexplained dispersion is lowest



SNEMO7

Constraining Model Parameters

- SNEMO7 can't be used for high redshift data (need UV)

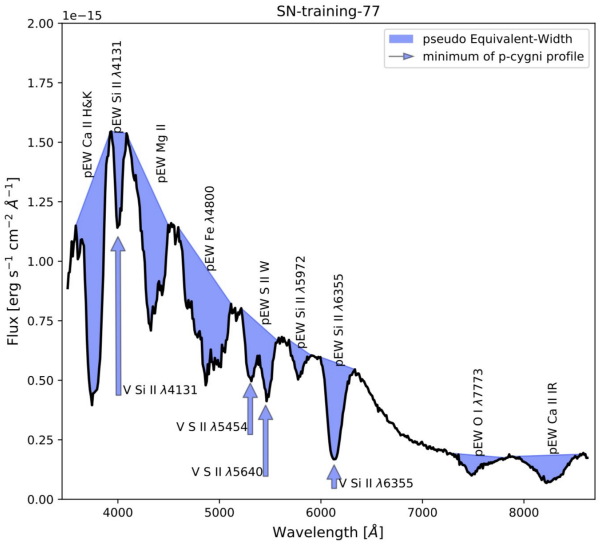


- CSP
- JLA
- Foundation

Benjamin Rose SCAM meeting october 2019

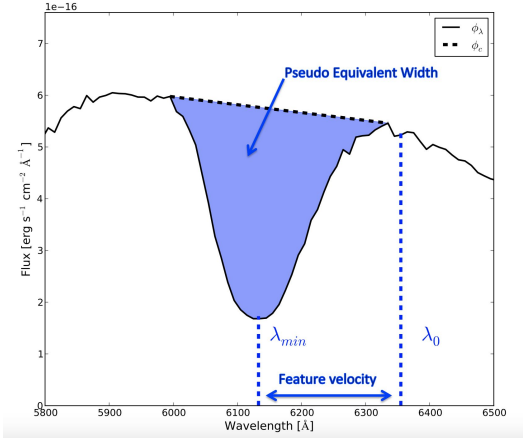
Spectral features describe SNIa variabilities

SUGAR



Spectral features of type Ia spectra :

- 9 Pseudo-equivalent width
- 4 P-cygni profile minima



Interest of spectral features :

- reduced dimensionality
- non linear estimator

Spectral features describe SNIa variabilities

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Spectral features of type Ia spectra :

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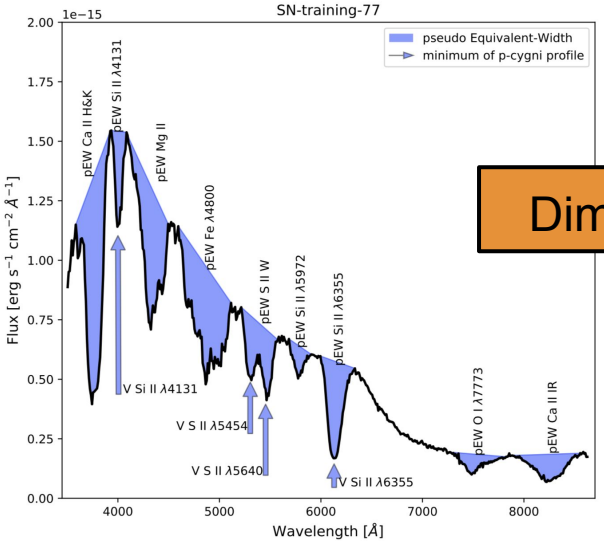
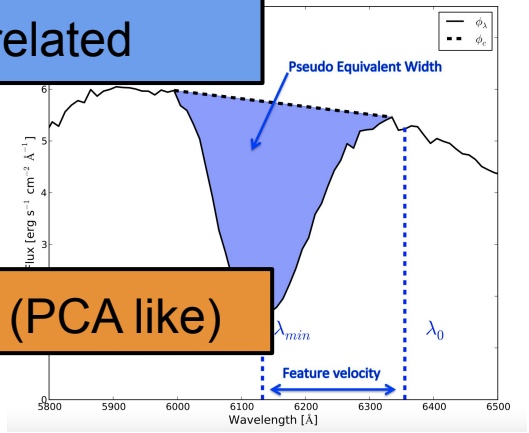
Features are highly correlated



Dimensionality reduction (PCA like)



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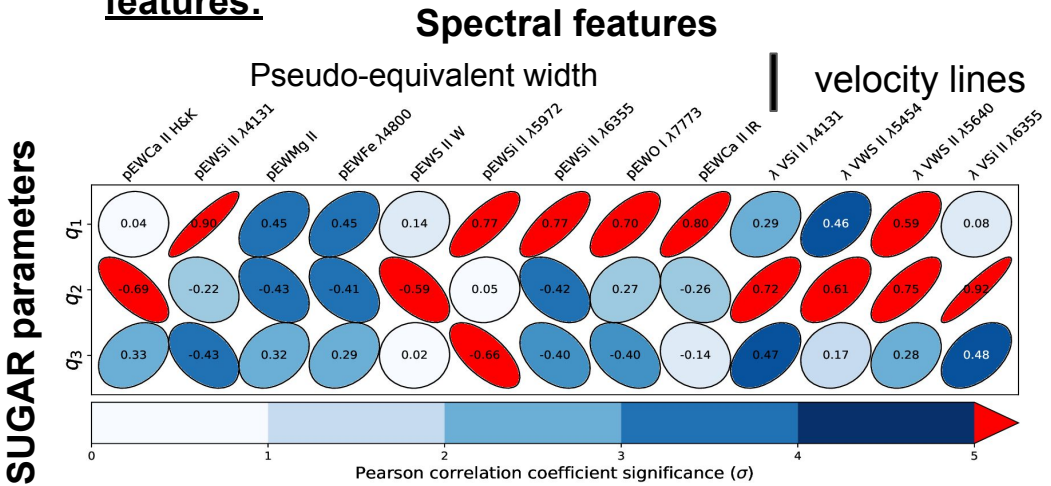
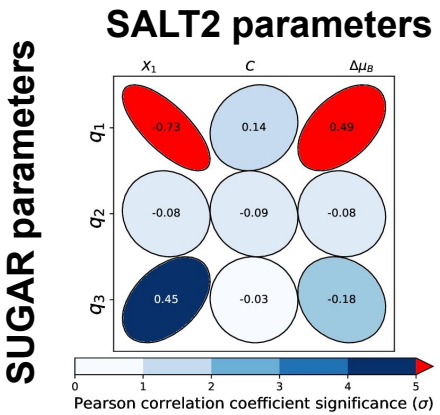
Factor analysis on spectral features

SUGAR

Correlation between PCA vectors and spectral features:



Correlation between PCA vectors and SALT2 parameters :



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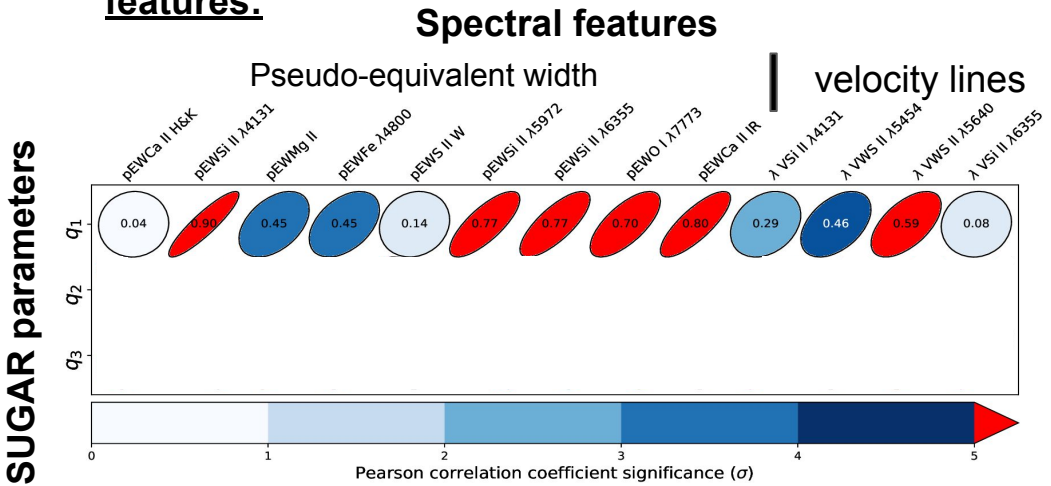

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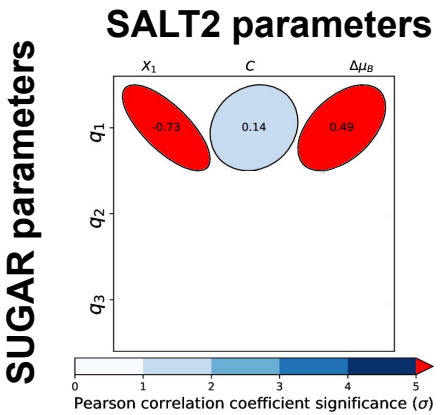

q1

- ~ pEW
- ~ Stretch, X1
- ~ Intrinsic color

Factor analysis on spectral features

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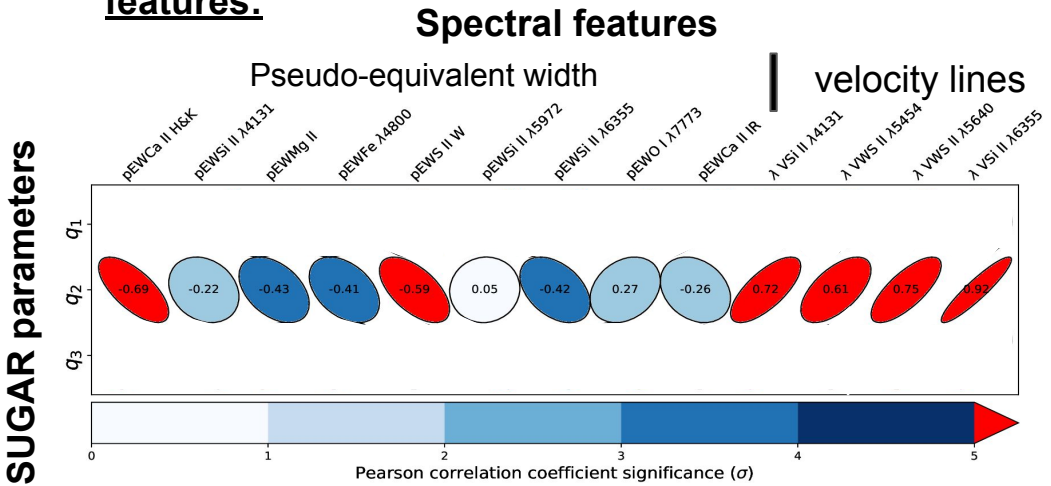

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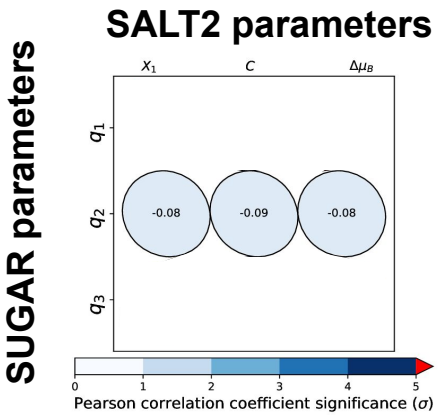

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q2

- ~ Velocities
- Impacts with infra-red
- Uncorrelated with X1, C

Factor analysis on spectral features

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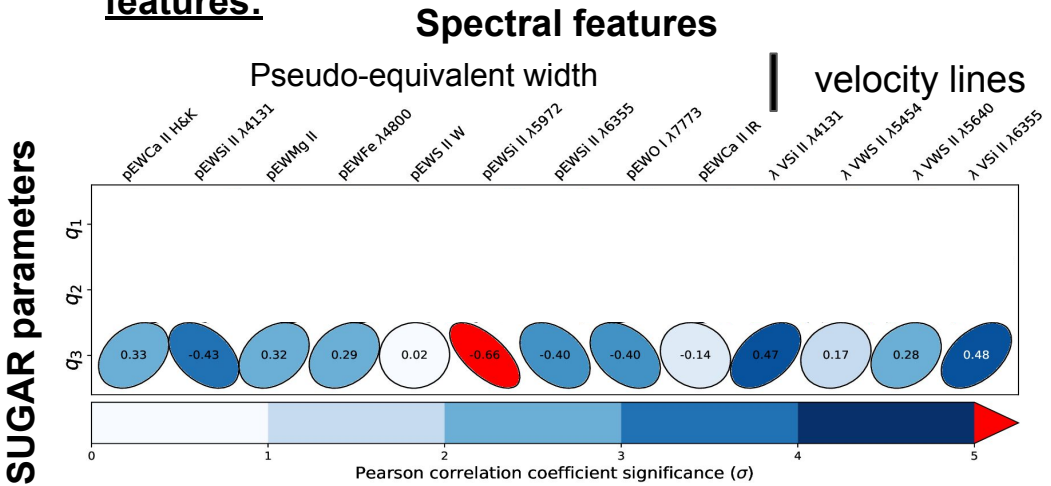

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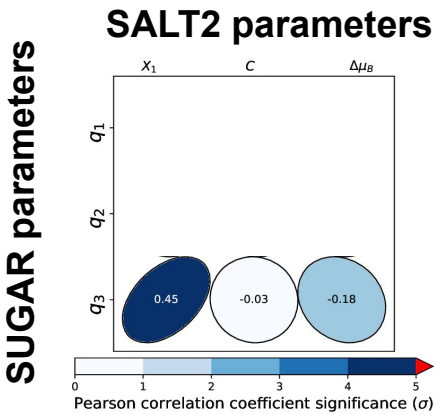
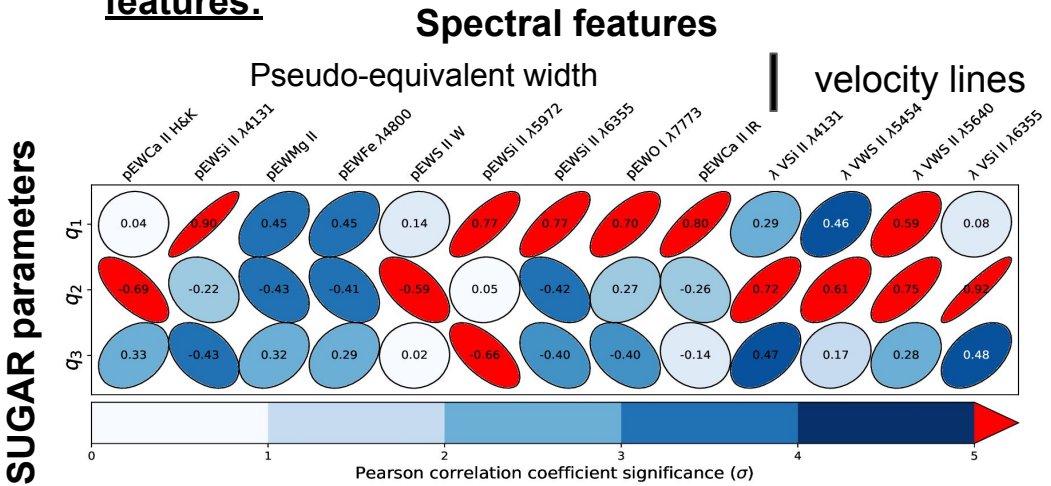


q1	q2	q3
● ~ pEW ● ~ Stretch, X1 ● ~ Intrinsic color	● ~ Velocities ● Impacts with infra-red ● Uncorrelated with X1, C	● Second stretch ● Little impact @ max light ● Play in light-curves width

Factor analysis on spectral features

SUGAR

Correlation between PCA vectors and spectral features:



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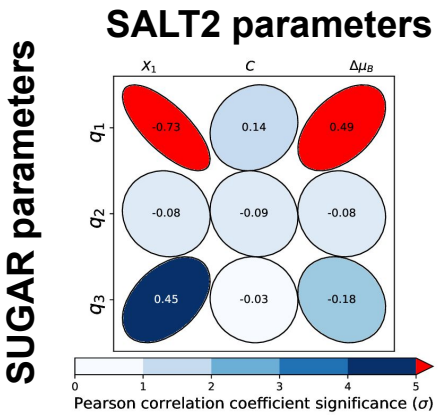

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q3

- Second stretch
- Little impact @ max light
- Play in light-curves width

SUpernova Generator And Reconstructor (SUGAR)

(Léget et al. 2019)

SUGAR equation :

$$M(t;\lambda) = M_0(t;\lambda) + \sum_{i=1}^{1=3} \alpha(t;\lambda) q_i + A_V f(\lambda; R_V) + \Delta M_{grey}$$

SUpernova Generator And Reconstructor (SUGAR)

(Léget et al. 2019)

SUGAR equation :

Model in magnitude

3 Intrinsic variabilities
(1 stretch for SALT2)

Grey offset
(X0 for SALT2)

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Average spectrum

Cardelli law
(Color law for SALT2)

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(Color law for SALT2)

SUGAR training :

trained with 105
time series spectra
from SNfactory

- Dimentionality reduction (PCA ~like)
- Estimation of the extinction law
- Interpolation of spectra (Gaussian Processes)
- Global SED fitting (orthogonal distance regression)

SUGAR Model
http://supernovae.in2p3.fr/sugar/
Léget et al. 2019 (A&A)
https://arxiv.org/abs/1909.11239

Hubble fit with SNf data

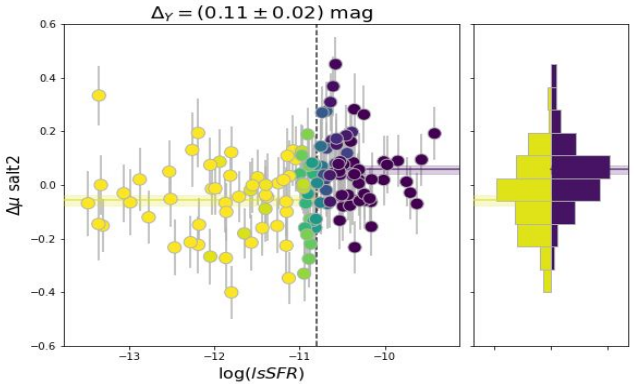
SALT2 standardization :

$$\mu_{salt2} = m_B^* - M_B - \alpha x_1 - \beta c$$

SUGAR standardization :

$$\mu_{sugar} = m_B^* - M_B - \sum_{i=1}^{3} \alpha_i q_i - \beta A_v$$

Correlation with host properties (LsSFR):



	LsSFR step
SALT2 UBVRI	(0.11 ±0.02) mag

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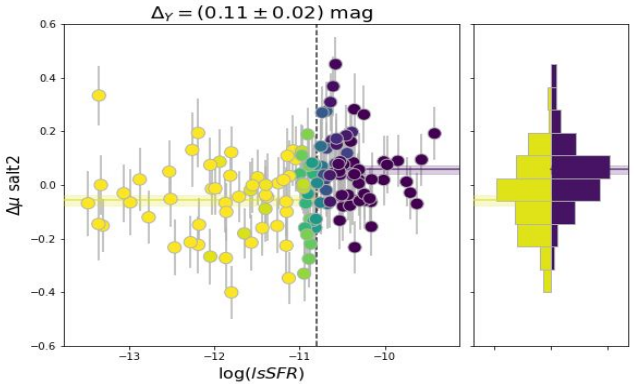
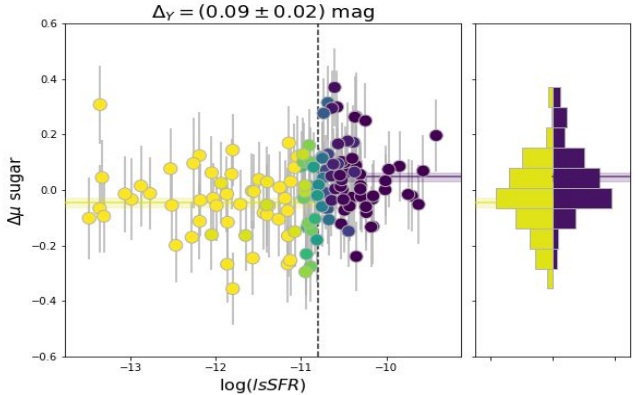




	LsSFR step
SALT2 UBVRI	(0.11 ± 0.02) mag
SUGAR UBVRI	(0.09 ± 0.02) mag

SUGAR gives small decrease of LsSFR step (need confirmation on other data set)

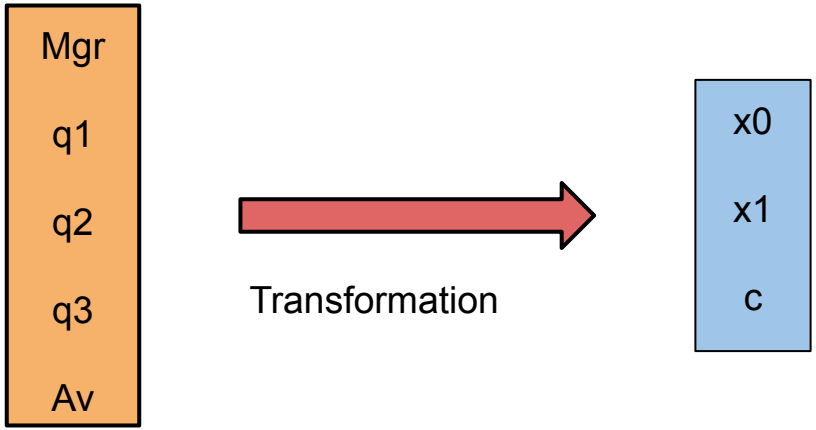
Extension of SUGAR in the UV

- SUGAR was trained with nearby SNIa (z < 0.08)
- SUGAR start at 3200 A restframe

Use SALT2 in the UV part

Sugar parameters :

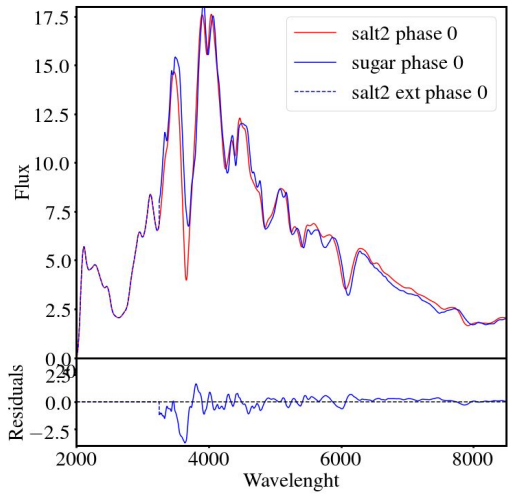
Salt2 parameters :

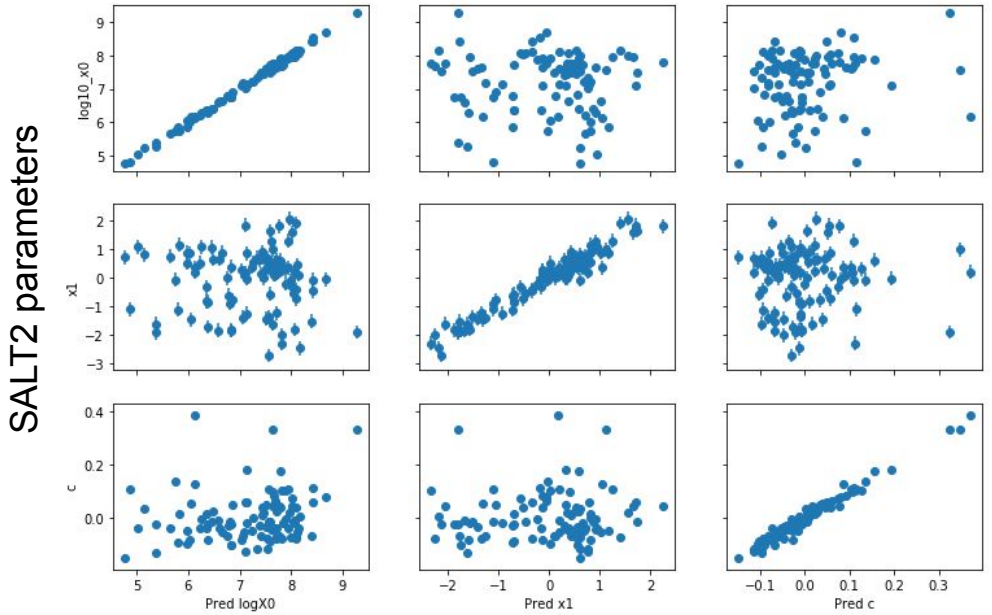


- Train this transformation matrix on SNf data.
- Implementation of this transformation in sncosmo

SNLS Light curves fitting with SUGAR

SALT2 correspondence spectrum for SUGAR average spectrum :

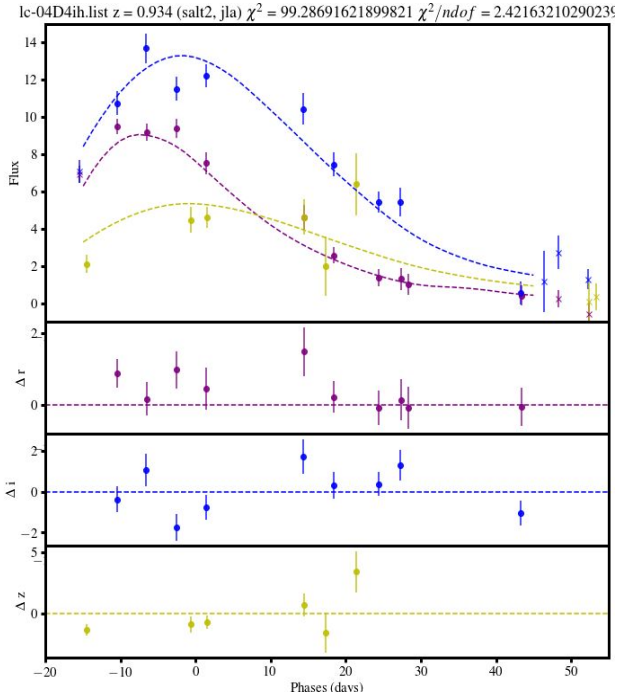




Predicted SALT2 parameters from SUGAR

SNLS Light curves fitting with SUGAR

Light curve fit with SALT2 :



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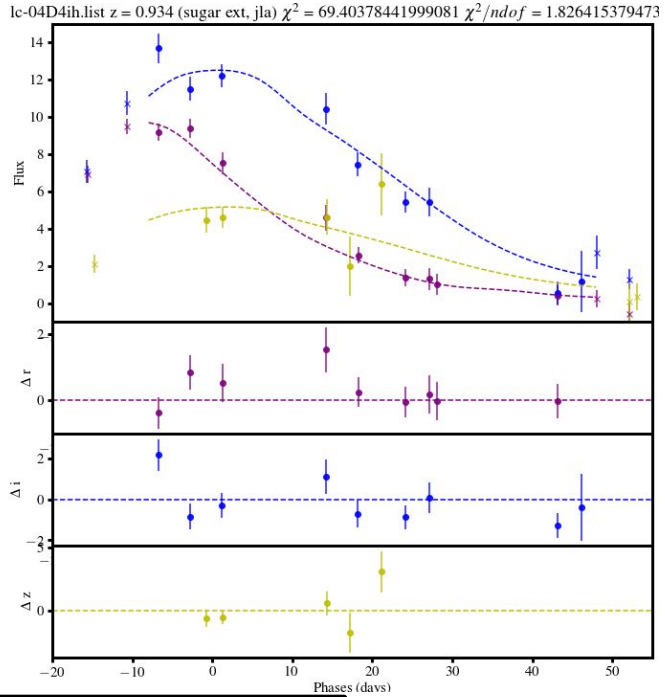
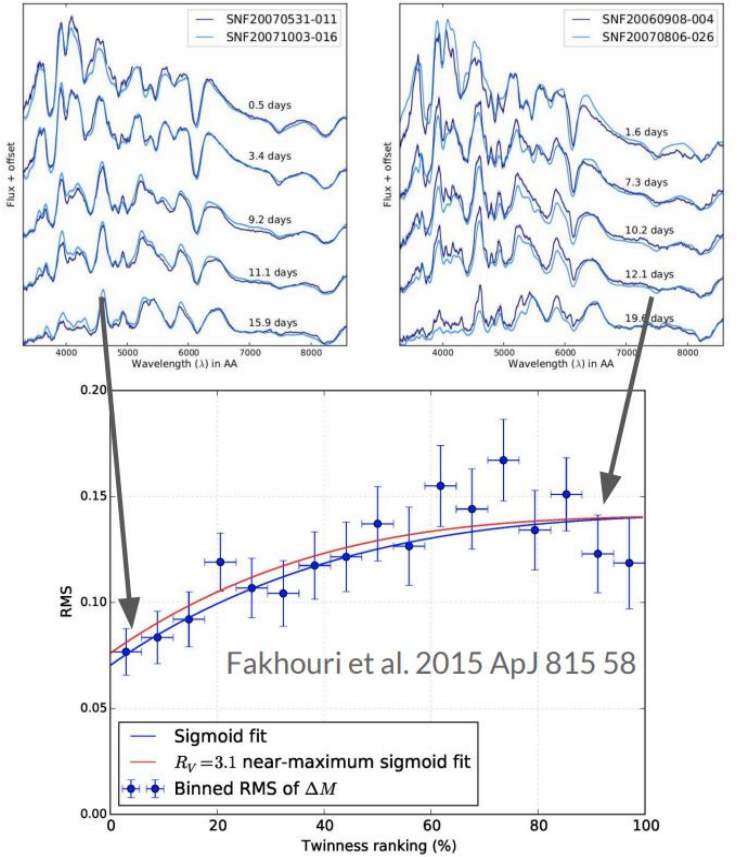


The mean of Chi2 per dof for SALT2 in SNLS sample is 2.72 and go to 1.86 for SUGAR

Use Supernova Twins for Improved Distances to Type Ia Supernovae

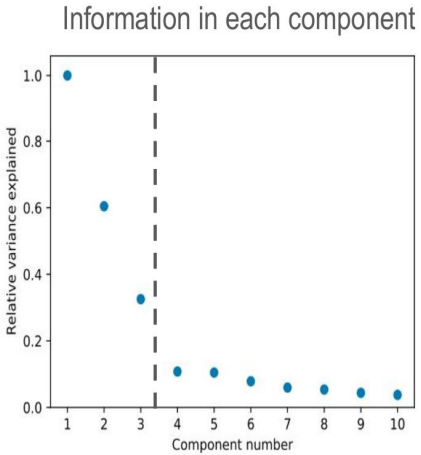
- Define as two SNIa with them spectral time series match at all wavelength
- Using twin supernovae, allow to standardize supernovae to 0.08 mag
- Statistic limited



Manifold Learning for Improved Distances to Type Ia Supernovae

- Method to take into account nonlinearity based on manifold
- Standardizes SNIa to 0.076 mag and reduces the correlation with host galaxy properties

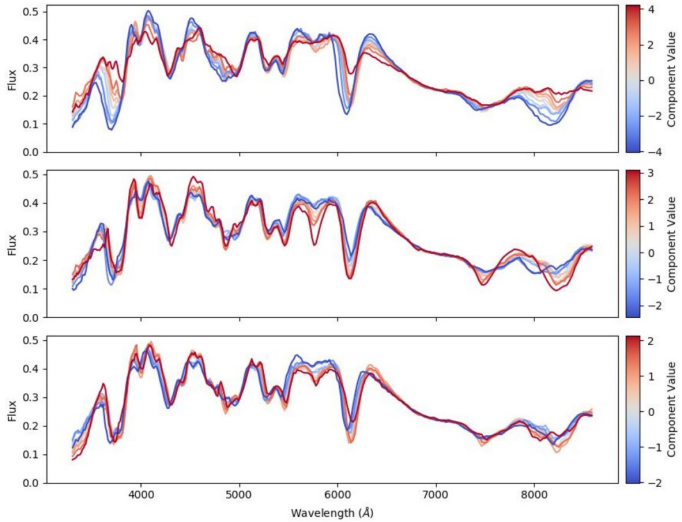
A 3-dimensional nonlinear manifold can explain the diversity of SNe Ia at maximum light.



Component 1
⇒ CaII variation

Component 2
⇒ SiII variation

Component 3
⇒ ejecta velocity



Summary of Kyle Boone slides DESC collaboration meeting winter 2020

Manifold Learning for Improved Distances to Type Ia Supernovae

- Method to take into account nonlinearity based on manifold
- Standardizes SNIa to 0.076 mag and reduces the correlation with host galaxy properties

SUGAR parameters look similar to the component of Kyle manifolds methods

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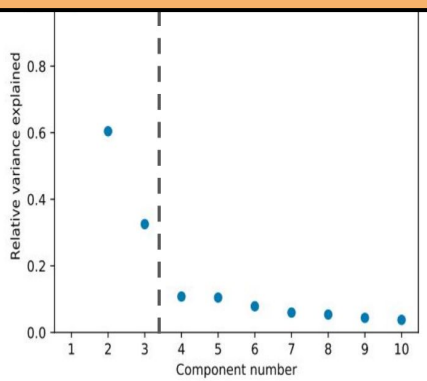
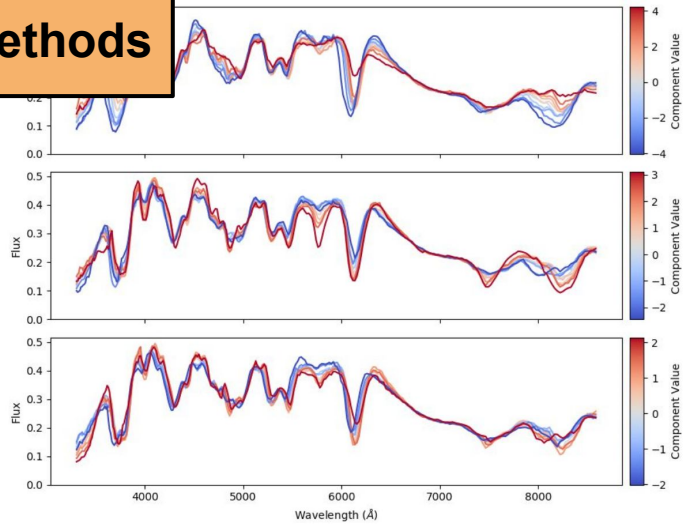


Component 2
⇒ SiII variation

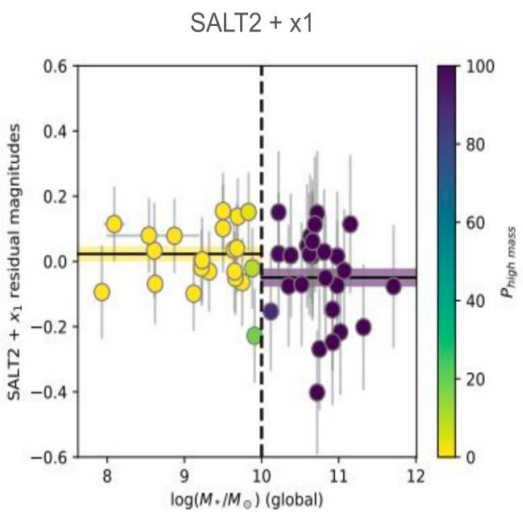
Component 3
⇒ ejecta velocity



Summary of Kyle Boone slides DESC collaboration meeting winter 2020

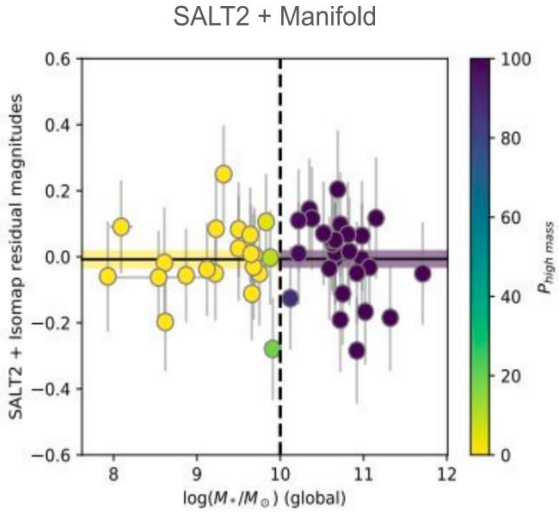
Manifold Learning for Improved Distances to Type Ia Supernovae

Before correction, have correlations with host galaxy properties.



* only half of sample. Holding back rest for validation.

After correction, host galaxy correlations decrease!



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Summary

	Strengths	Weaknesses
SALT2	• Well establish model	• reusability of the training code
SUGAR	• Based on nonlinear estimator	• UV extinction (in construction) • error model (in construction)
SNEMO7	• Details description of SNIa variabilities	• Same than SUGAR • To many parameters for a photometric fit
Twins	• Promised idea	• Required spectra • Limited statistic
Manifolds	• Take into account nonlinearity	• Applicability to a full cosmological analysis?