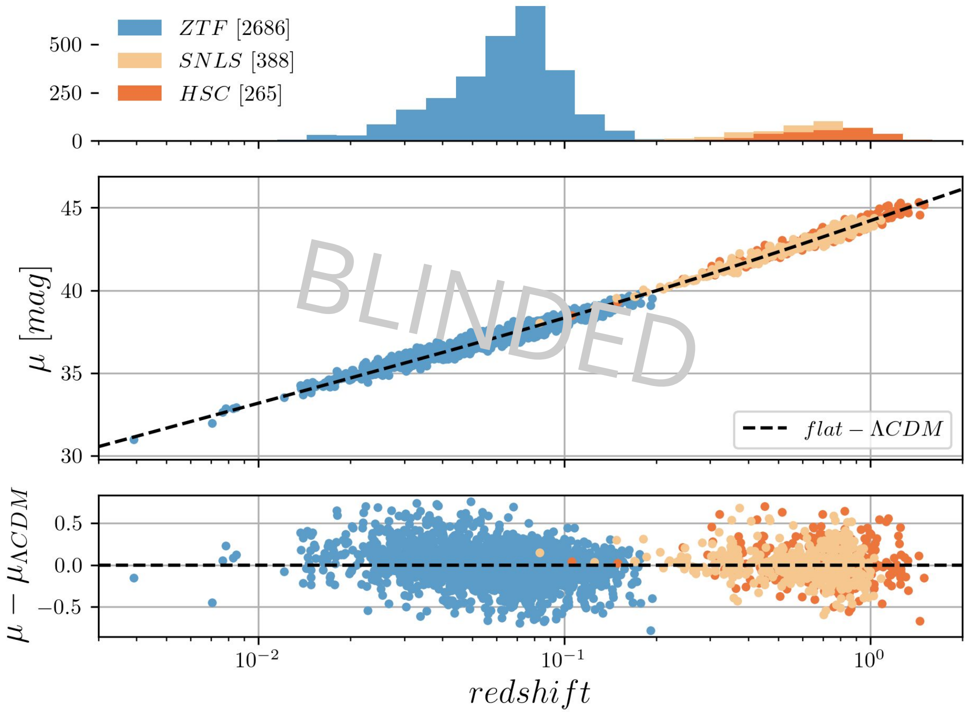
Towards an independent measurement of Dark Energy's equation of state from a novel set of SNeIa

Cosmological inference in Lemaitre

Dylan Kuhn, October 29th 2024
on behalf of the Lemaitre collaboration

The blinded Lemaitre (Hubble) diagram



- Independent analysis
- 12 photometric bands
- Strong statistical power with 3 new surveys

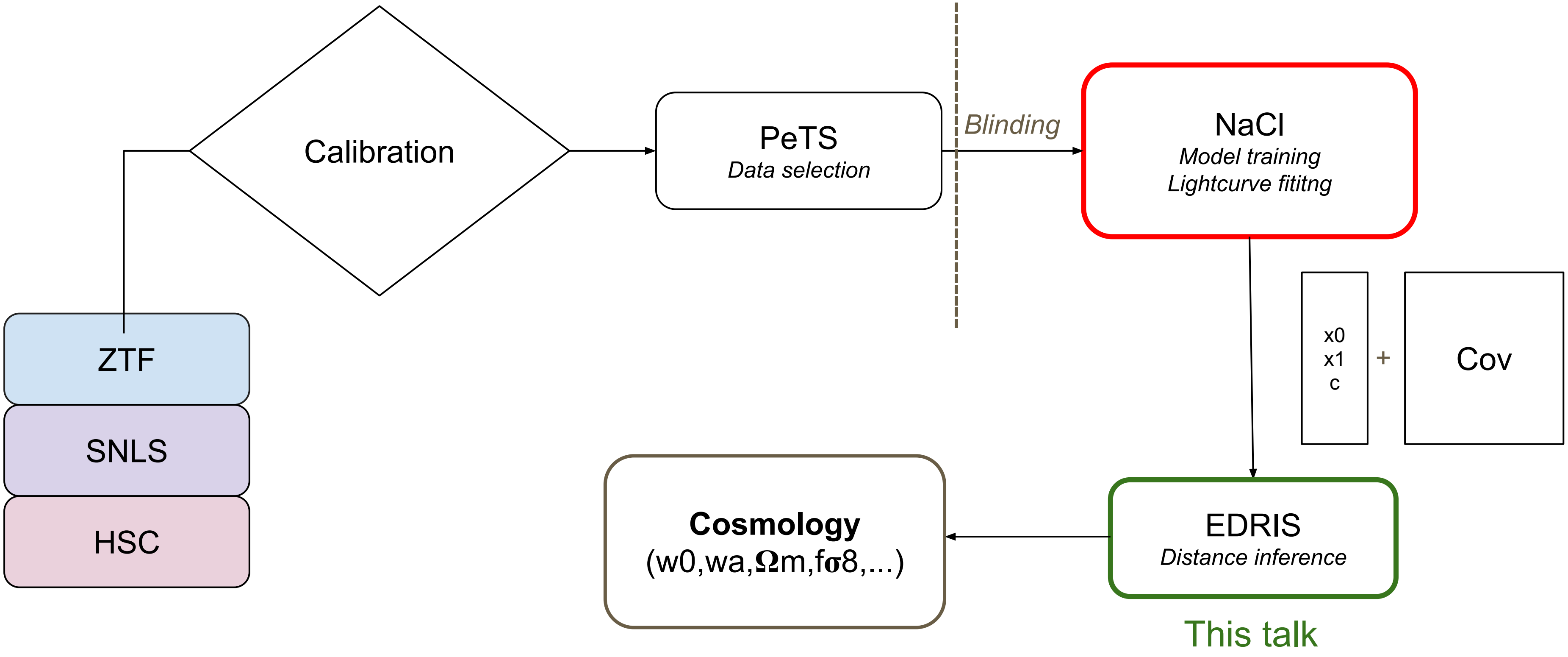
  source: Rubin et al., 2024 ; DES collaboration, 2024

  → $\sigma(\Omega_m)_{forecast}$ = 0.011 [stat]

  → $\sigma(\Omega_m)_{UNION3}$ = 0.028 [stat+syst]

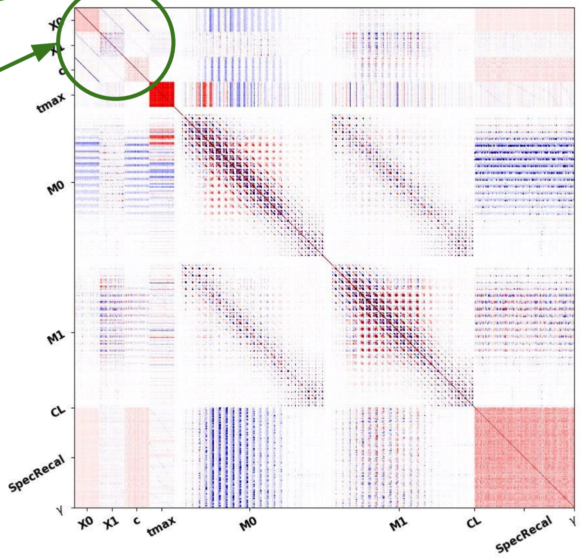
  → $\sigma(\Omega_m)_{DES\text{-}SN5yr}$ = 0.017 [stat+syst]
- _Goal:_ independent assessment of the w0wa tension, simplify inference process, enhance reproducibility of the results

The Lemaitre analysis pipeline



Cosmological inference

$$\begin{bmatrix} x_0 \\ x_1 \\ c \\ t_{max} \\ M_0 \\ M_1 \\ CL \end{bmatrix}$$



1- Standardization

$$\mu(z,\theta) = -2.5\log_{10}(x_0) - M + \alpha x_1 + \beta c$$

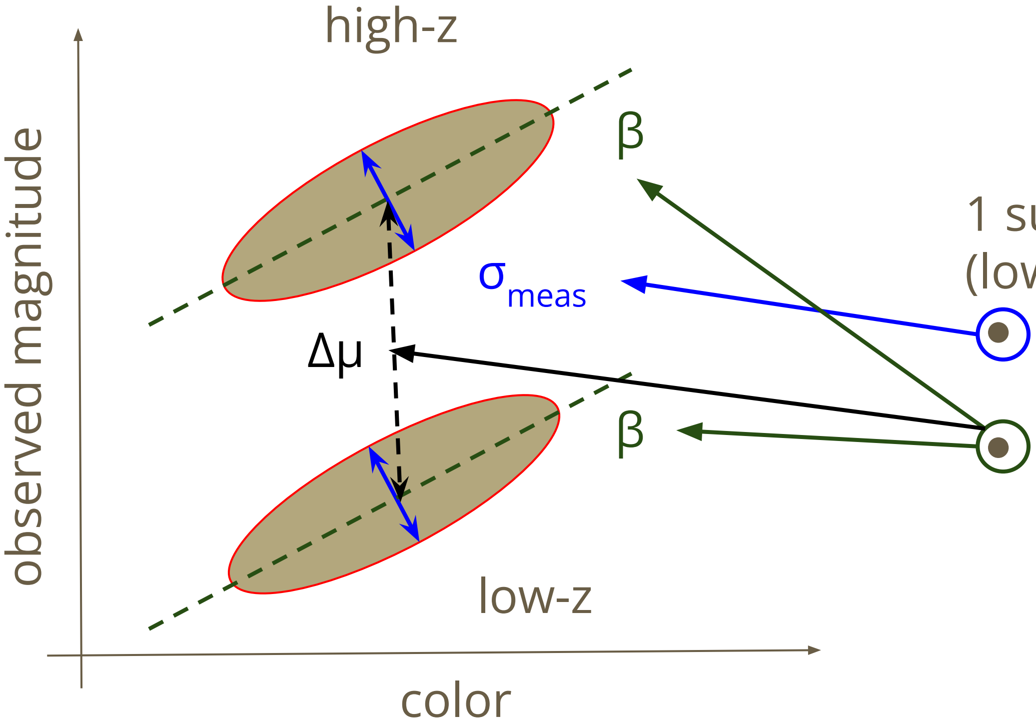
~45% dispersion at max

~15% dispersion at max

2- Estimation of residual dispersion σ

3- Estimation and correction of intrumental selection bias Δμ(σ)

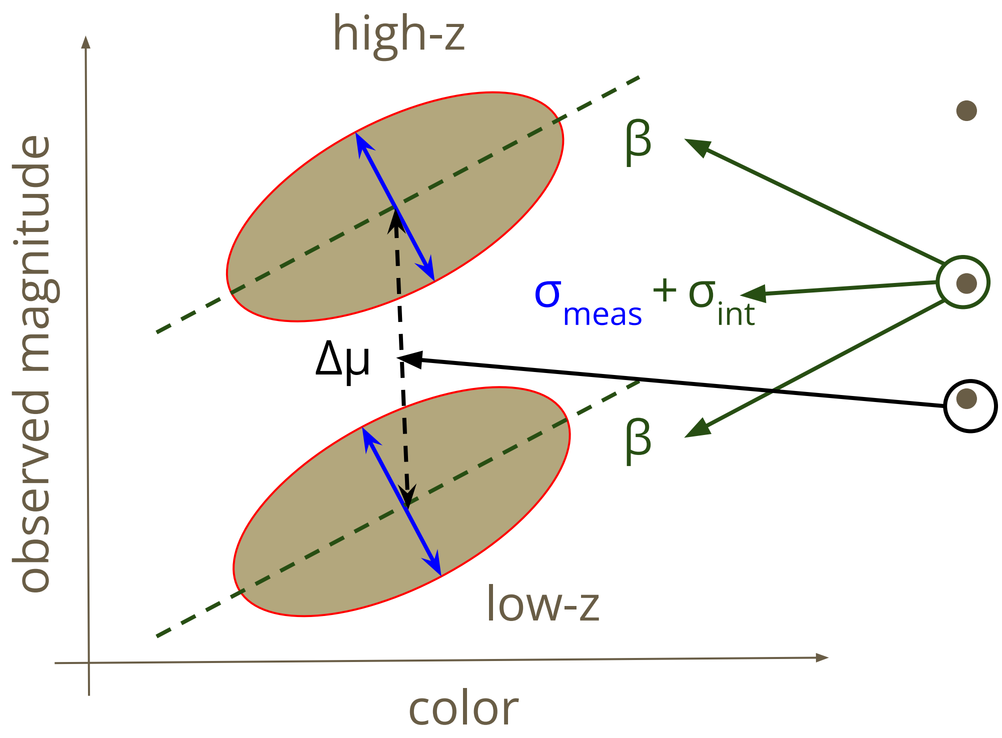
Instrumental selection bias: the “Malmquist bias”



1 survey, 2 populations (low-z, high-z)

- known measurement noise
- *estimation* of β, Δμ

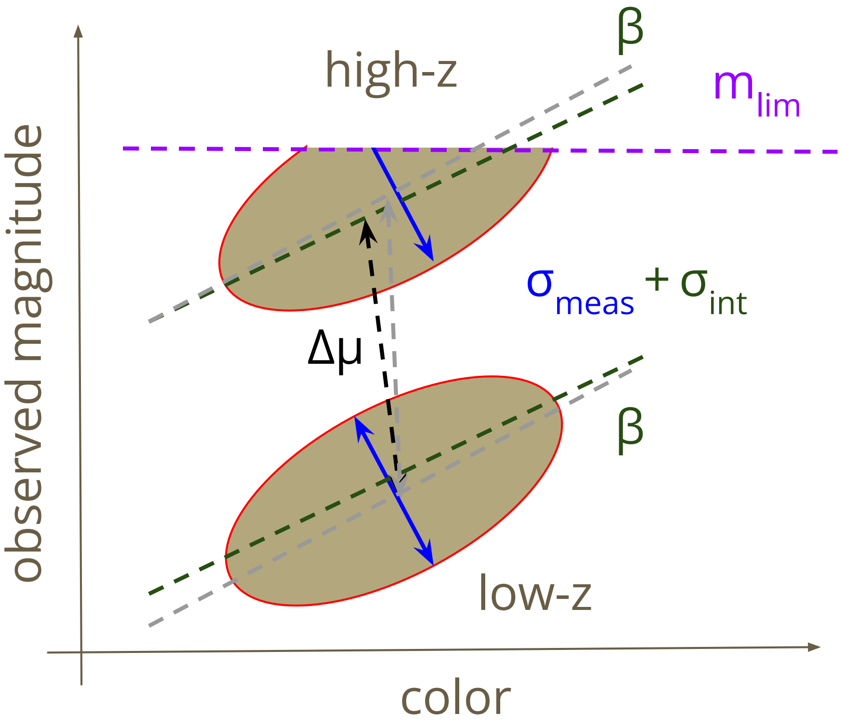
Instrumental selection bias: the “Malmquist bias”



- known measurement noise
  + *intrinsic noise*
  biased estimation of β, σ_{int}
  estimation of Δμ

Not well defined problem but cosmology does not change

Instrumental selection bias: the “Malmquist bias”



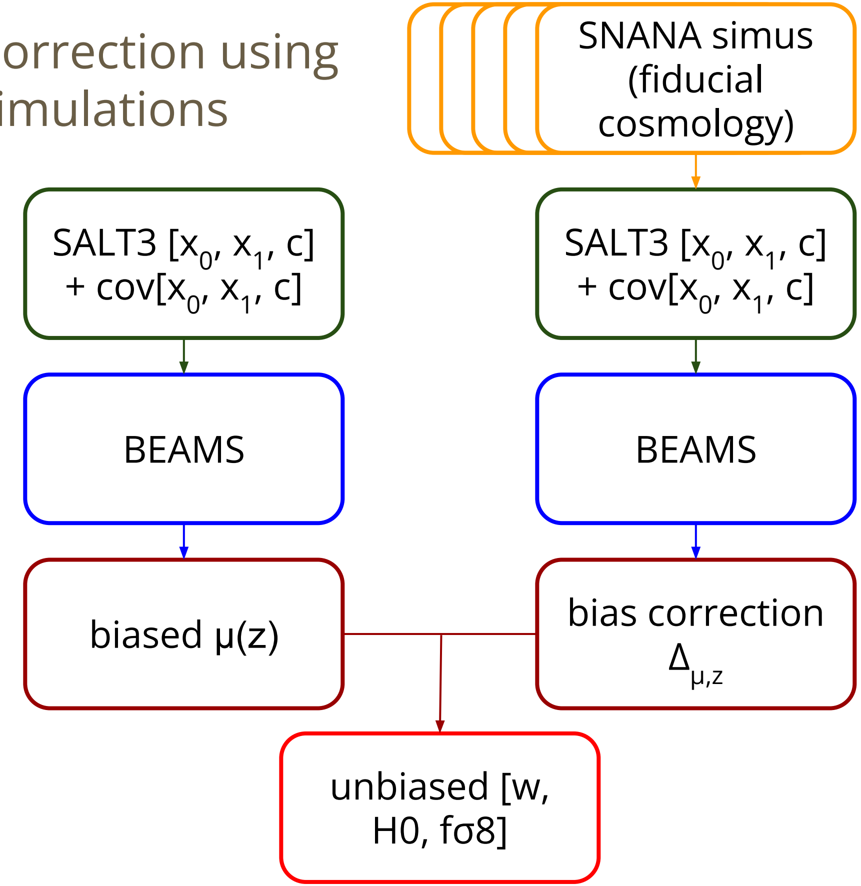
In practice, only the *intrinsically brightest supernovae* are detected:

- *truncation of data* by m_{lim}
- *biased* estimation of β, σ_{int}, Δμ

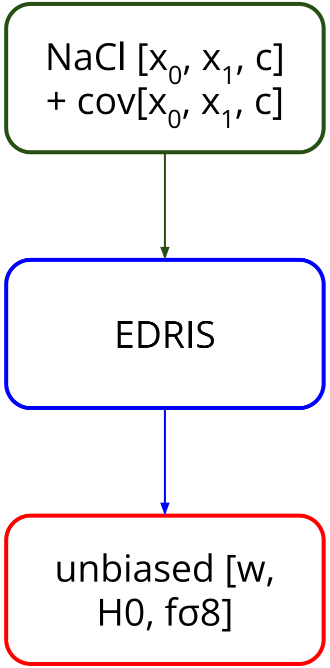
Not well defined problem and cosmology is biased by truncation

How to tackle this issue

Correction using simulations



Account for the selection effects in the statistical model



Our approach: NaCl + EDRIS

EDRIS:

- cosmology from NaCl [x_0, x_1, c]
- includes selection in statistical model

$$m_{obs,i} = m_{obs,i}^{*} + \eta_i \text{ if } m_{obs,i}^{*} \leq m_{lim} + \kappa_i$$

$$\text{with } \eta_i \sim \mathcal{N}(0, C_i) \text{ and } \kappa_i \sim \mathcal{N}(0, \sigma_{m_{lim}}^{2})$$

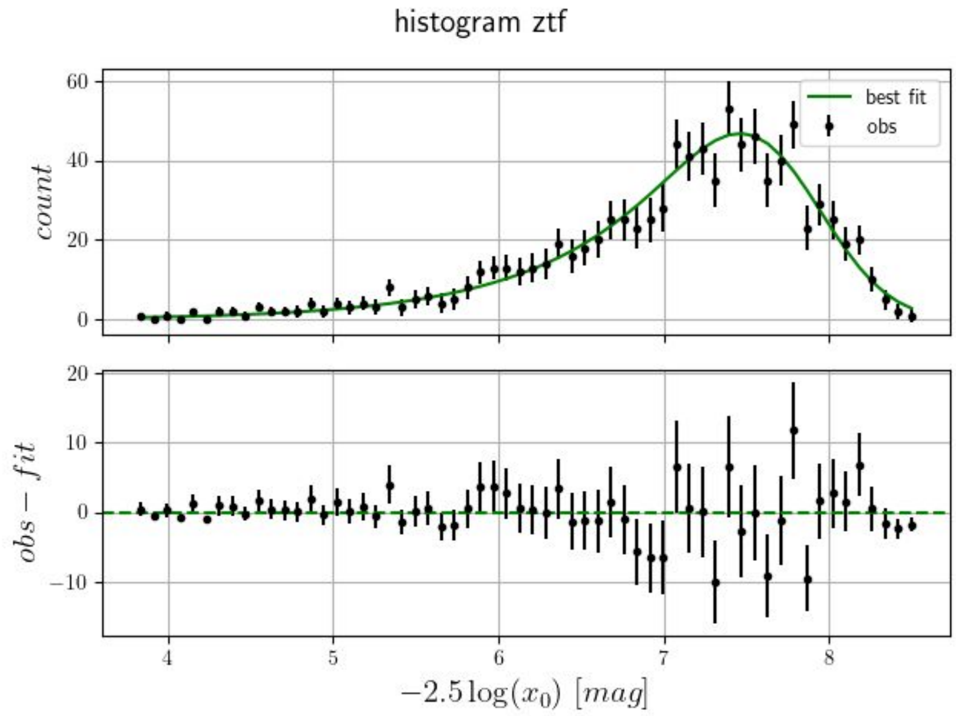
$$m_{obs,i} \text{ is unobserved otherwise}$$

Two-step estimator:

- estimation of the selection functions [m_{lim}, σ_{mlim}] from m_{obs} histograms
- standardization & estimation of distances

Estimation of the selection function

Estimation of [m_{lim}, σ_{mlim}] for each survey from observed magnitudes histogram



Estimation of the selection function

Density of SNeIa

$$\rho(z,m) = R\frac{\partial V_c}{\partial z}(z)\,\Phi\left(\frac{m - m_{lim}}{\sigma_{m_{lim}}}\right)\frac{1}{\sqrt{2\pi}\sigma_m}e^{-\frac{1}{2}\left(\frac{m-\mu(z)-M}{\sigma_m}\right)^2}$$

SNeIa rate (supposed constant)

Gaussian CDF

$$\sigma_m = \sqrt{\sigma^2 + \alpha^2\sigma_{x_1}^2 + \beta^2\sigma_c^2}$$

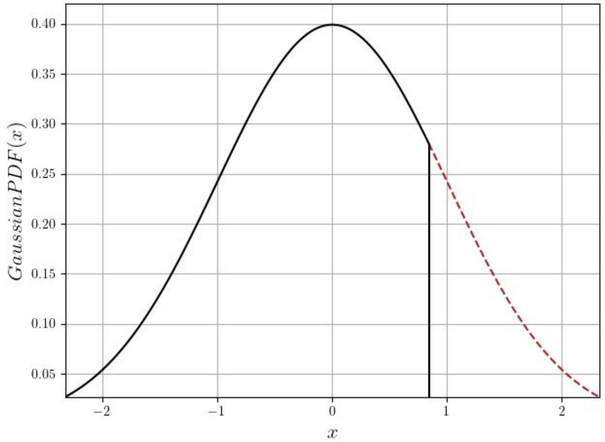
Number of SNeIa in a bin

$$N_b = \int_0^\infty \int_{m_b}^{m_{b+1}} \rho(z,m)\,\mathrm{d}z\,\mathrm{d}m$$

Poisson likelihood maximization

$$\mathscr{L}_{selection} = \prod_i \frac{N_{b,i}^{N_{obs,i}}}{N_{obs,i}!}e^{-N_{b,i}}$$

Standardization & estimation of distances



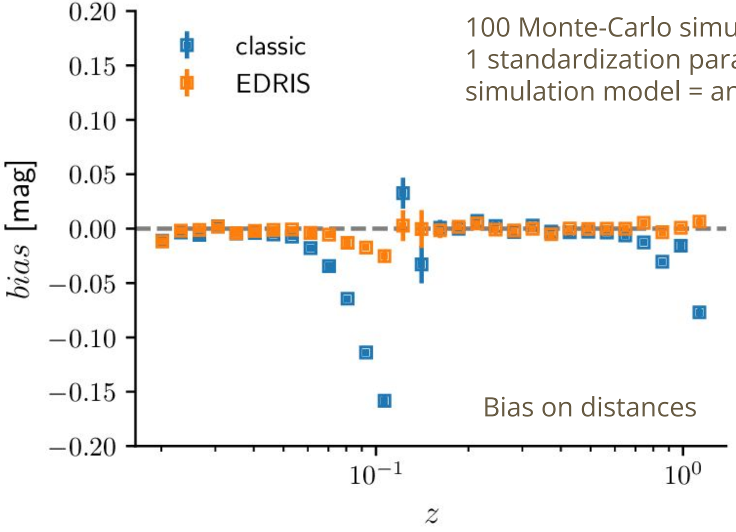
term that takes into account the truncation of data

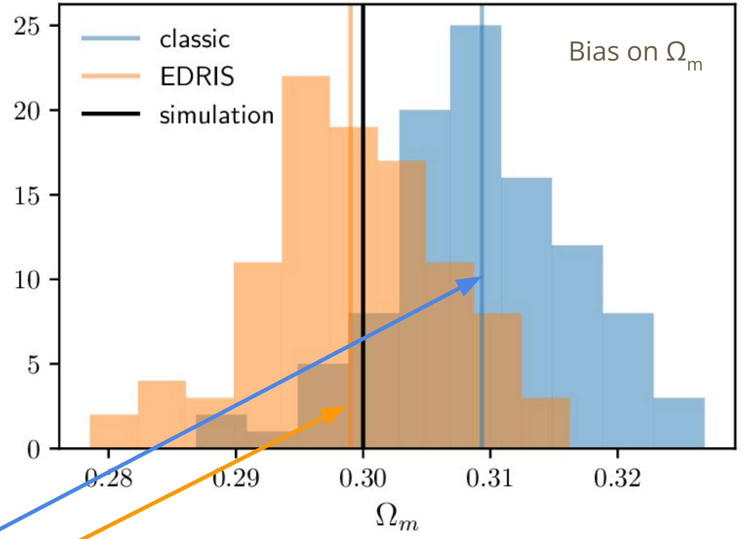
classic likelihood for multivariate normal distributions

$$\Gamma = -\ln\left(\left|C(\sigma)^{-1}\right|\right) + r^t C(\sigma)^{-1} r + \sum_i 2\ln\left(\Phi\left(\frac{m_{lim} - M^* - \mu_i - \alpha x_{1,i}^* - \beta c_i^*}{\sqrt{\sigma^2 + \sigma_{m_{lim}}^2}}\right)\right) - 2\ln\left(\Phi\left(\frac{m_{lim} - m_{obs,i}}{\sqrt{\sigma_{m_{lim}}^2 + f(C_i)}}\right)\right)$$

$$with\ \Phi(z) = \frac{1}{2}\left(1 + \text{erf}\left(\frac{z}{\sqrt{2}}\right)\right)\ and\ r = m_{obs} - M^* - \mu - \alpha x_1 - \beta c$$

Bias on distances and cosmological parameters

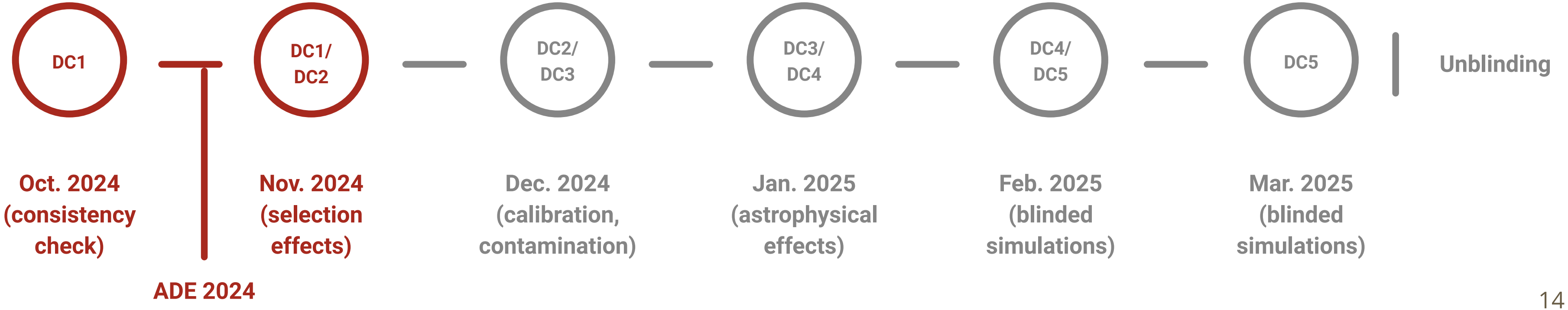




Estimator	Bias on Ω_m	Mean of reconstructed Ω_m	$\sigma(\Omega_m)$
classic	0.0093 ± 0.0007	0.309	0.007
EDRIS	-0.0010 ± 0.0007	0.299	0.007

End-to-end validation on simulations: data challenges

- 5 data challenges towards data unblinding
- Increasing complexity and realism
- Pipeline extensively tested through continuous integration
- After pipeline validation, no need for simulations anymore



Goals achieved by data challenges

- Ensuring that the inference pipeline can reconstruct unbiased cosmology taking into account several effects:

  - correlated uncertainties

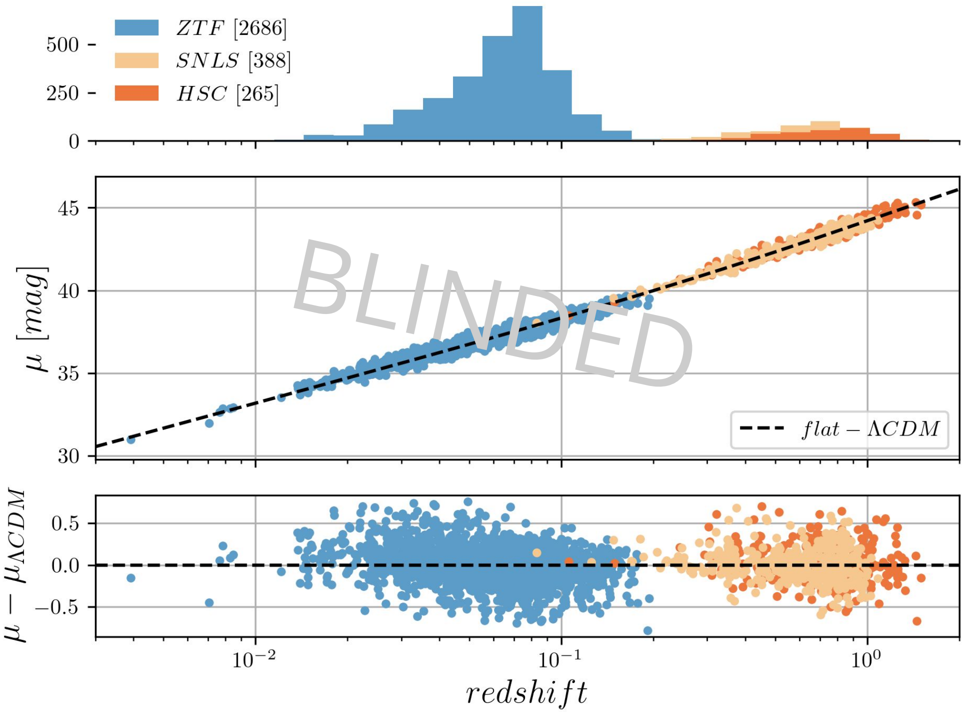
  - realistic selection functions

  - foregrounds (dust, lensing, etc)

  - increasingly complex evolution effects

- Ensuring that the error on cosmological parameters incorporates all sources of uncertainties: calibration, measurement, model, color scatter, etc

Take-home message

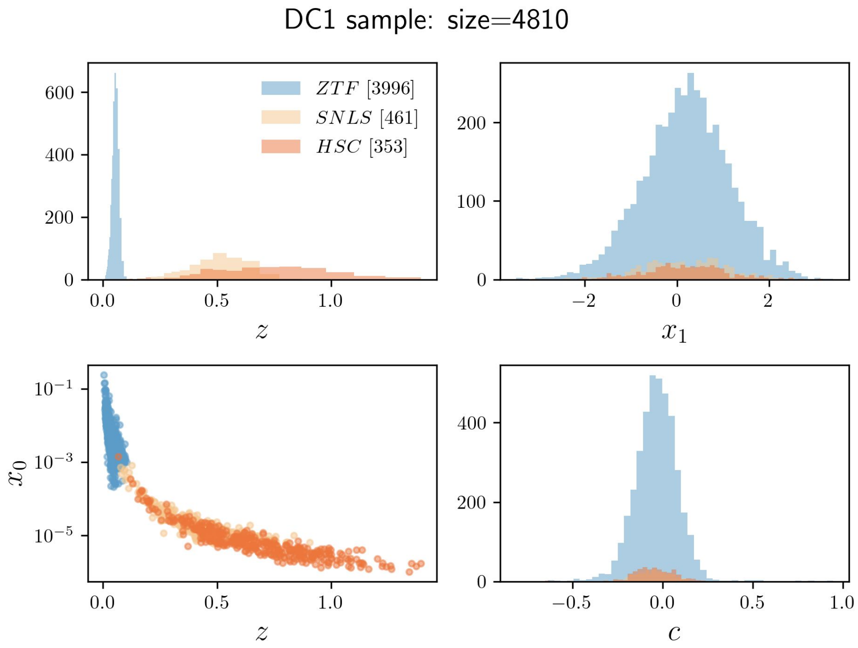


- Lemaitre: new independent measurement of w, fσ8, H_0
- new inference chain (simulation-free)
- both NaCl and EDRIS show promising results on consistency checks
- 5 Data Challenges towards data unblinding (mid-2025)

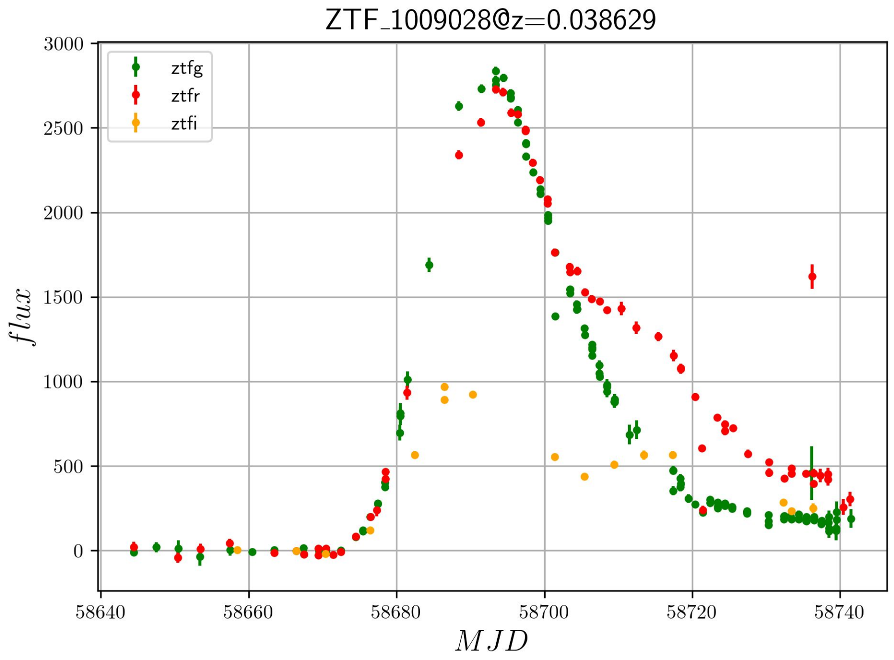
Back-up slides

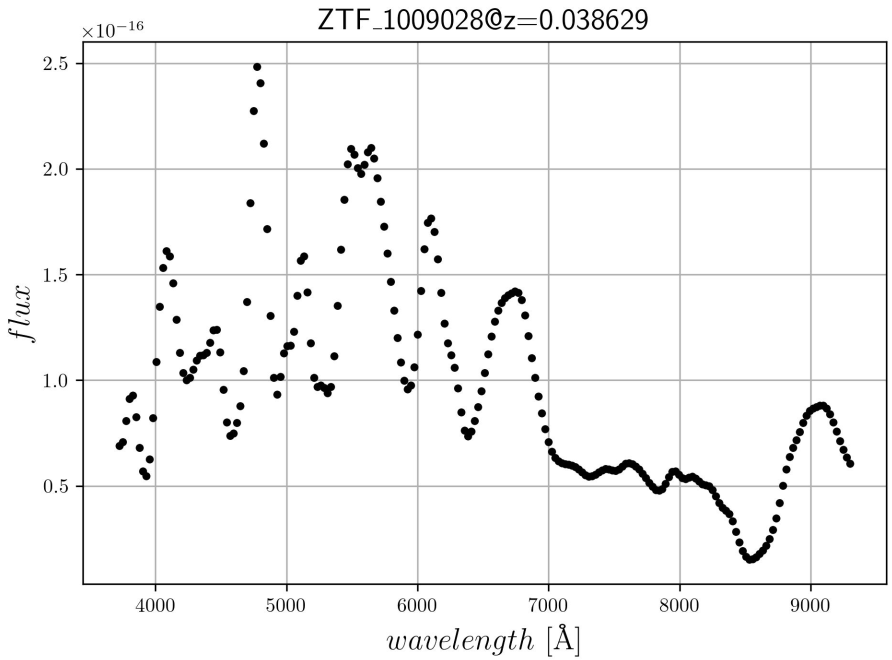
Data challenge 1: ideal simulations

- *Goal:* consistency test of the chain
- Lemaitre sampling (real observation logs)
- Realistic measurement errors for light-curves and spectra
- 100 noise realizations

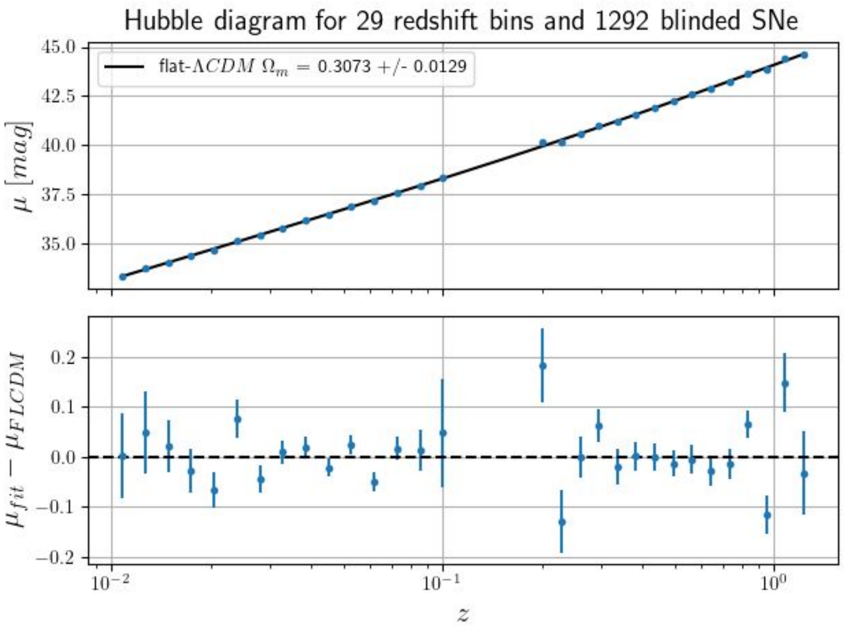


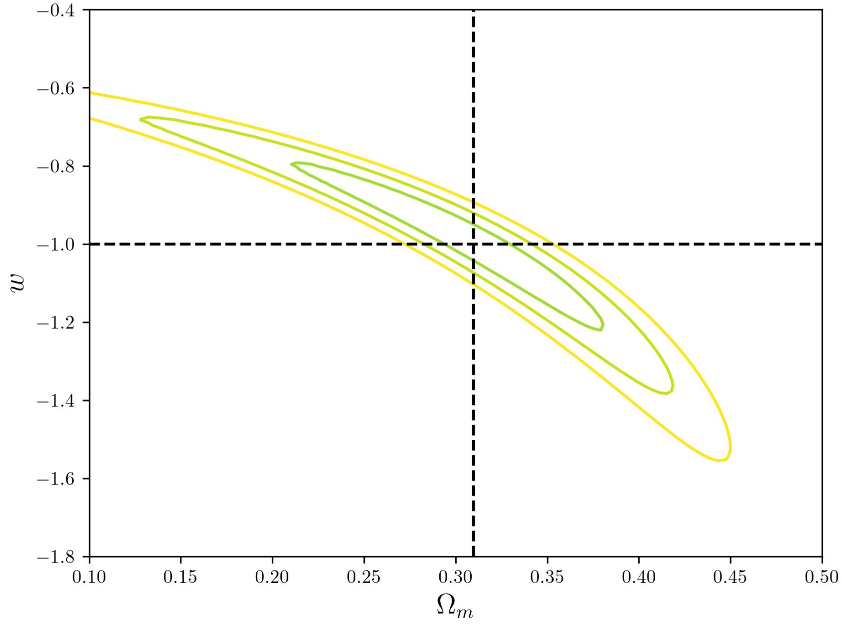
Example of simulated SNeIa





Binned hubble diagram and Ω_m-w contours





Novelties in next data challenges

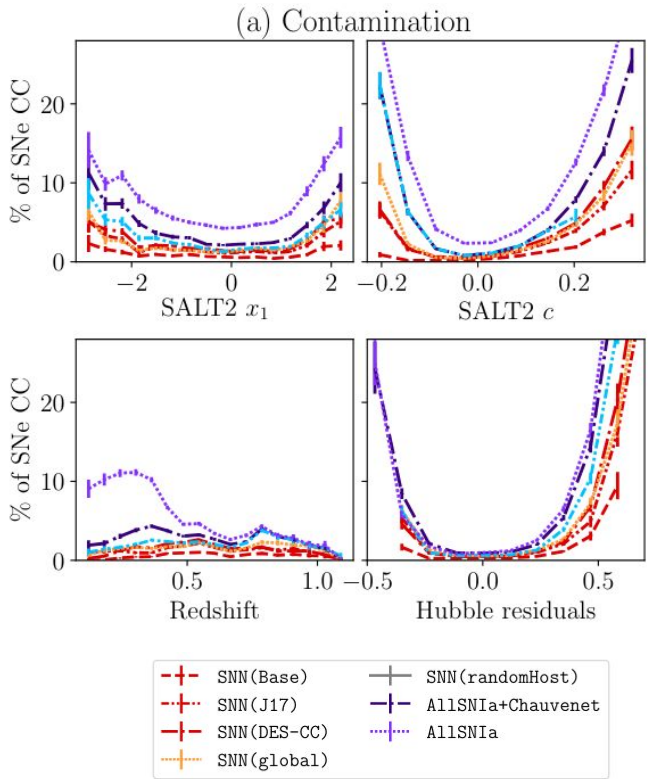
source: Vincenzi et al., 2021

- Data challenge 2:

  Adding selection effects to all samples

- Data challenge 3:

  Adding calibration uncertainties + modeling of contamination



Novelties in next data challenges

source: Ginolin et al., 2024a

- Data challenge 4:

  Adding astrophysical effects (cf. Madeleine's talk)

- Data challenge 5:

  Blinded simulations

Final goal: Lemaitre **unblinding** on real data between **March-May 2025**