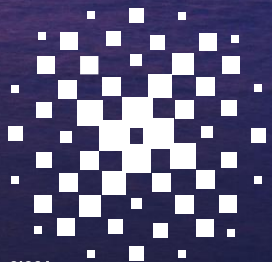


SICRET:
Supernova Ia Cosmology
with
(TMN) Ratio EsTimation

[arXiv:2209.06733](https://arxiv.org/abs/2209.06733) & the near future

Image: personal archive



SISSA
DATASCIENCE
Machine Learning for the Natural Sciences

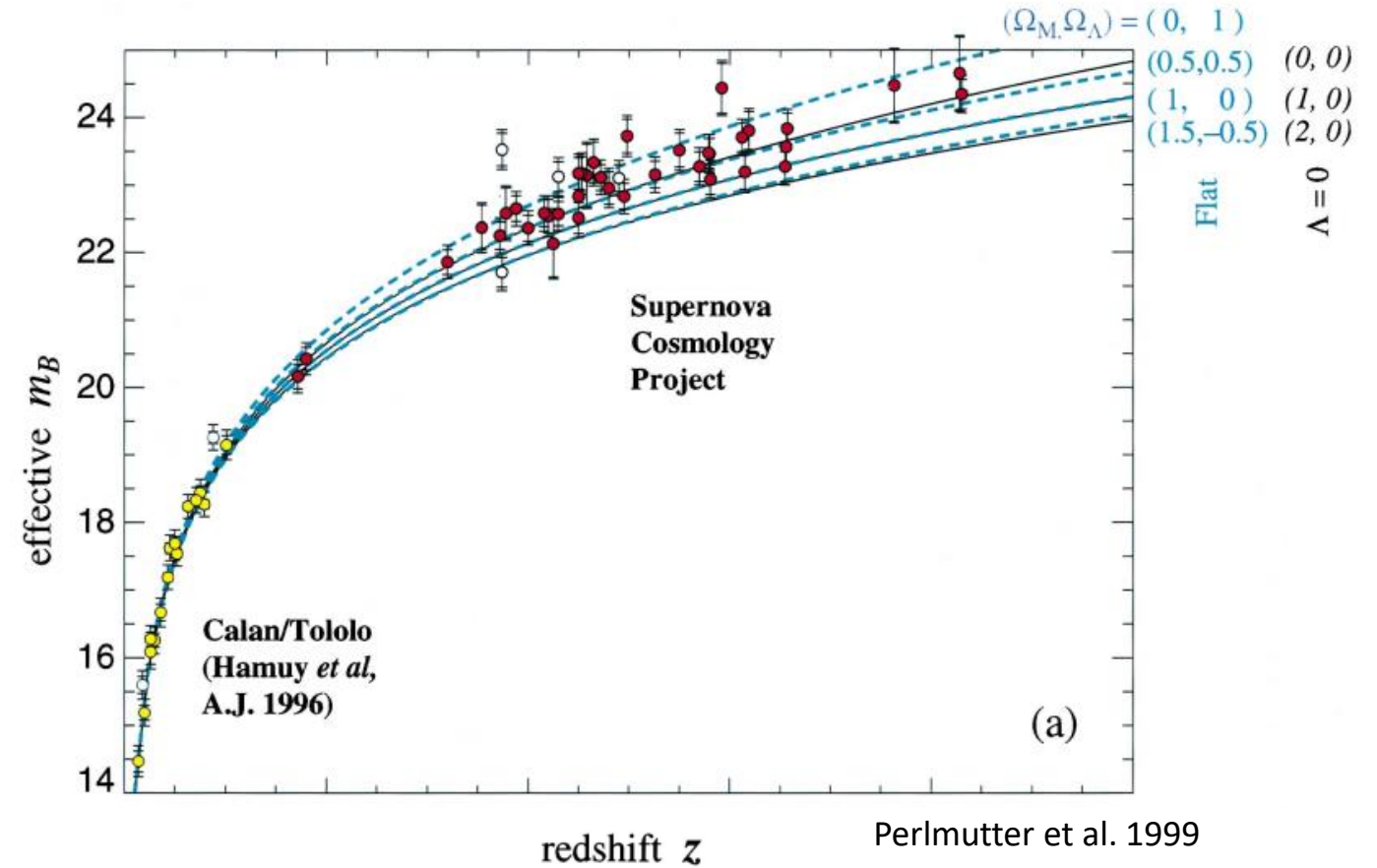
Kosio Karchev

supervisors:

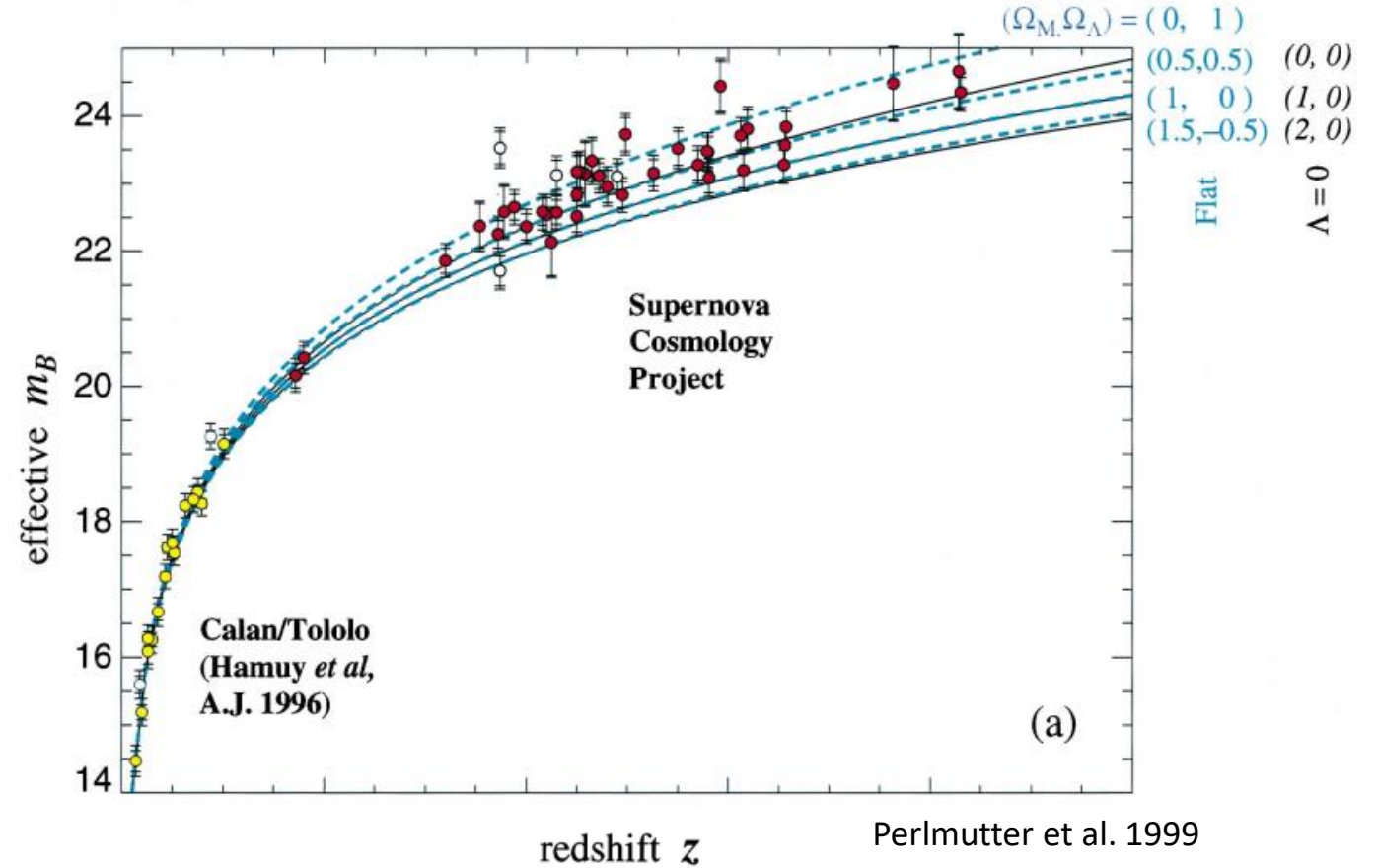
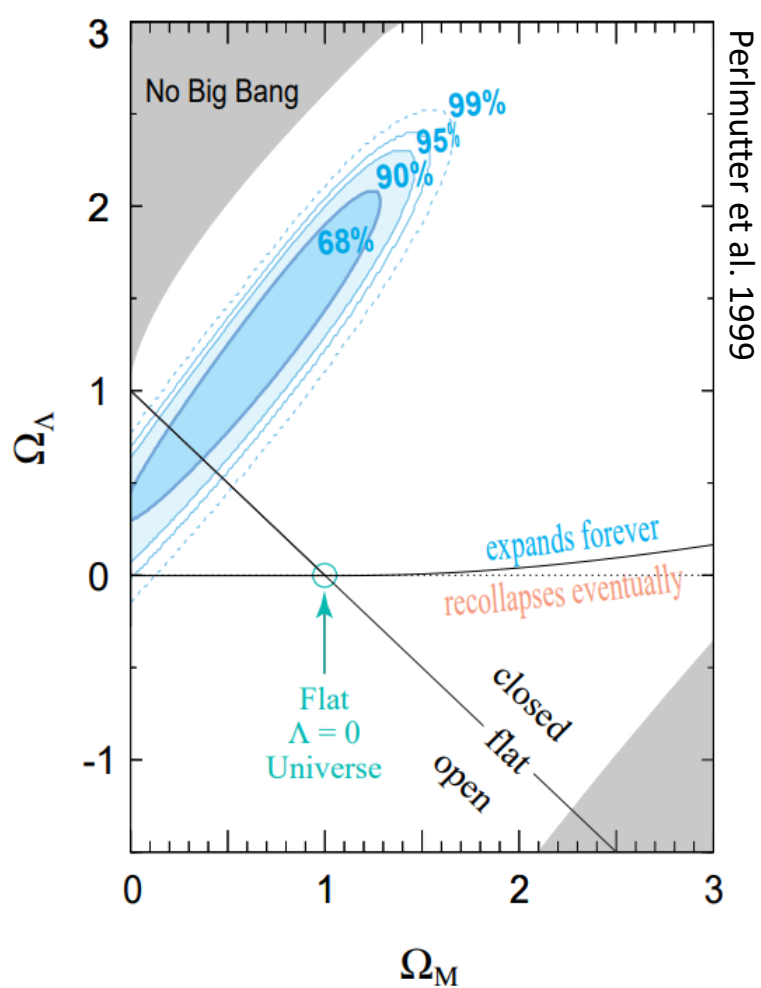
Roberto Trotta & Christoph Weniger

Cosmology
2023 in Miramare
2023-08-31

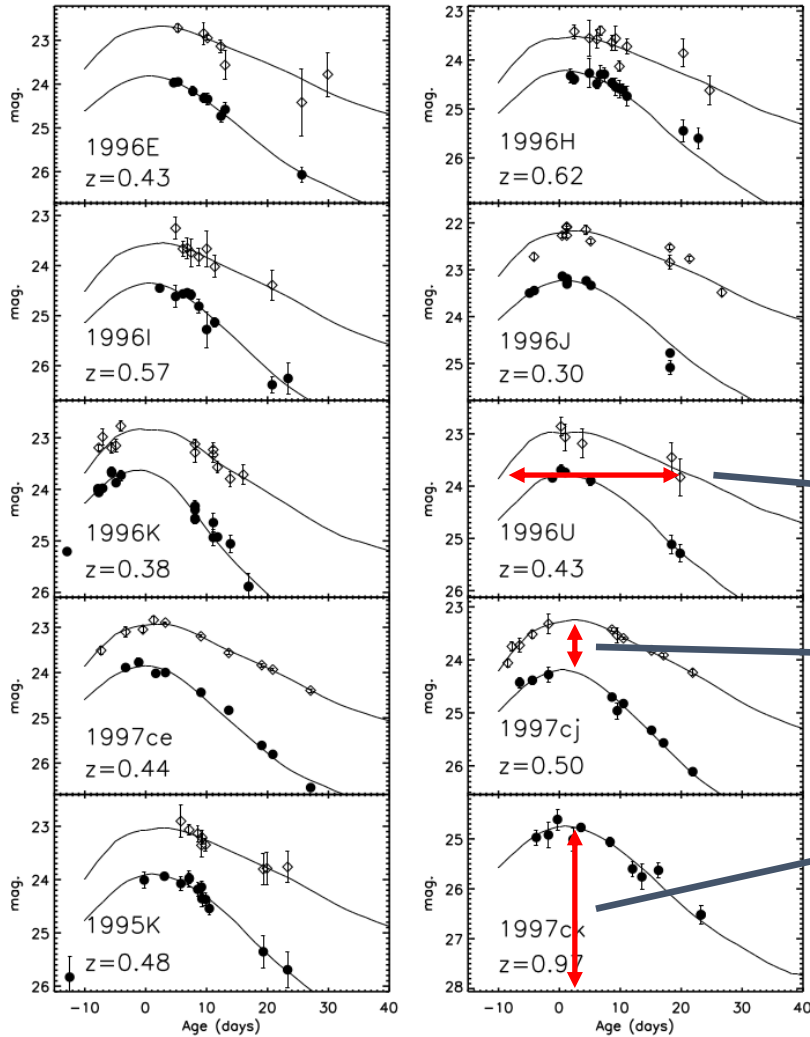
Cosmology with standard candles



Cosmology with standard candles



SN Ia cosmology: a Nobel prize



hand-crafted summaries

$x_1^S \pm \sigma_{x_1^S}$
"stretch"

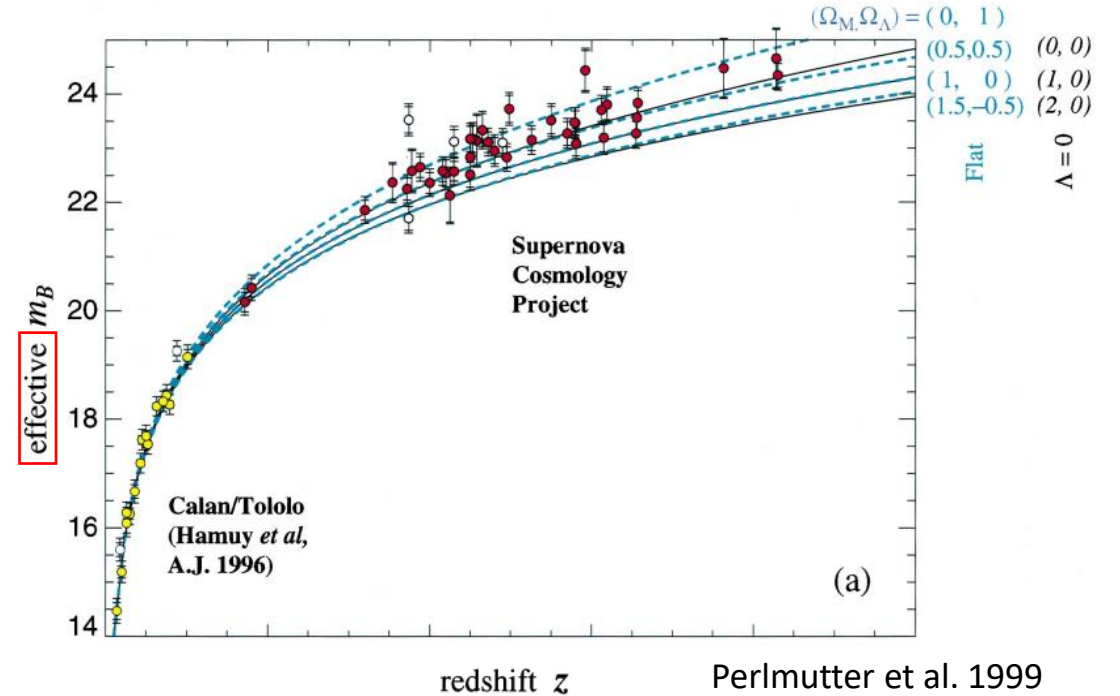
$c^S \pm \sigma_{c^S}$
"colour"

$m^S \pm \sigma_{m^S}$
brightness

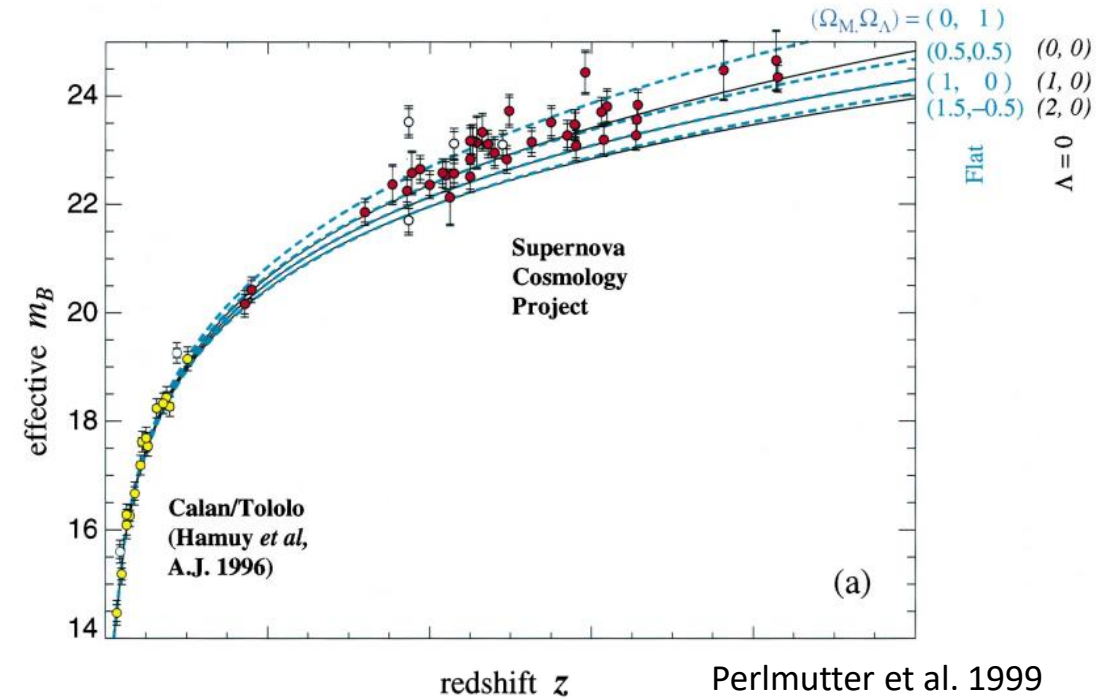
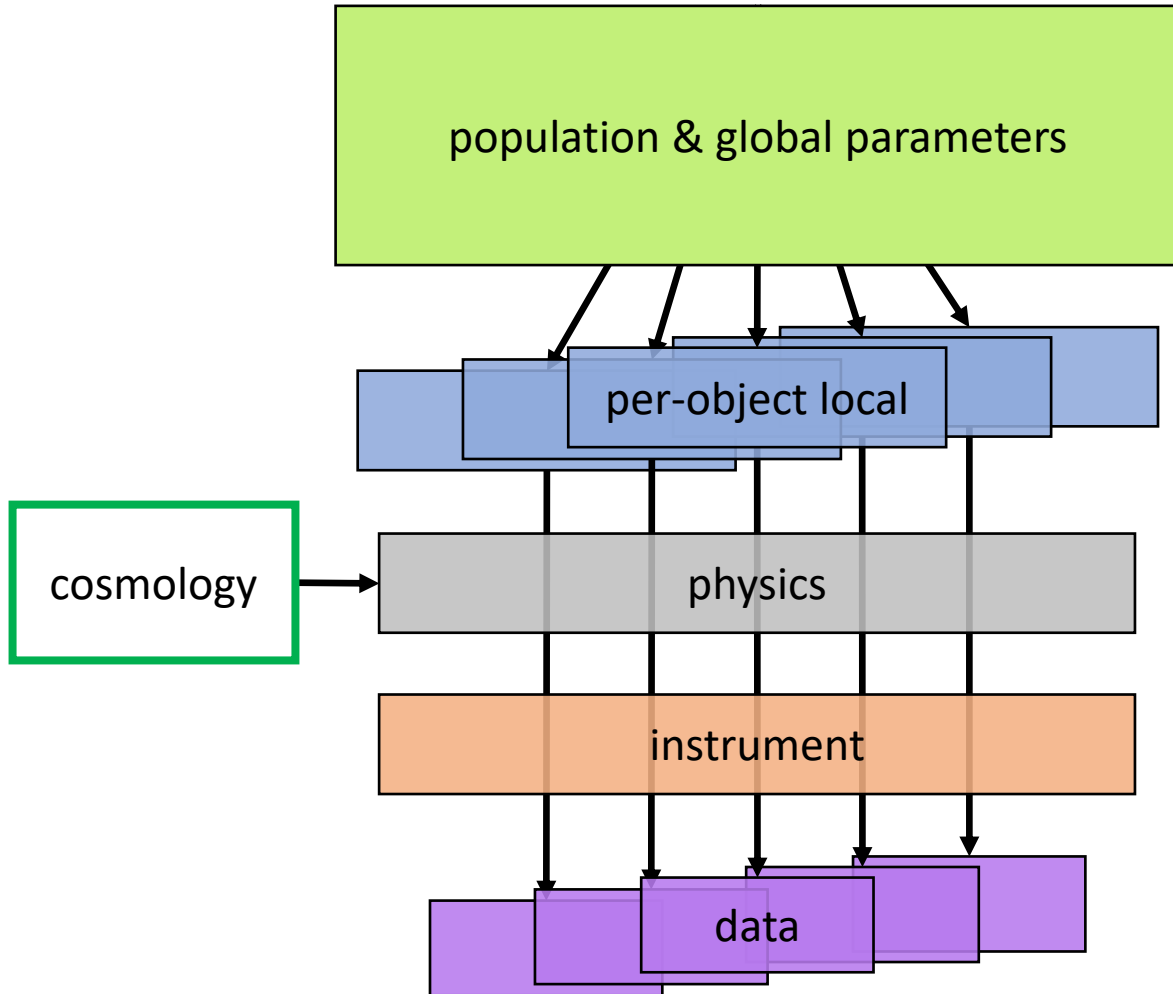
$$m^S + \alpha x_1^S - \beta c^S = M + \mu(z^S, \mathcal{C}) + \text{"noise"}$$

$\mathcal{C} \pm \sigma_{\mathcal{C}}$
posterior

Riess et al. 1999



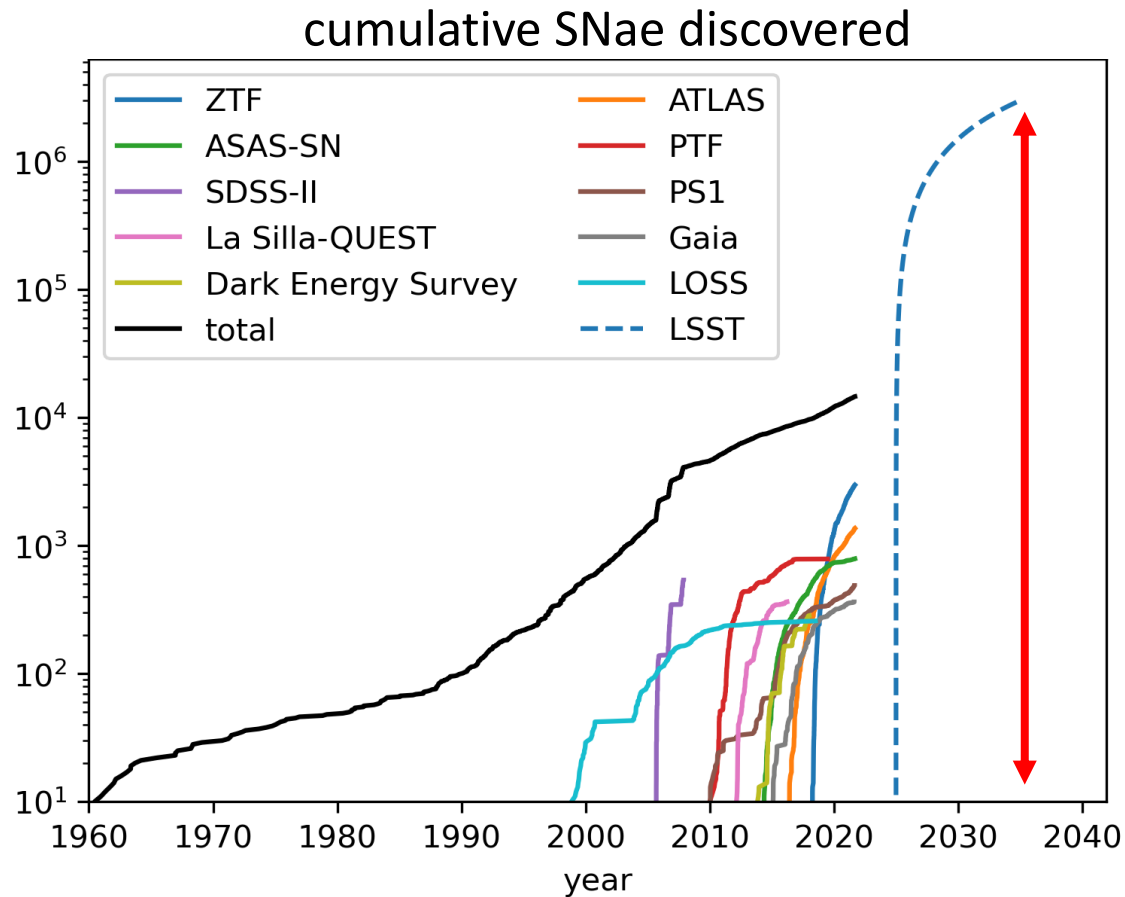
Hierarchical SN Ia cosmology



$$m^S + \alpha x_1^S - \beta c^S = M_0^S + \mu(z^S, \mathcal{C}) + \text{"noise"}$$

population priors

SN Ia cosmology: future

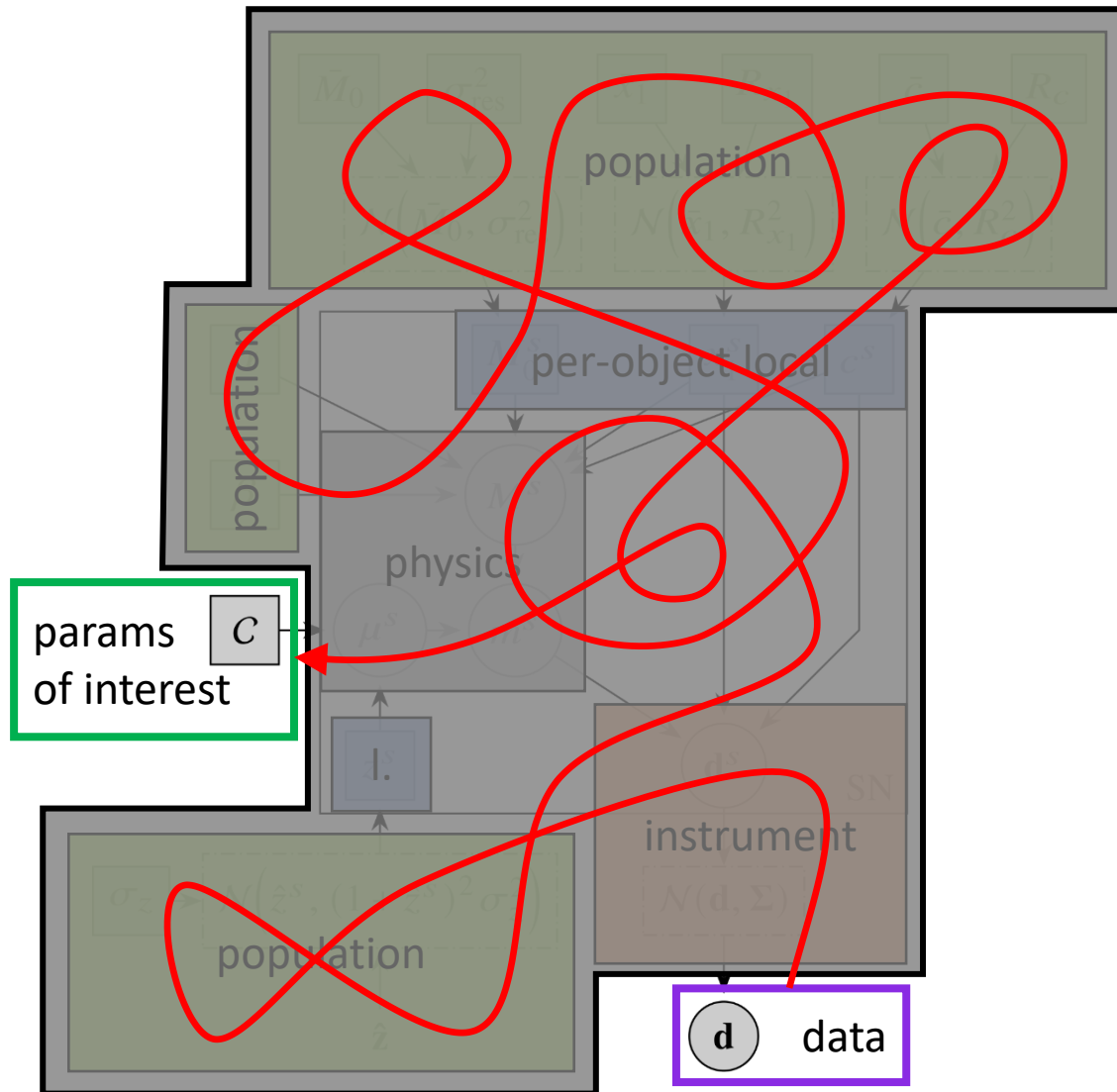


$\sim 10^5$ SNe Ia

$\sim 10^6$ “contaminants”

- large datasets
 - high-dimensional inference
- photometric redshift uncertainty
 - non-Gaussian, non-linearities
- non-Ia contamination
- selection effects

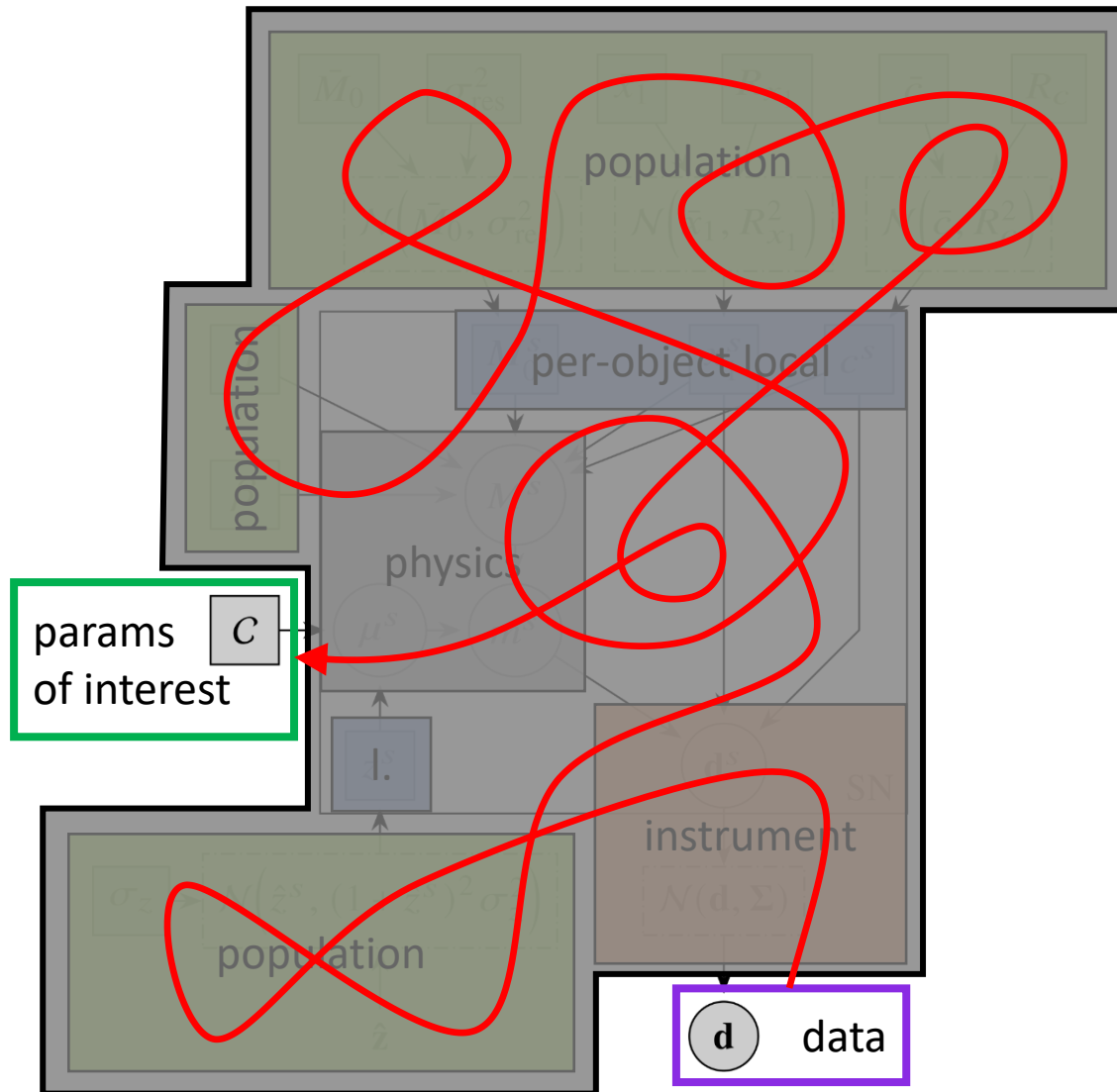
Likelihood-based SN Ia cosmology



Inference is painful:

- large datasets
 - high-dimensional inference
- photometric redshift uncertainty
 - non-Gaussian, non-linearities
- non-Ia contamination
- selection effects

Likelihood-based SN Ia cosmology



Realism is painful:

- lightcurve population
- environmental effects & dust
- Instrument model

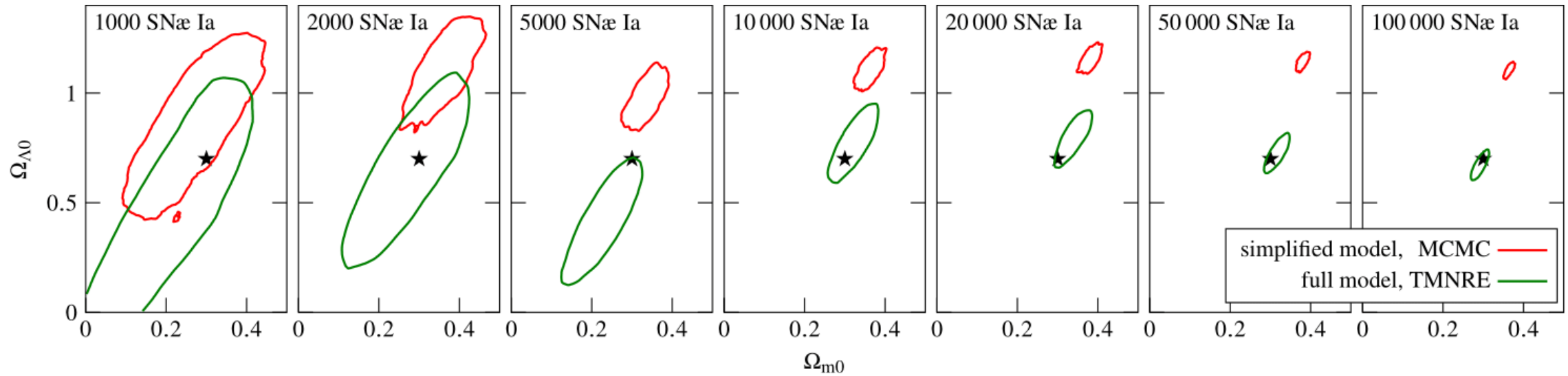
Inference is painful:

- large datasets
 - high-dimensional inference
- photometric redshift uncertainty
 - non-Gaussian, non-linearities
- non-Ia contamination
- selection effects

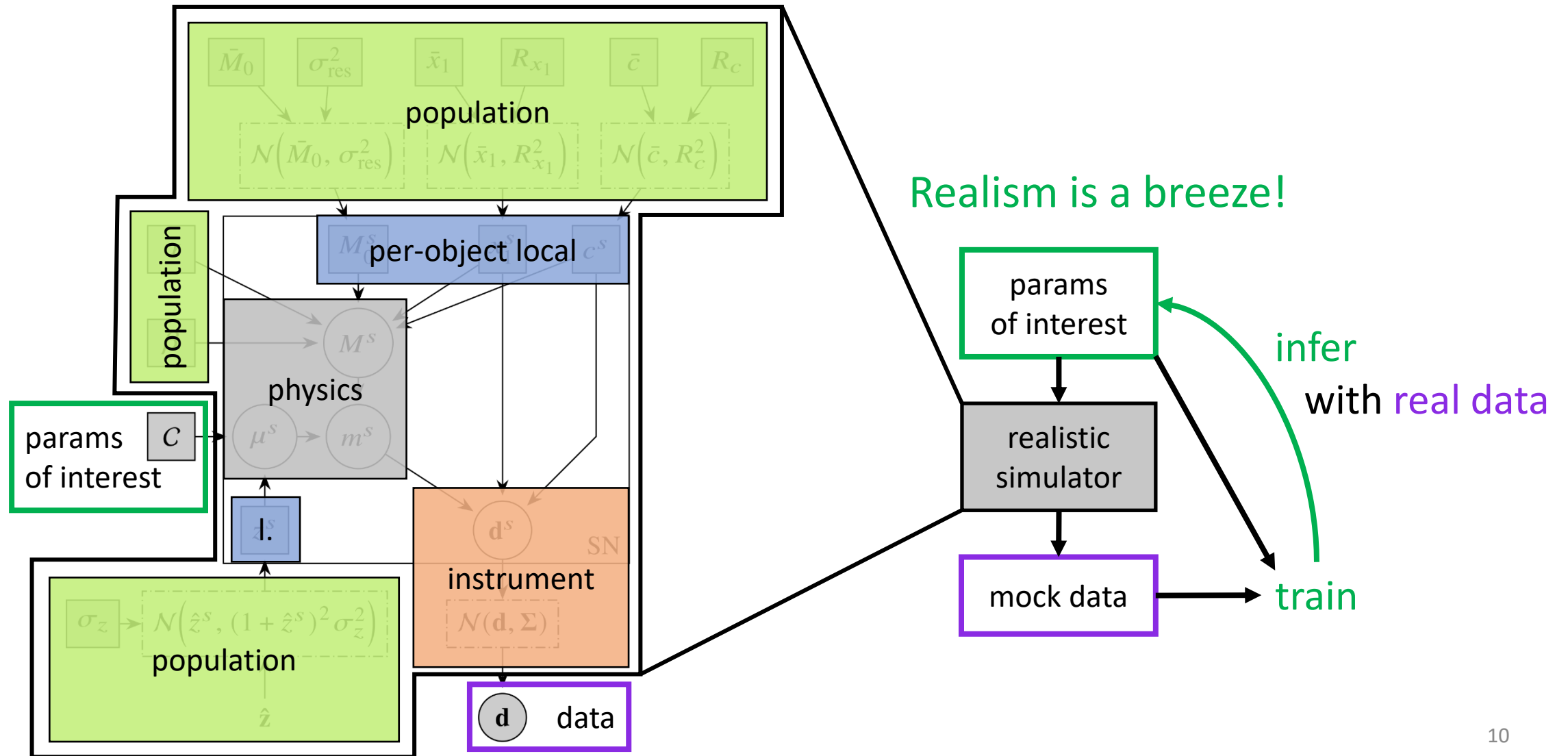
The importance of model realism

present

future

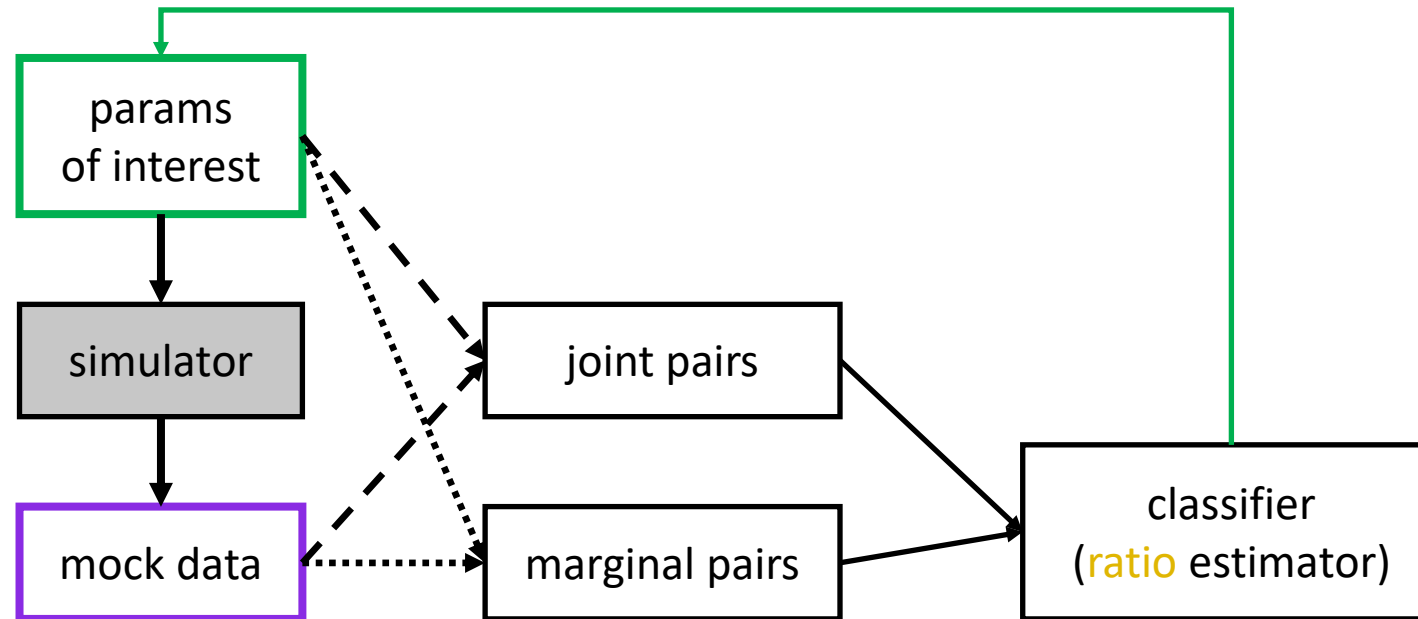


Simulation-based SN Ia cosmology

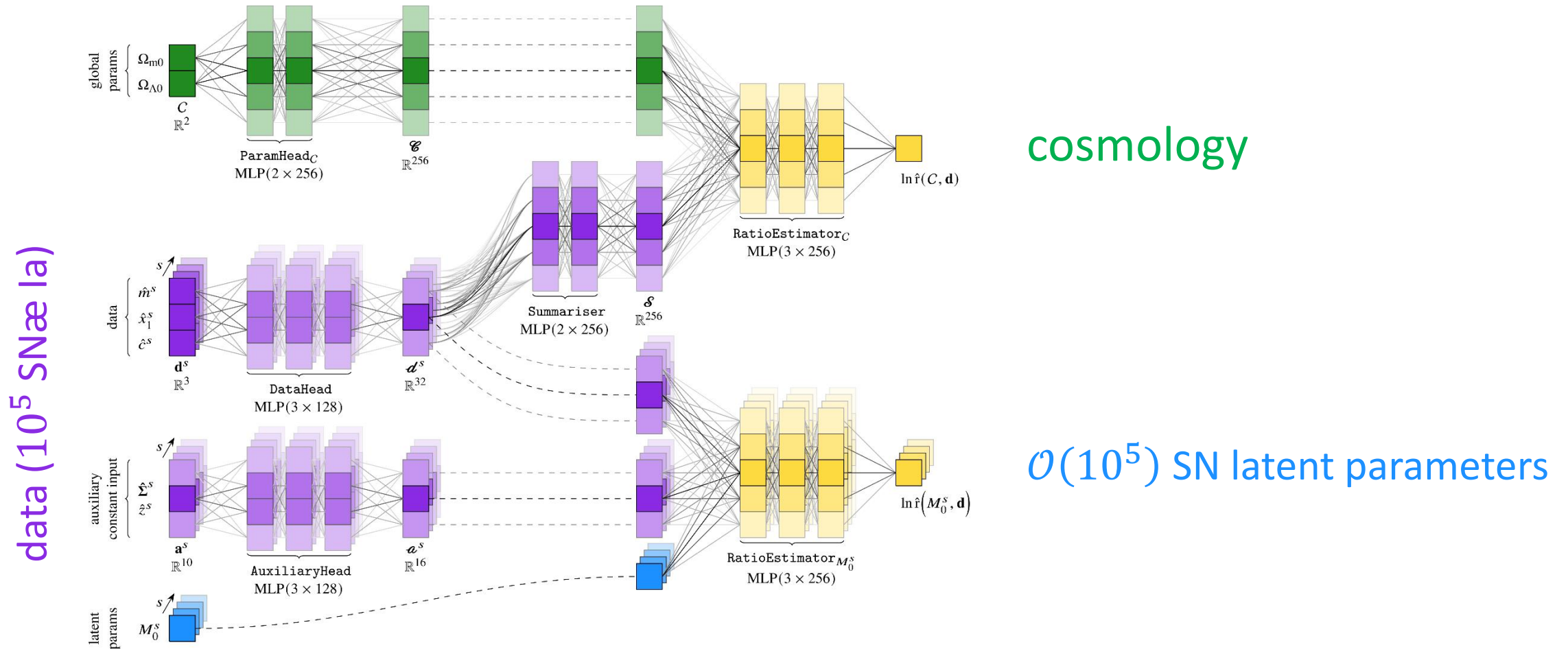


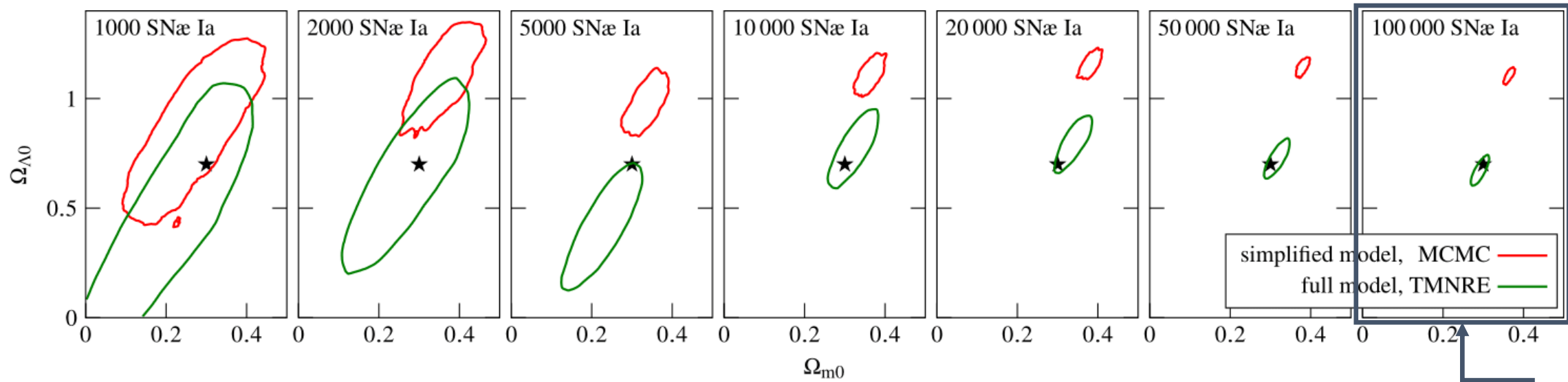
Ratio Estimation: Bayes theorem

$$\frac{p(\theta|d)}{p(\theta)} = \frac{p(\theta, d)}{p(\theta)p(d)} \equiv r(\theta, d)$$

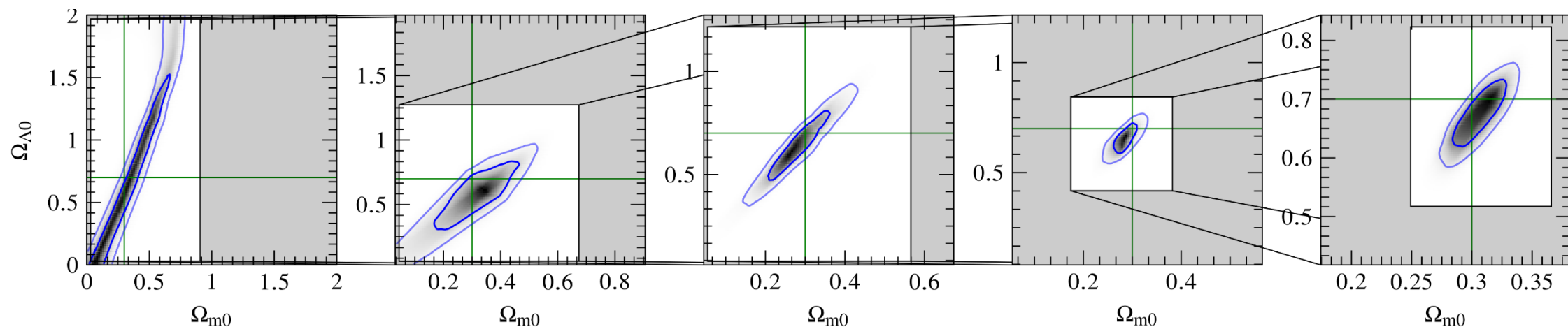


Marginal Neural Ratio Estimation





stage 0 → stage 1 → stage 2 → stage 3 → stage 4



train (~ 2 h)

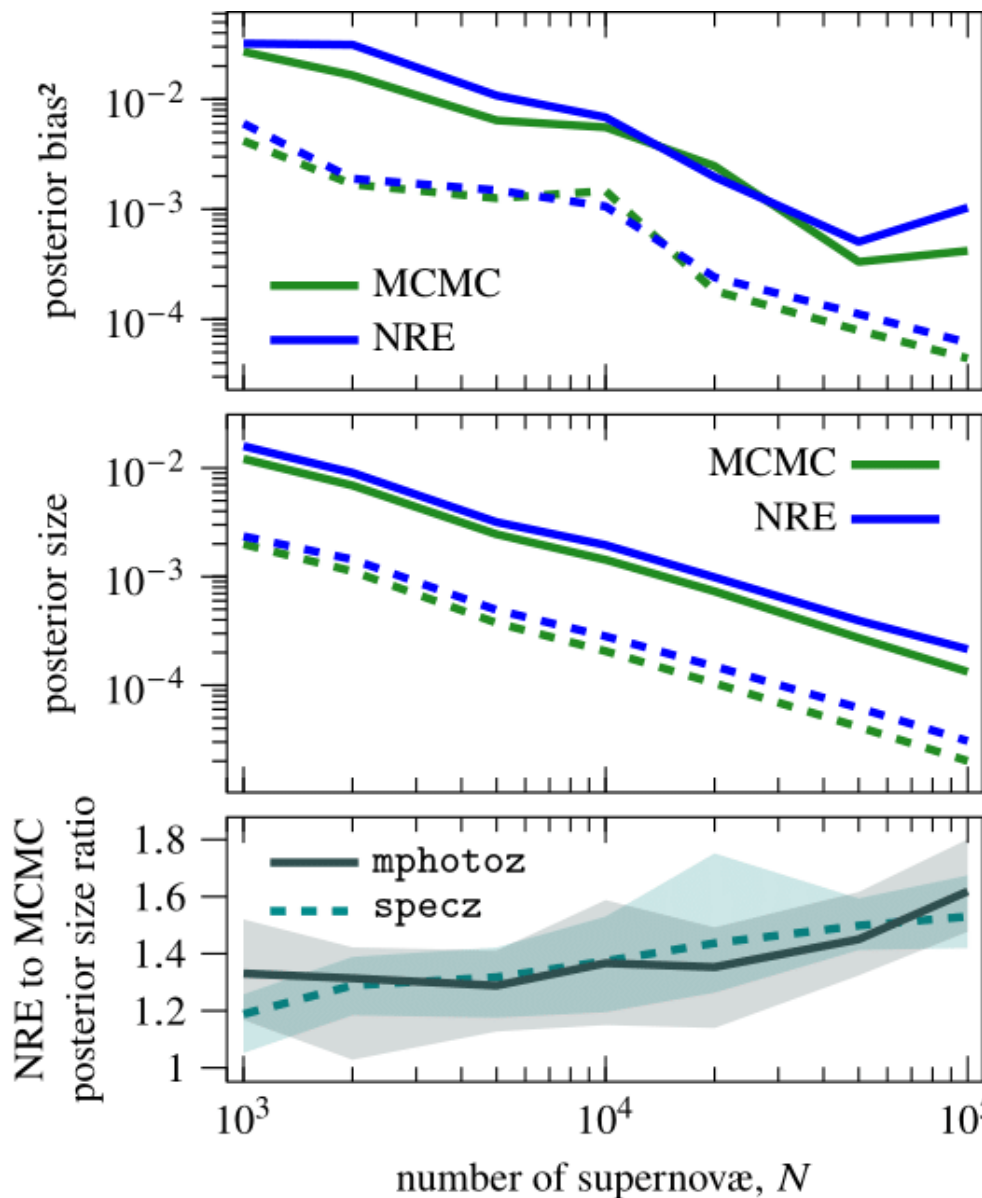
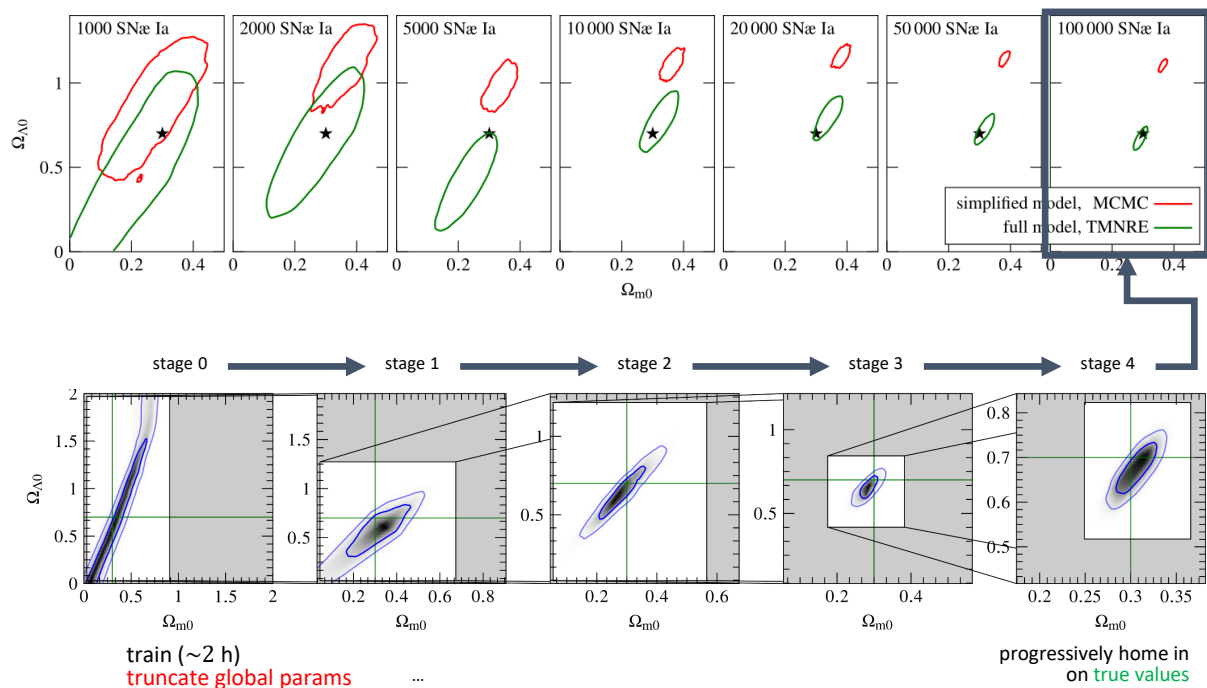
truncate global params

...

progressively home in
on true values

Global inference

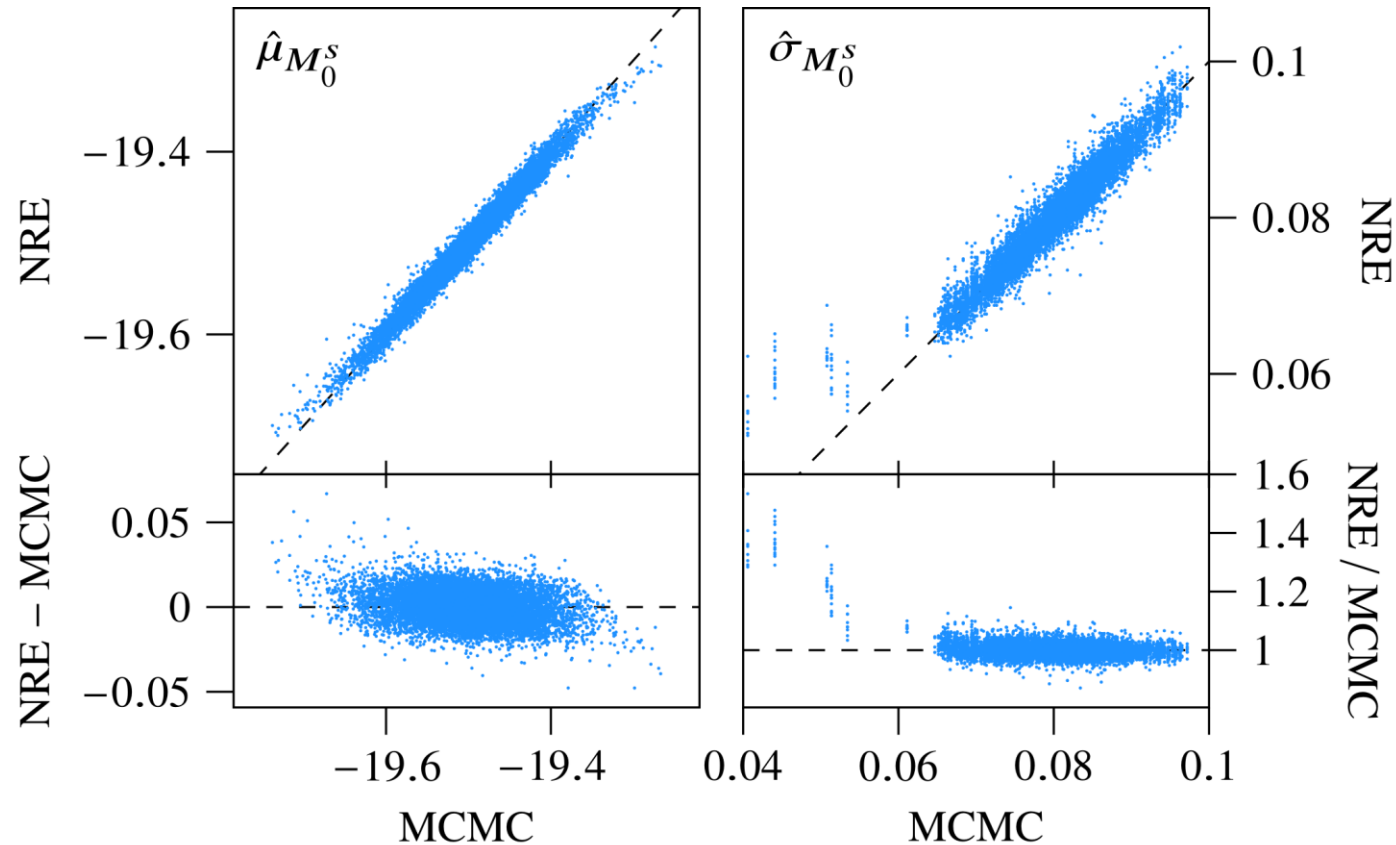
- scaling to $\mathcal{O}(10^5)$ observations



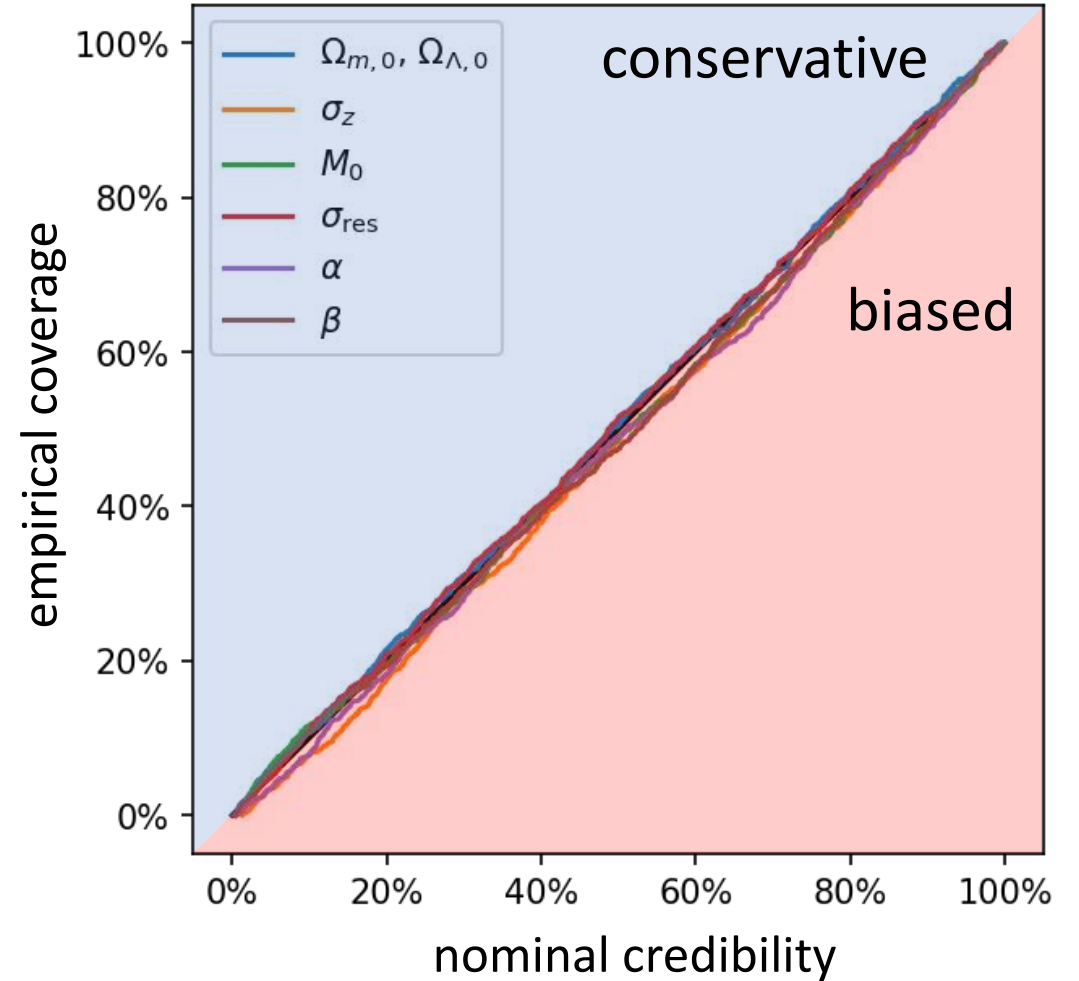
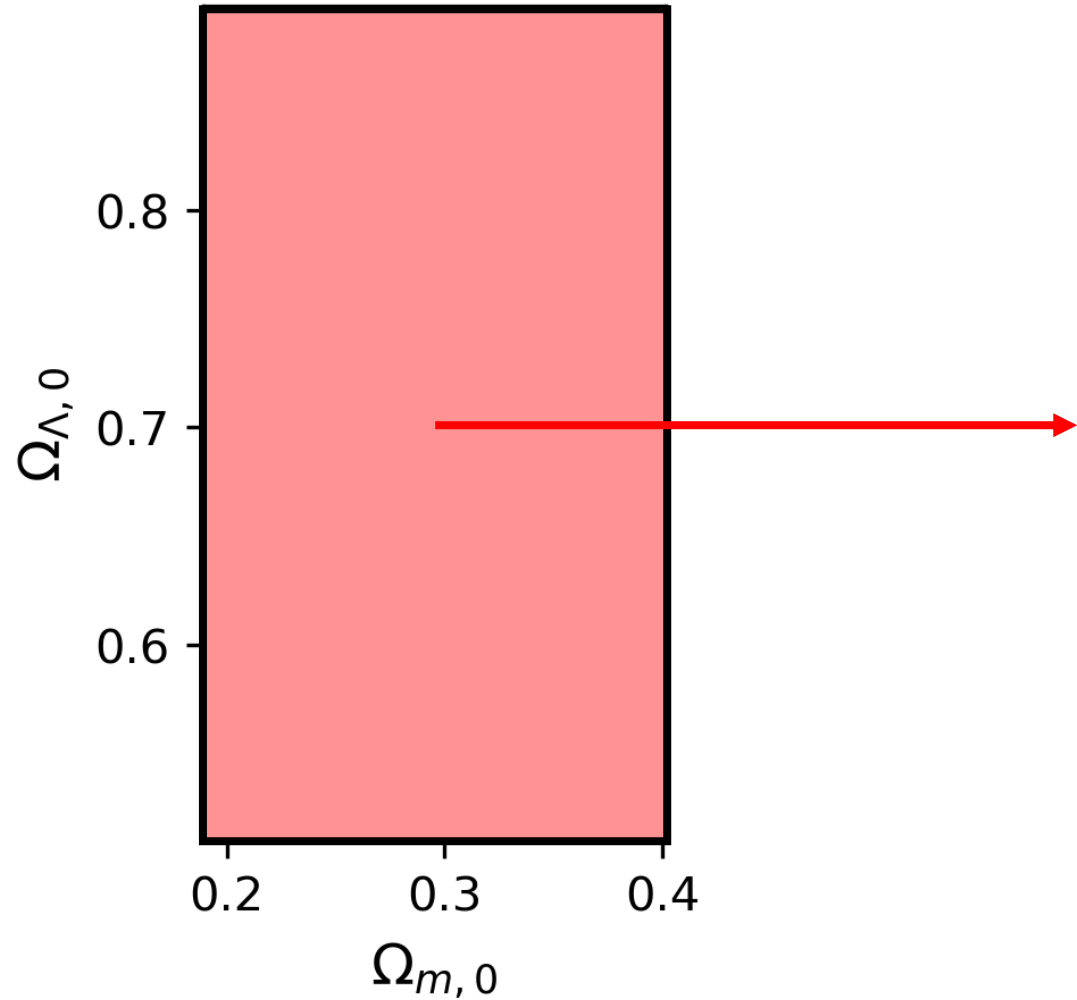
Local variable inference

MALFOI: MArginal Likelihood-Free Object-level Inference

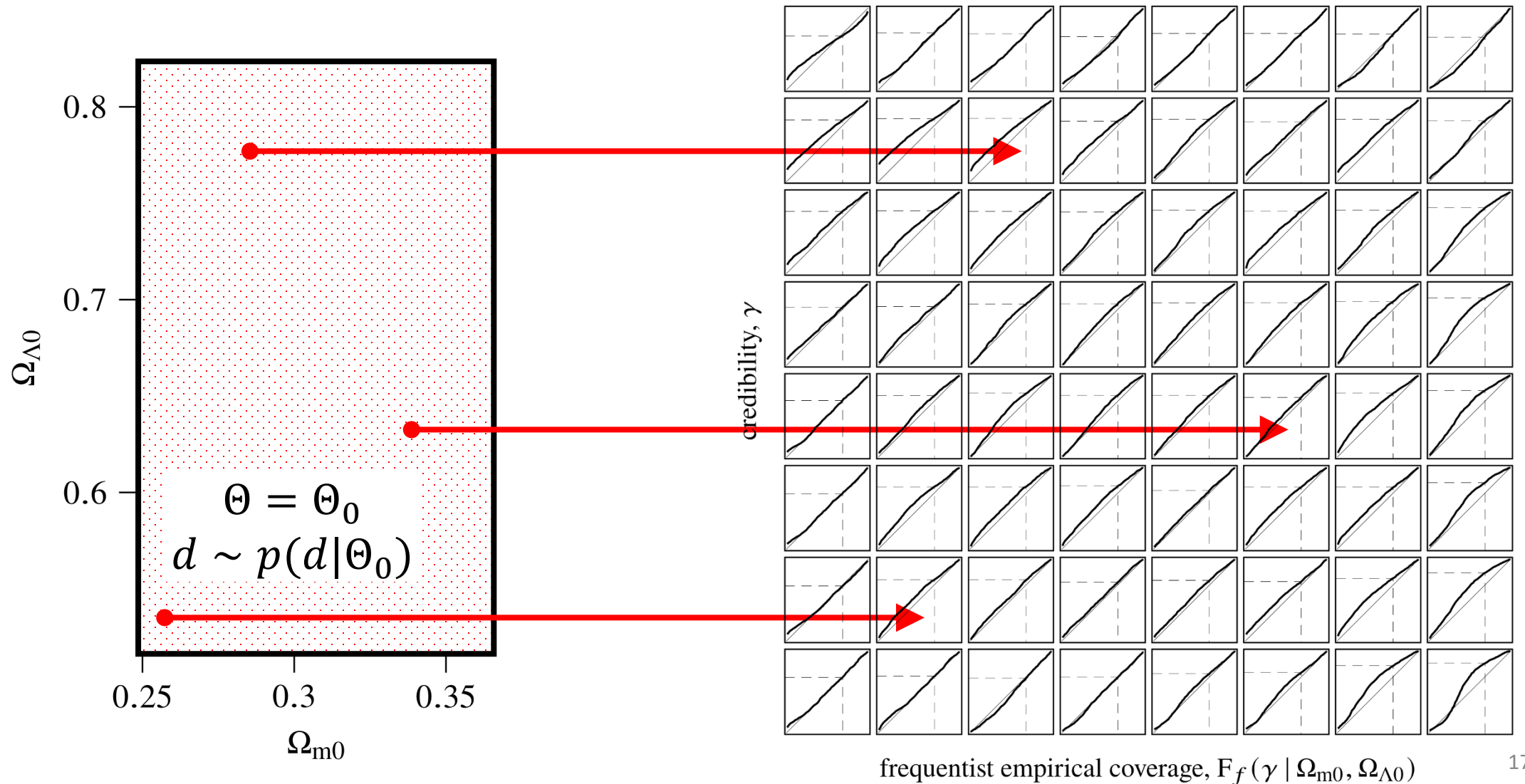
- $\mathcal{O}(10^5)$ marginal posteriors simultaneously



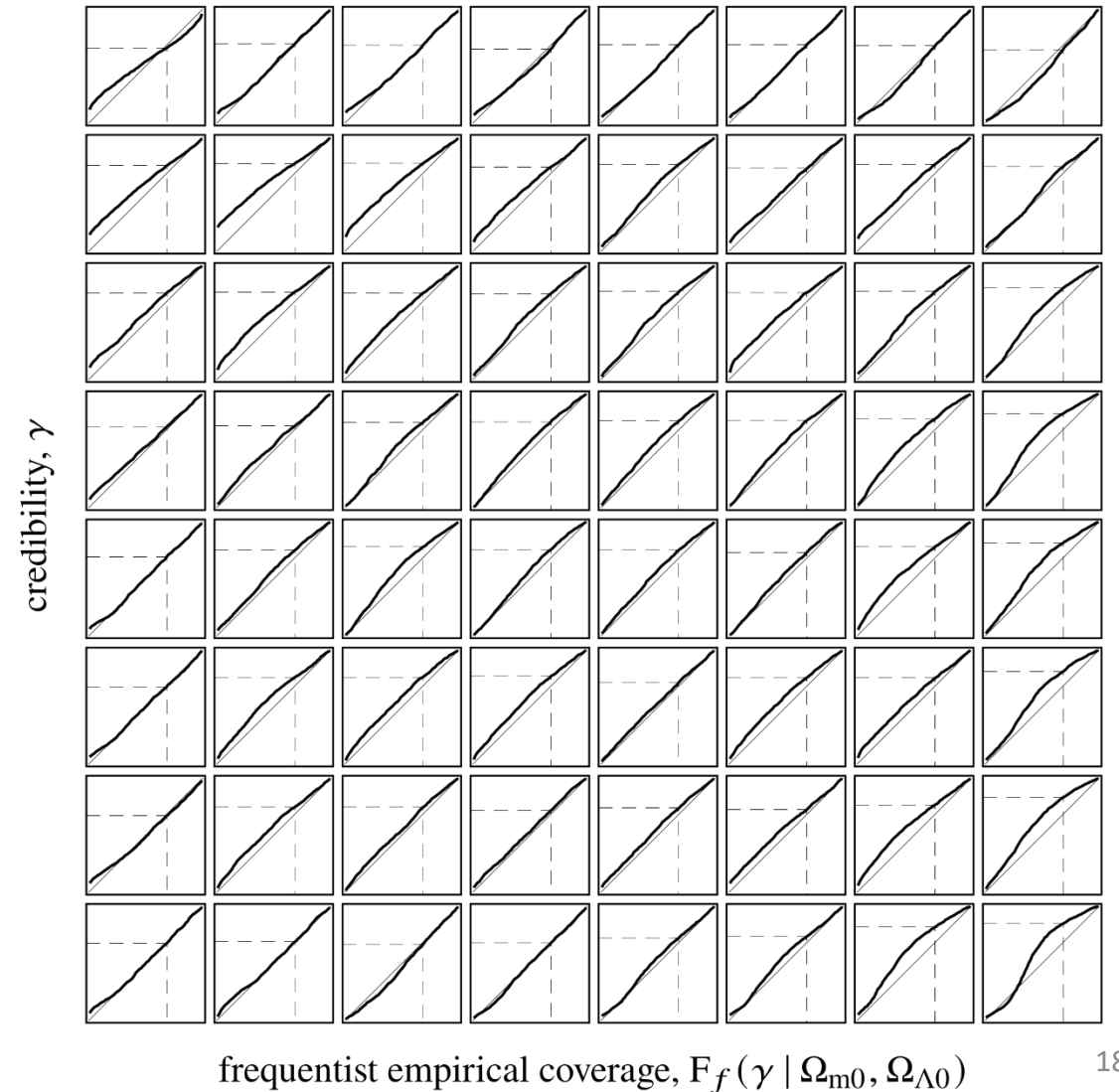
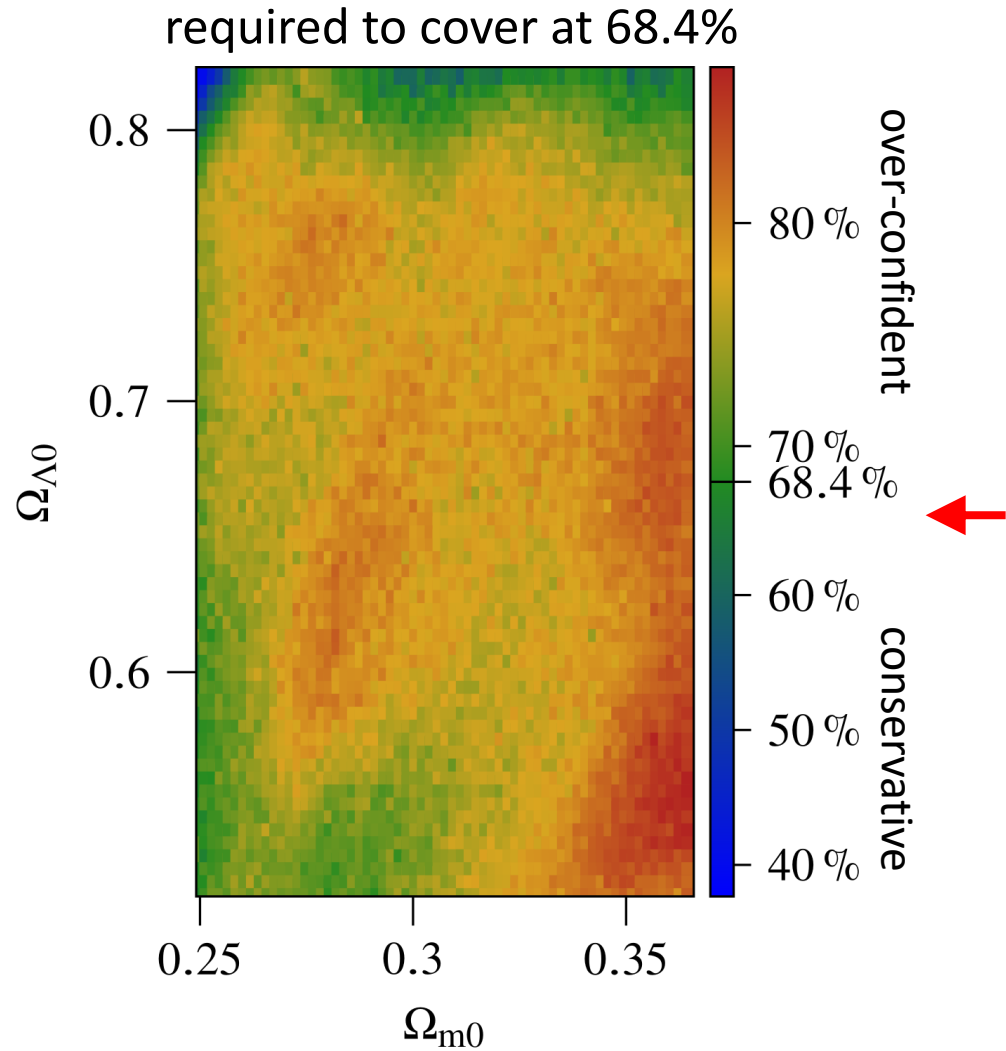
Validation: Bayesian coverage



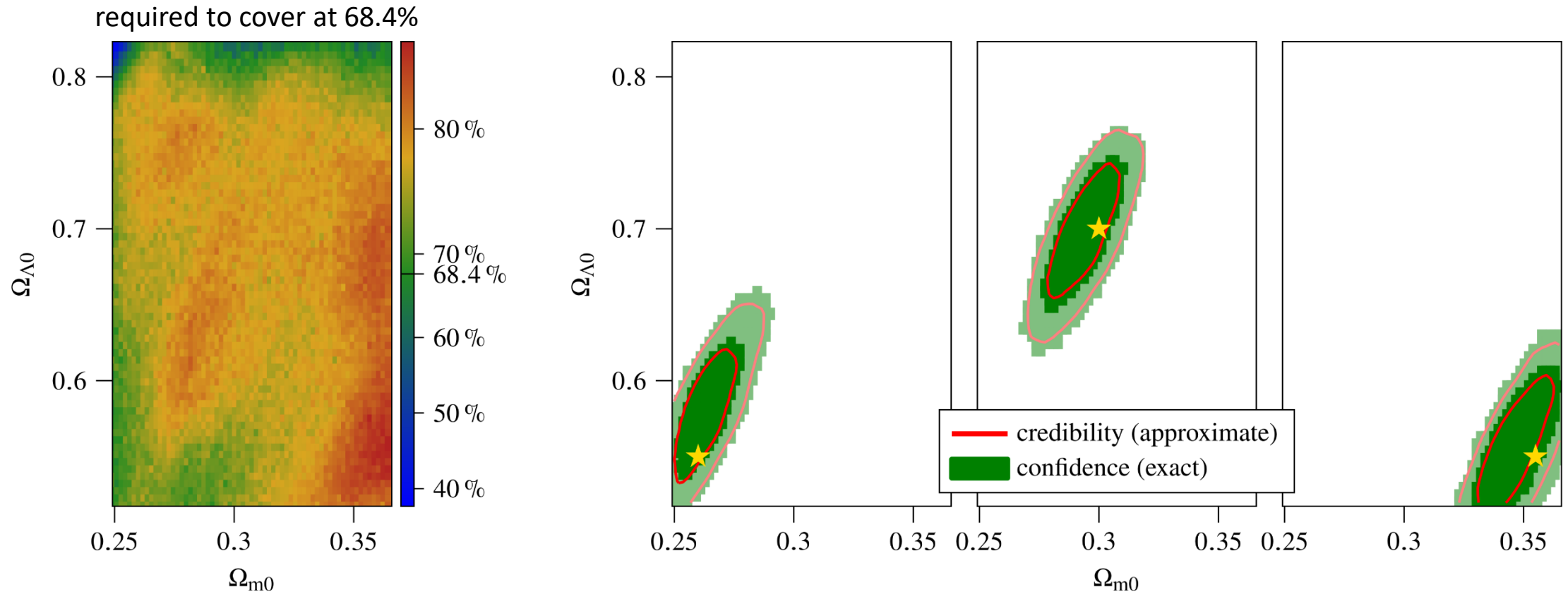
Calibration: frequentist coverage



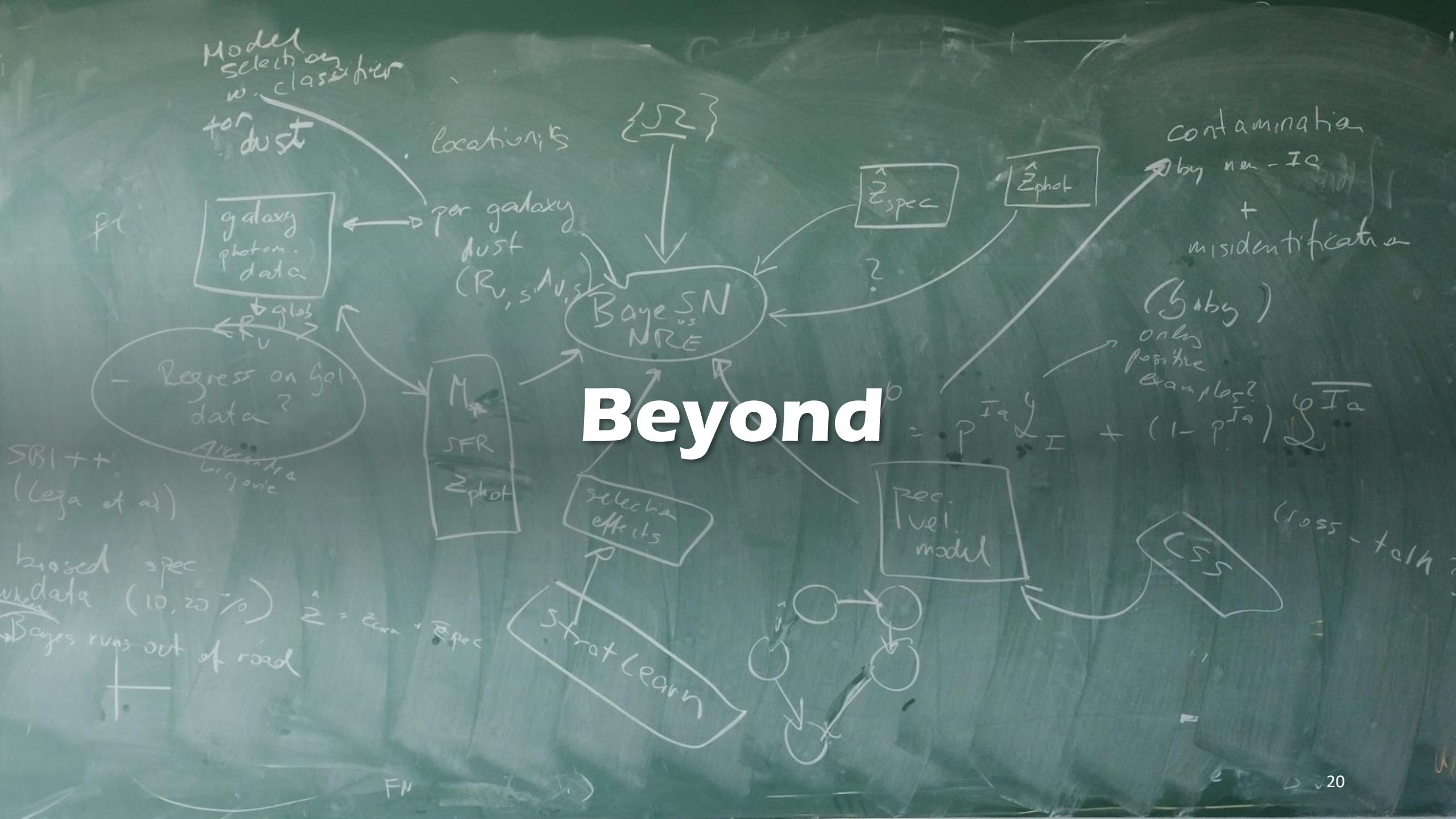
Calibration: frequentist coverage



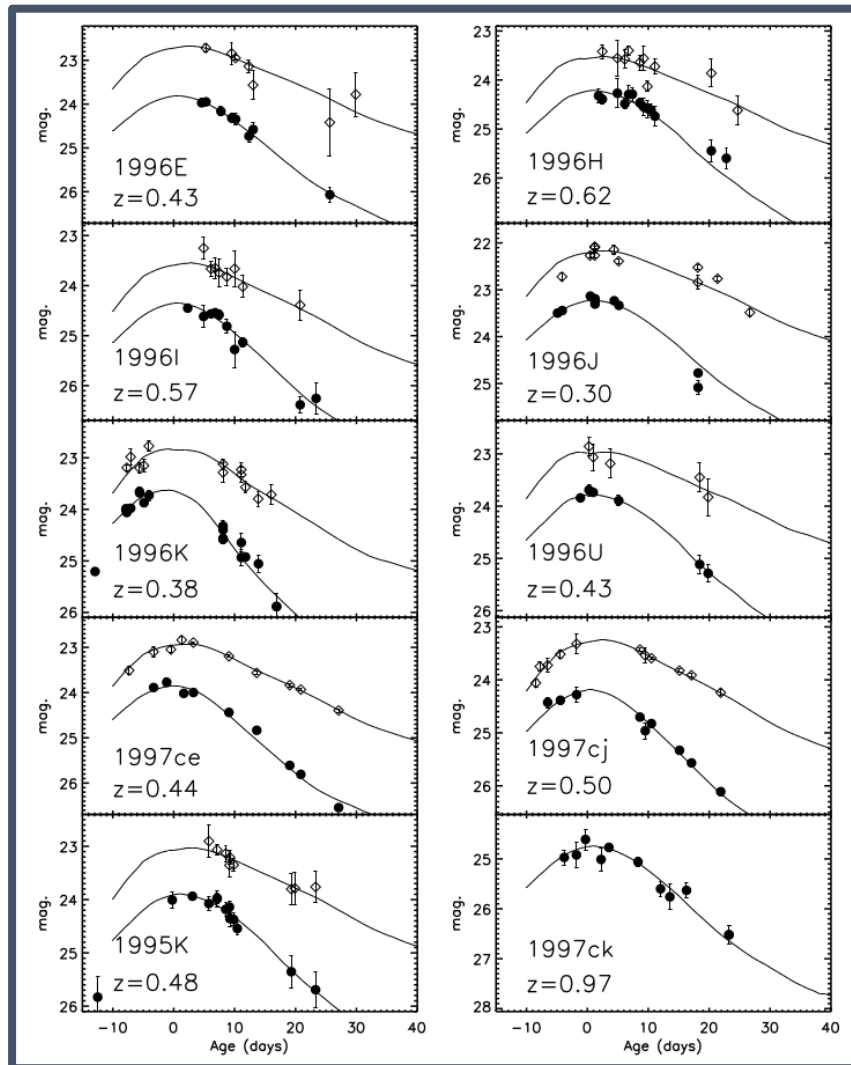
Calibration: **guaranteed** coverage



Beyond



Where SBI shines: **realism**



- lightcurve model (+ dust, host):
(pre-trained) BayeSN ([Mandel et al.](#))

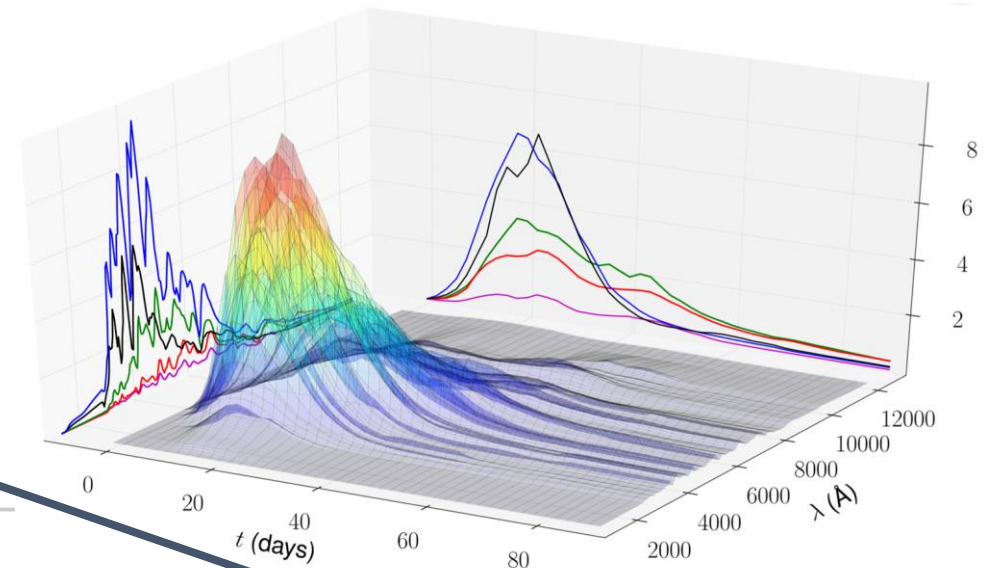
hand-crafted
summaries

$x_1^s \pm \sigma_{x_1}^s$
"stretch"
 $c^s \pm \sigma_c^s$
"colour"
 $m^s \pm \sigma_m^s$
brightness

$m^s +$

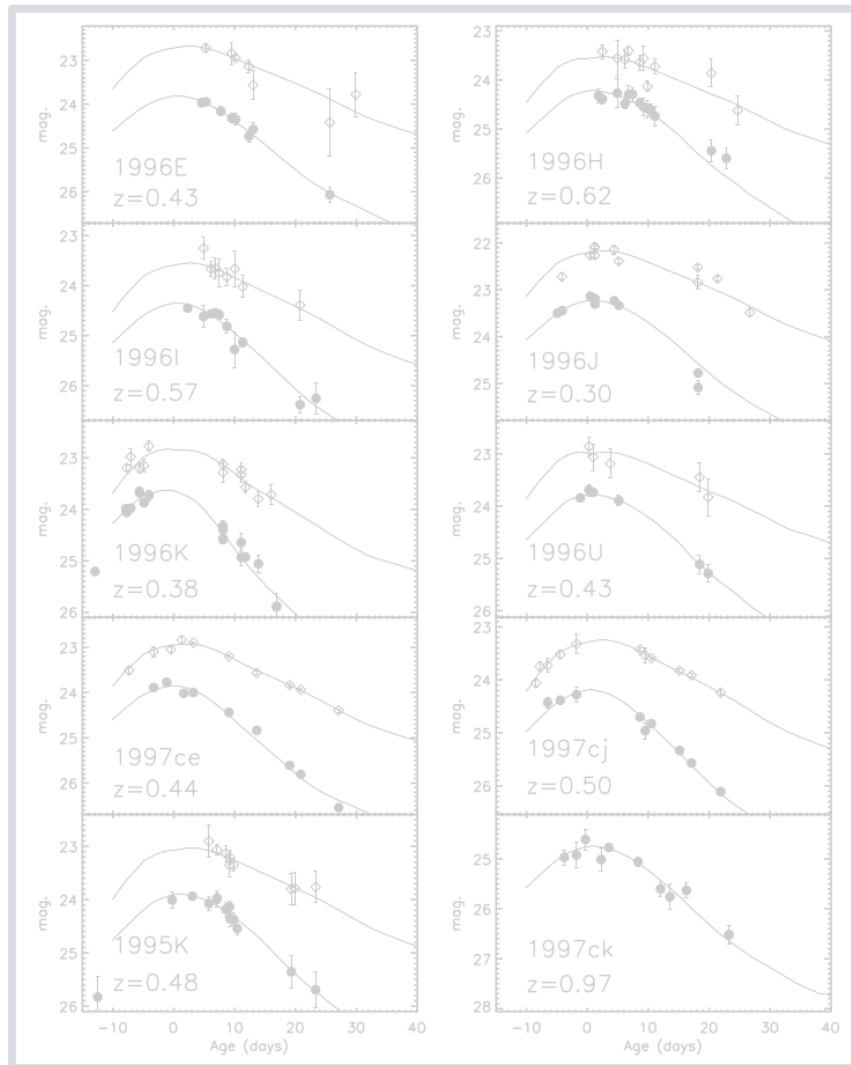
population
priors

$c \pm \sigma_c$
posterior



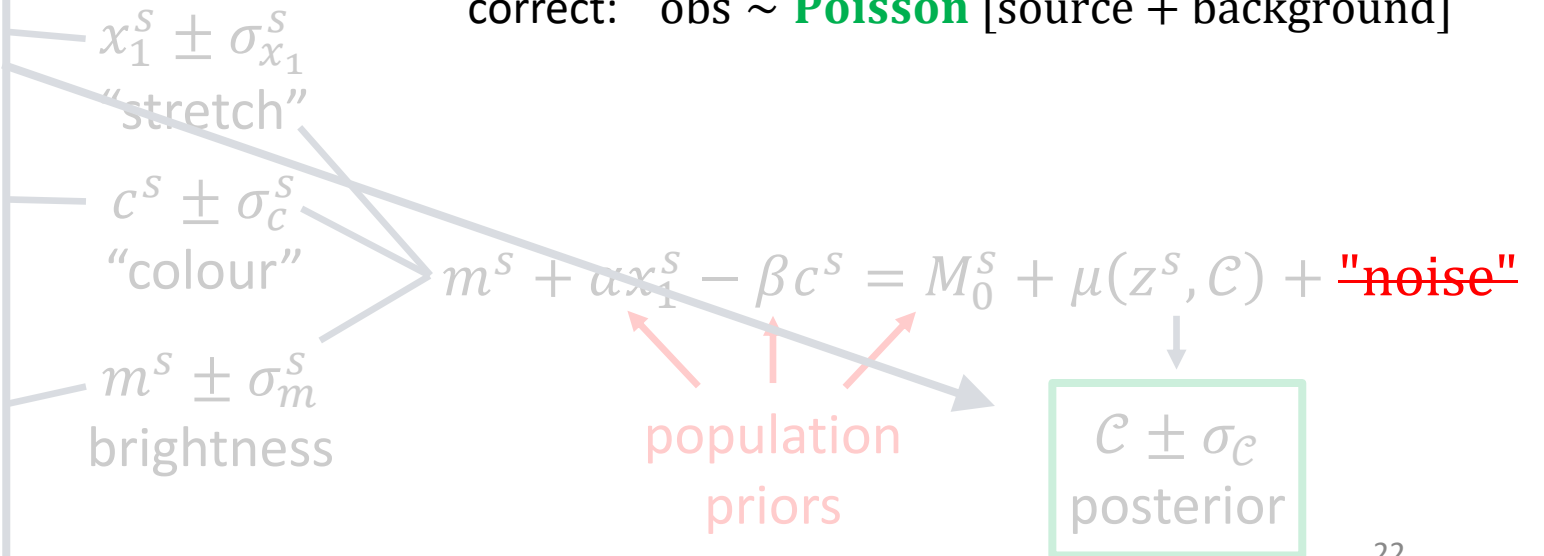
Where SBI shines: **realism**

- lightcurve model
- instrument model (+ calibration)

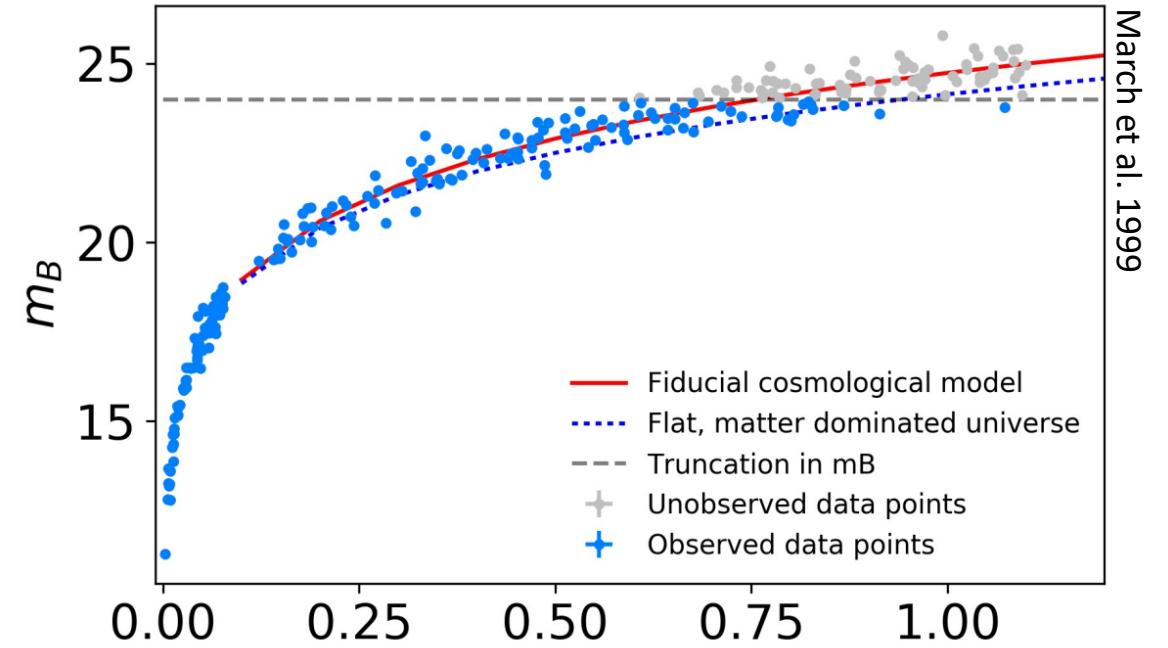
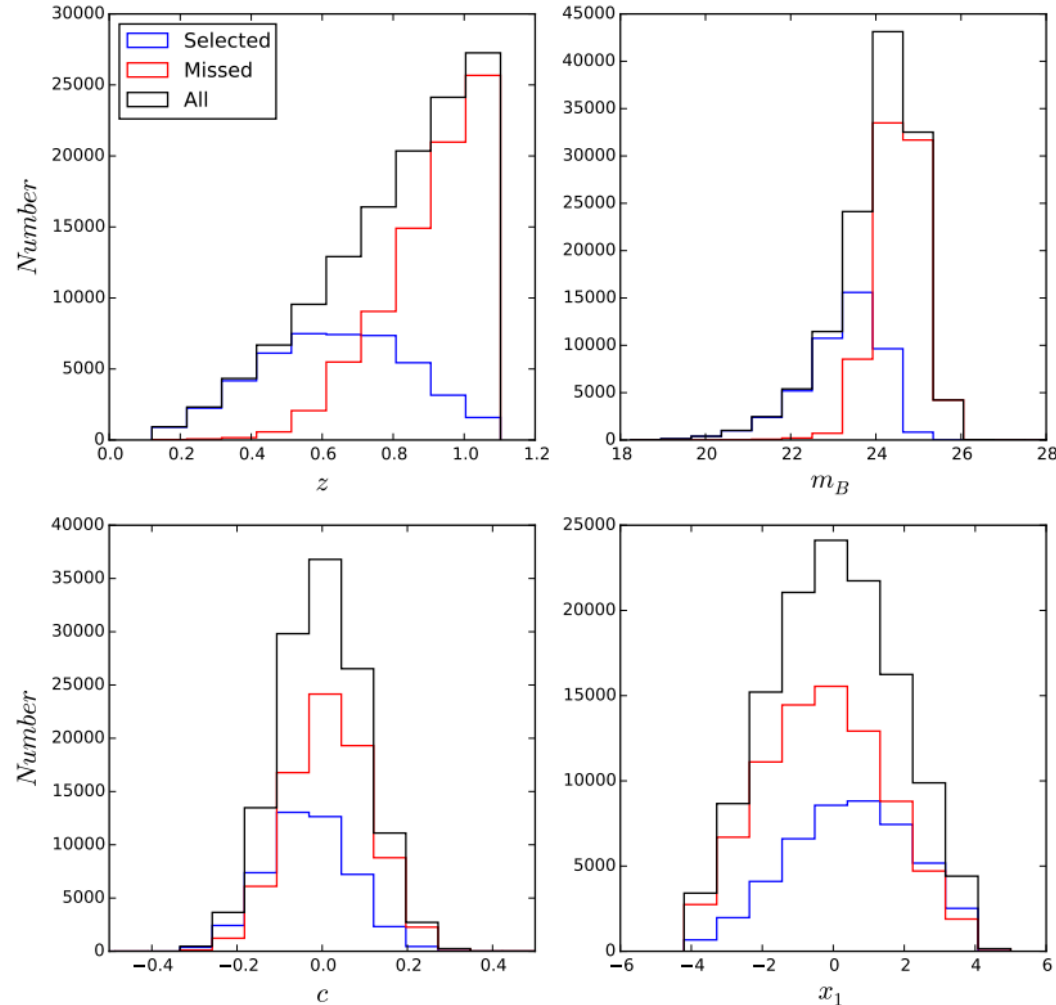


hand-crafted
summaries

wrong: source = obs - background
correct: obs ~ **Poisson** [source + background]



Where SBI shines: selection effects



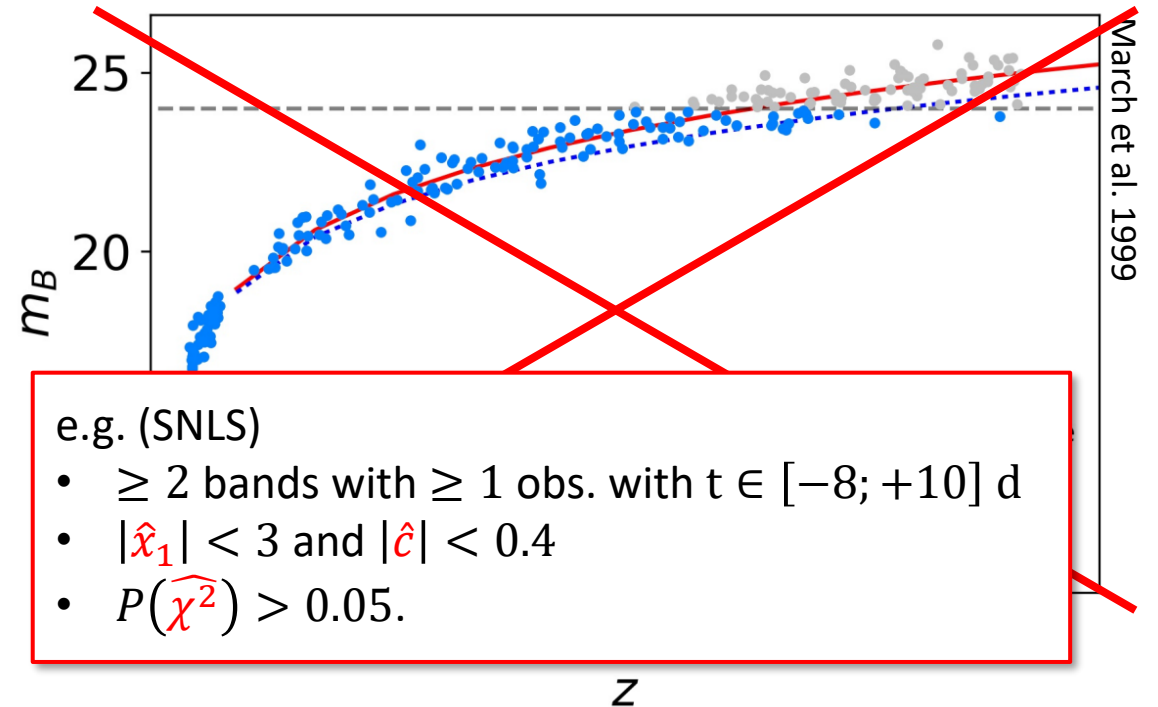
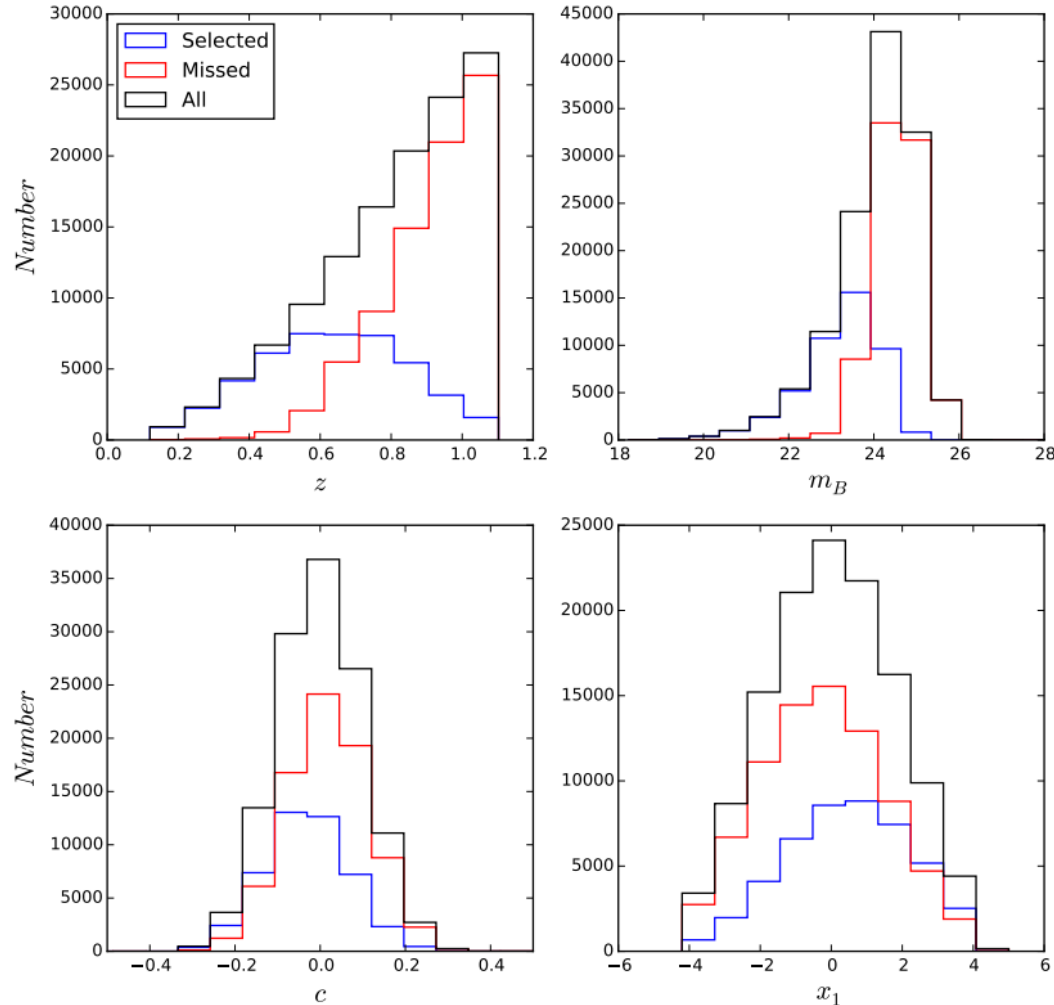
March et al. 1999

$$m^s + \alpha x_1^s - \beta c^s = M_0^s + \mu(z^s, \mathcal{C}) + \text{"noise"}$$

α , β , M_0^s → population priors given SN is observed
 $\mathcal{C} \pm \sigma_c$ → posterior

(cf. "Detection is truncation" (Anau Montel & Weniger 2022))²³

Where SBI shines: realistic selection effects



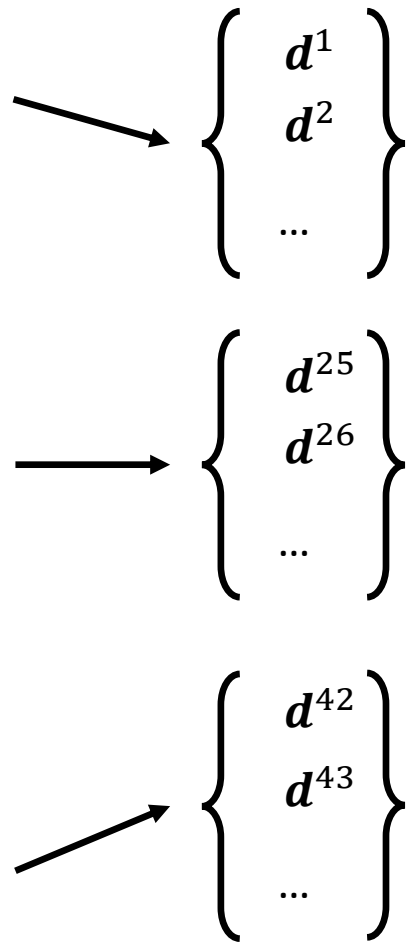
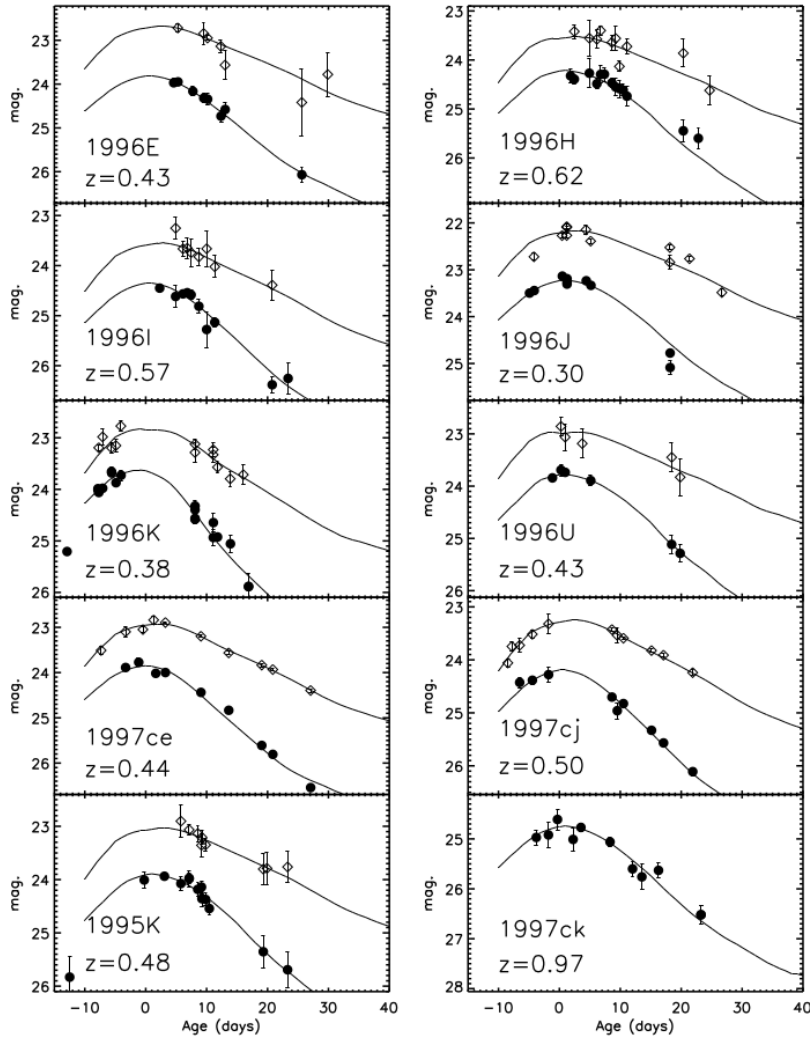
$$m^s + \alpha x_1^s - \beta c^s = M_0^s + \mu(z^s, \mathcal{C}) + \text{"noise"}$$

population priors
given SN is observed

$\mathcal{C} \pm \sigma_c$
posterior

(cf. "Detection is truncation" (Anau Montel & Weniger 2022))²⁴

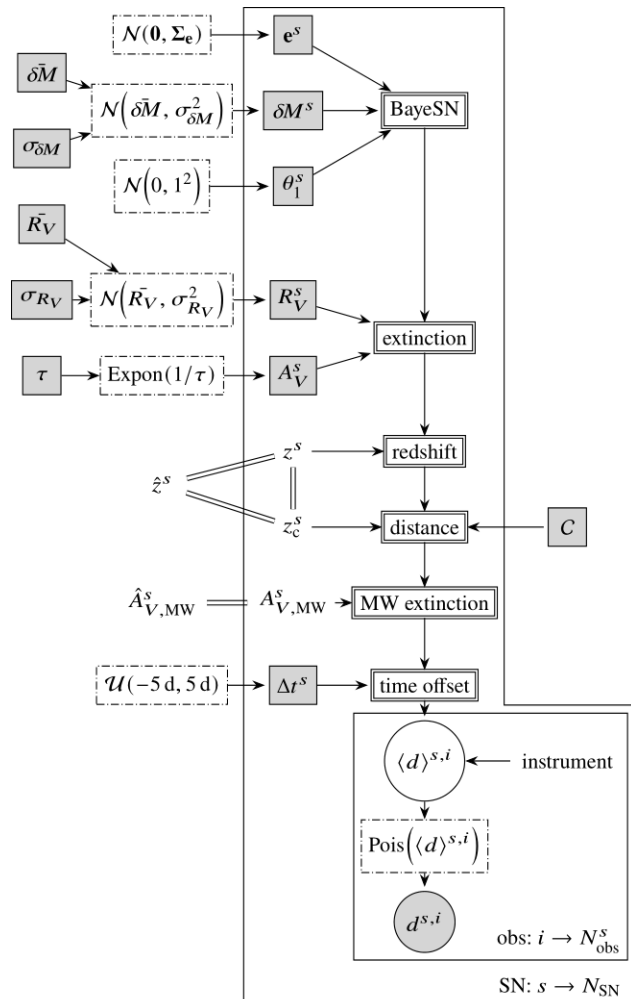
SN Ia cosmology: a set dataset



$$\left. \begin{aligned}
 \mathcal{S}^1 &= \rho_{\text{NN}}^{\text{obs}} \left[\sum_{i \in \text{SN}^1} \phi_{\text{NN}}^{\text{obs}}(\mathbf{d}^i) \right] \\
 \mathcal{S}^2 &= \rho_{\text{NN}}^{\text{obs}} \left[\sum_{i \in \text{SN}^2} \phi_{\text{NN}}^{\text{obs}}(\mathbf{d}^i) \right] \\
 \mathcal{S}^3 &= \rho_{\text{NN}}^{\text{obs}} \left[\sum_{i \in \text{SN}^3} \phi_{\text{NN}}^{\text{obs}}(\mathbf{d}^i) \right]
 \end{aligned} \right\} \mathcal{S} = \rho_{\text{NN}}^{\text{SN}} \left[\sum_s \phi_{\text{NN}}^{\text{SN}}(\mathcal{S}^s) \right]$$

State of affairs

SIDE-real: Sn Ia Dust Extinction with real(istic) data

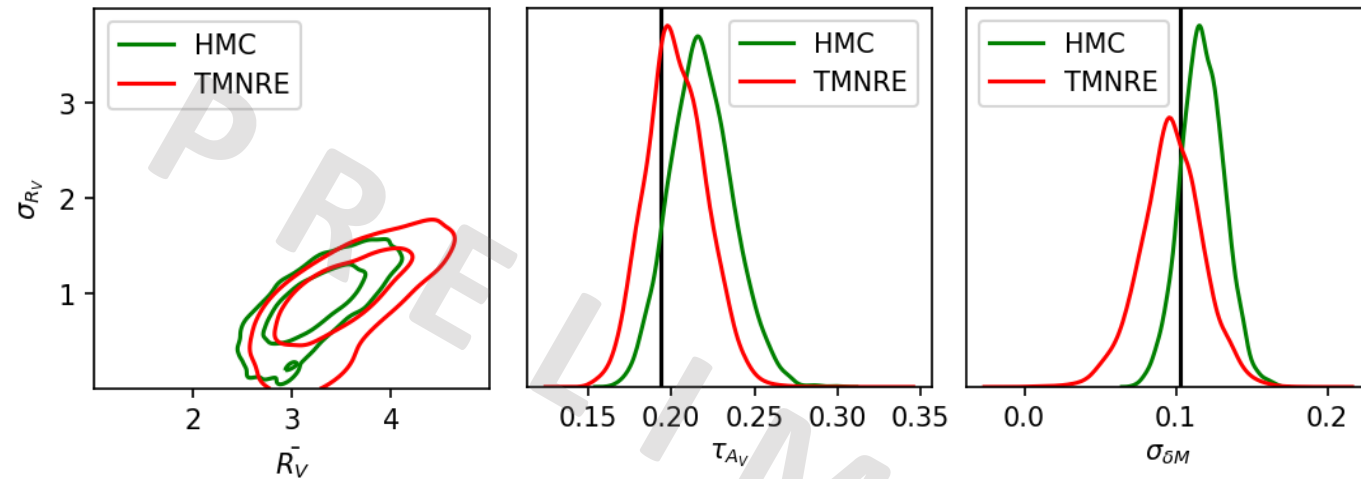
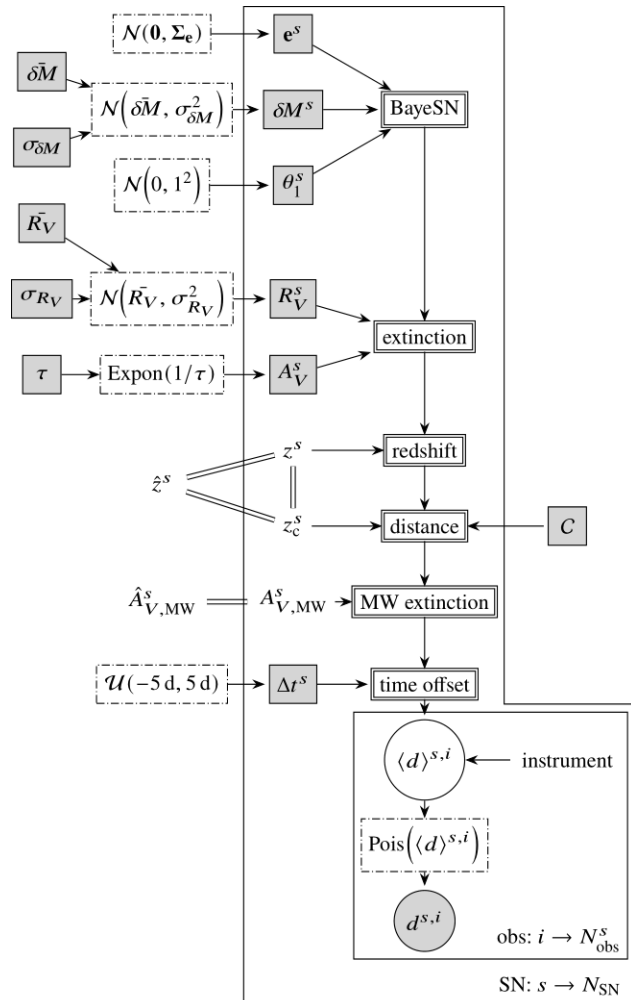


- BayeSN
 - pre-trained lightcurve model (for now?)
 - host & MW extinction
- “calibrated fluxes” (for now) vs. raw counts
- fixed redshifts and distances (for now)
- CSPDR3 (for now), Pantheon+
 - $\sim 100 - 200$ low-redshift SNæ Ia with spec-z
 - ~ 10000 observations (data vector)

➤ tackle real data, assuming completeness

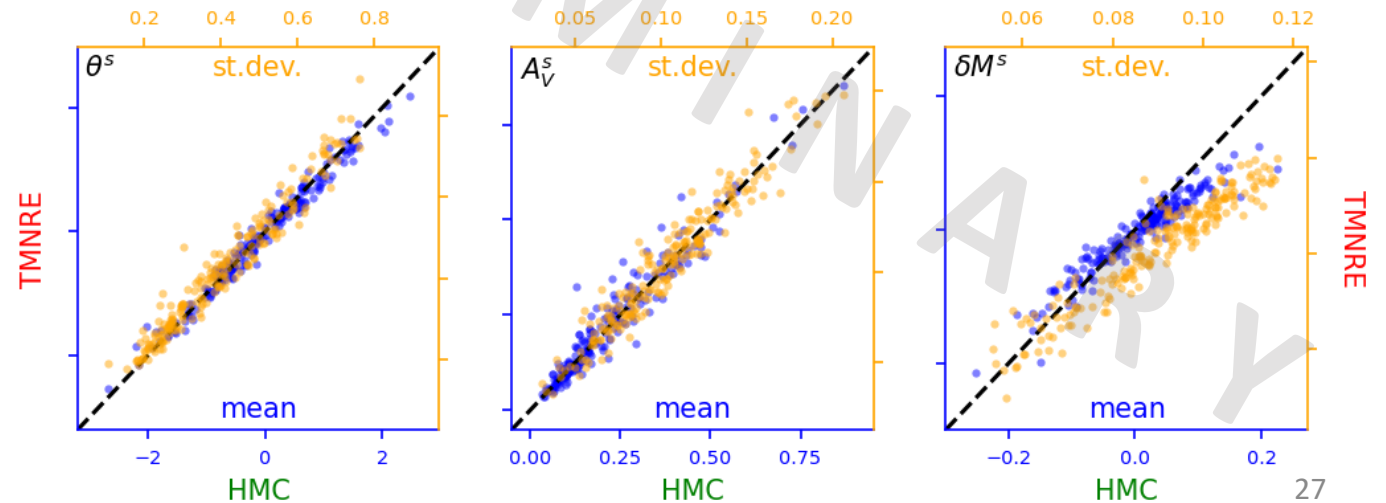
State of affairs

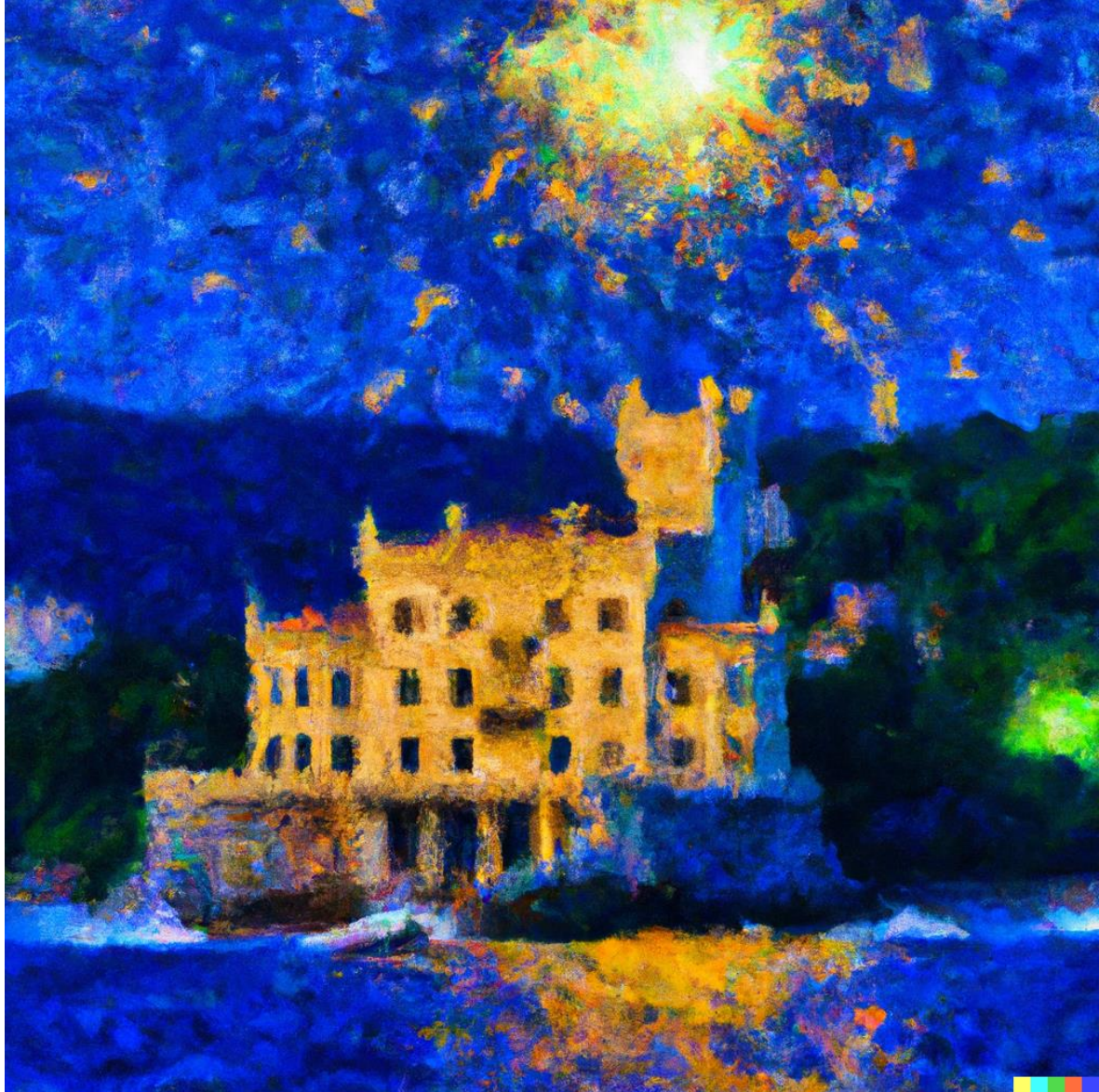
SIDE-real: Sn Ia Dust Extinction with real(istic) data



HMC by
Matt Grayling
using numpyro

HMC: ~ 1 h
NRE: ~ 2 h / stage
(not optimised)





**Thank you for
your attention!**

“A supernova explosion
over the Miramare castle;
painting in the style of Van Gogh”

image by DALL·E