Simulation Based Inference for SNe Ia cosmology

Adam Trigui

Under the supervision of Mickaël Rigault and Florian Ruppin

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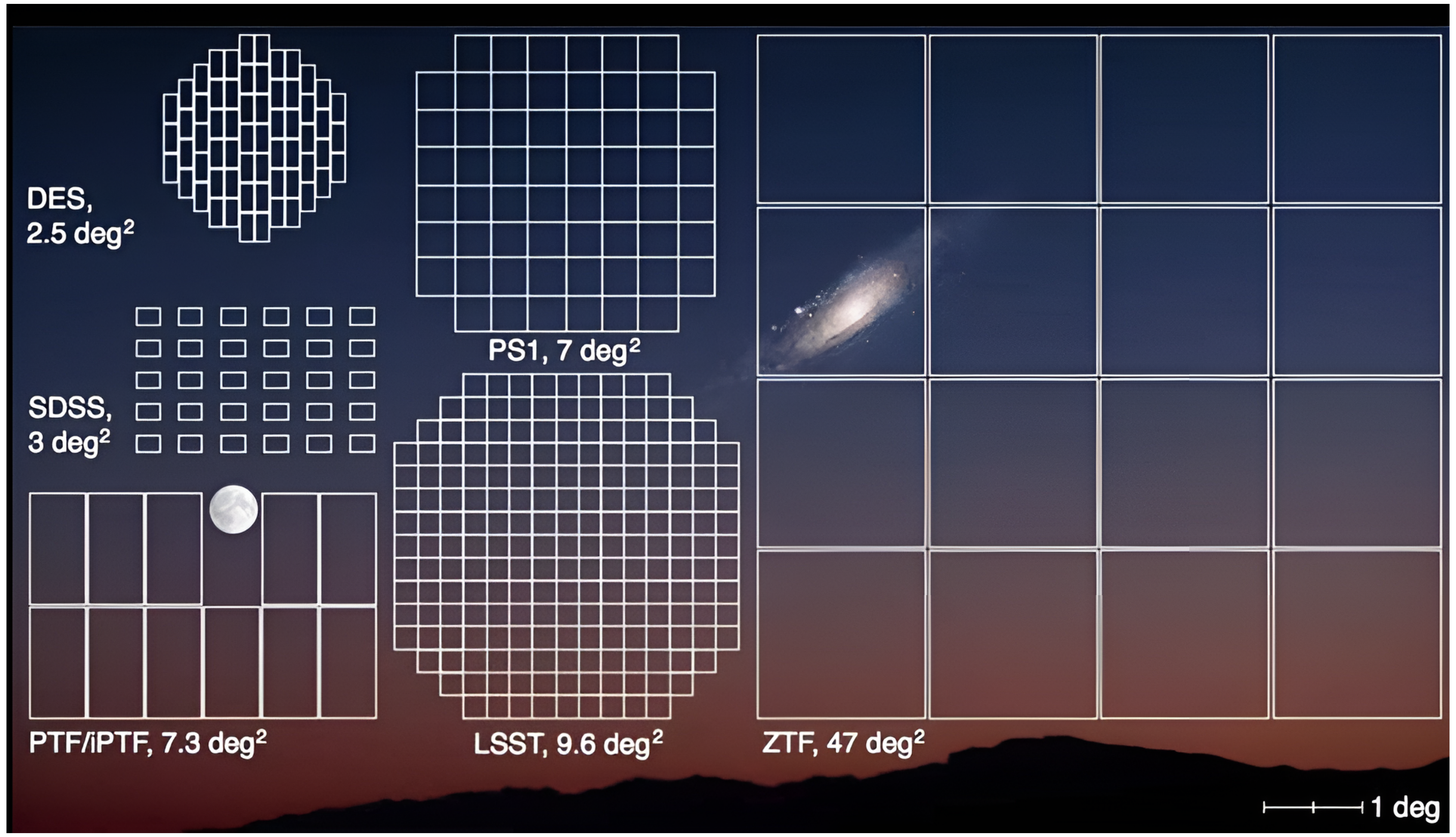
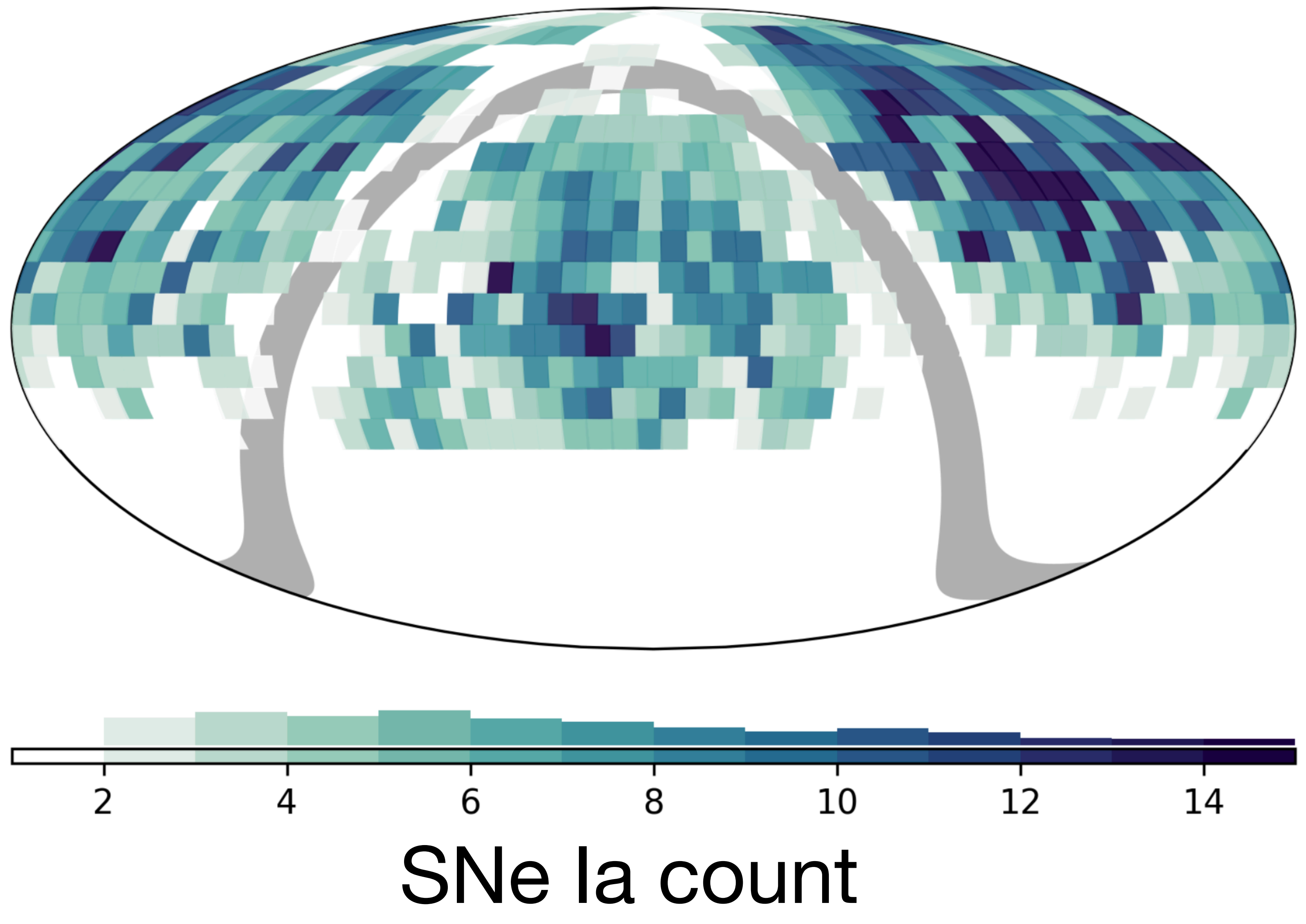
ZTF survey

Mount Palomar, California

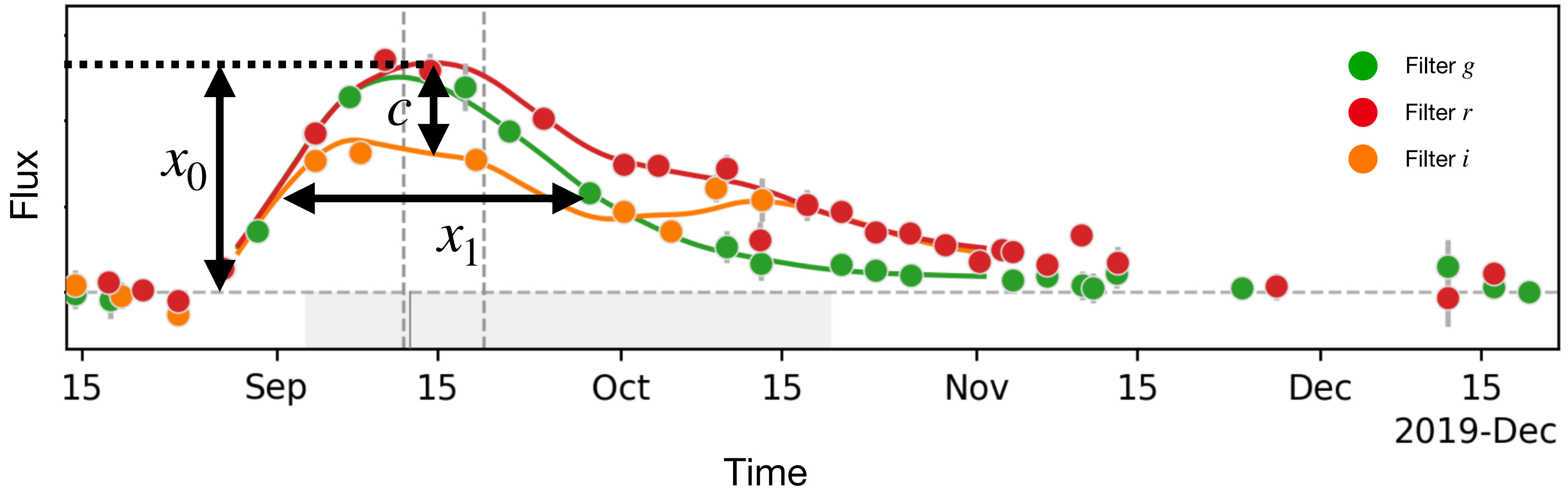




Total > 3000 (DR2)

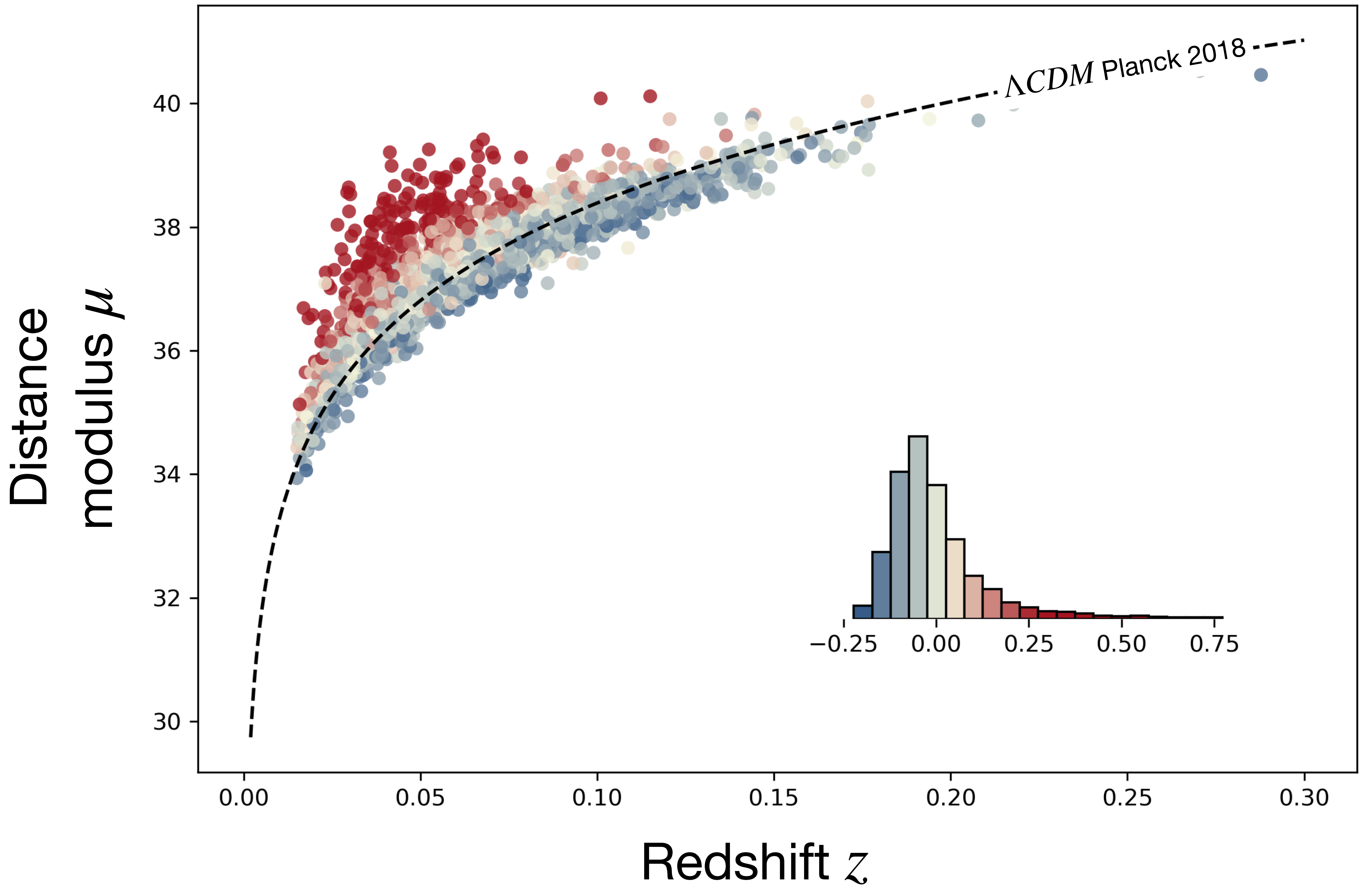
Type Ia Supernovae

ZTF DR2 : ZTF19abuonnx



- Flux x_0
  - Distance modulus $\mu \propto -log(x_0)$
- Stretch x_1
- Colour c

ZTF DR2 data
(Rigault et al. 2025)

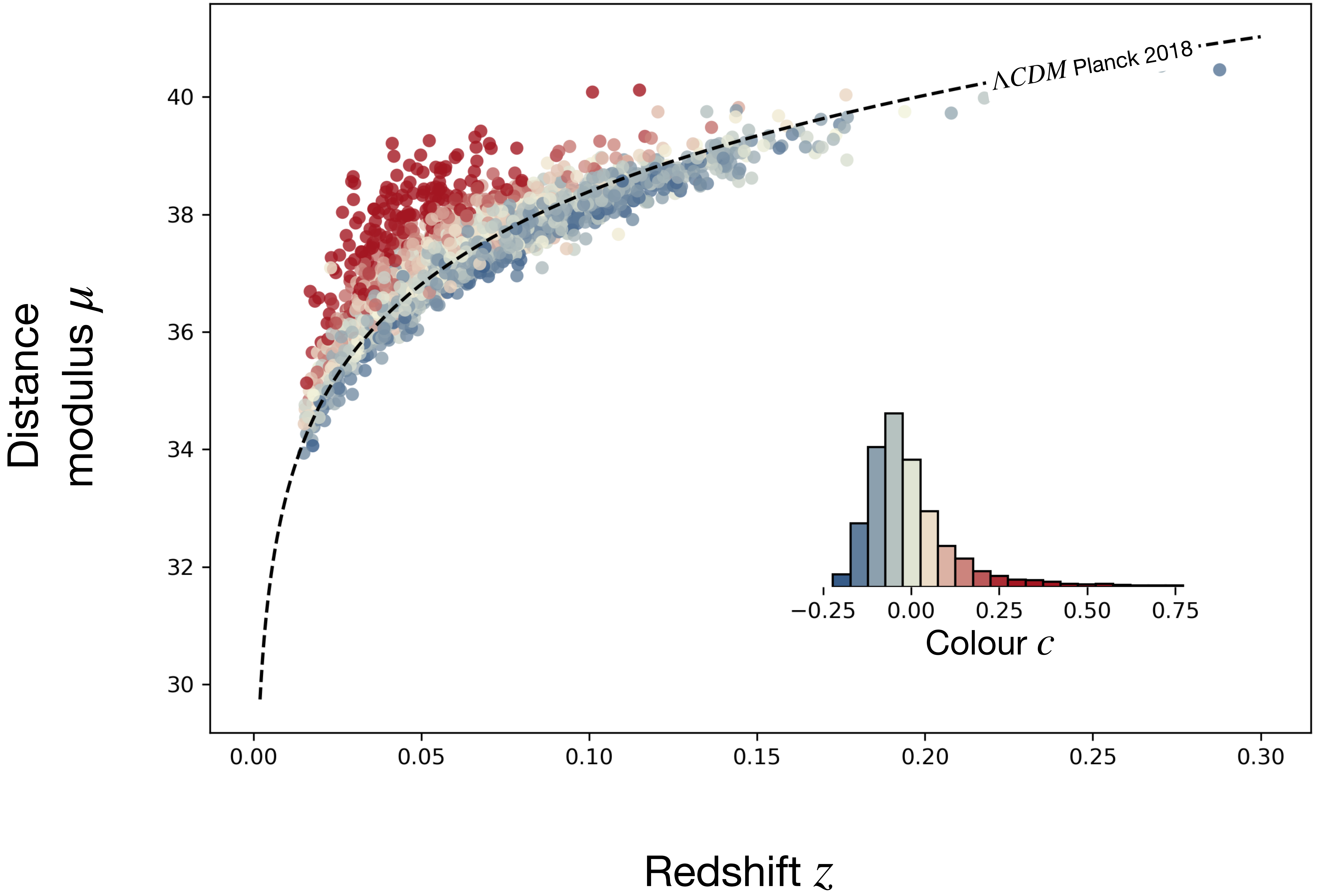


SNe Ia standardisation

Standardisation : $M = M_0 + \beta c - \alpha x_1 + \gamma p$

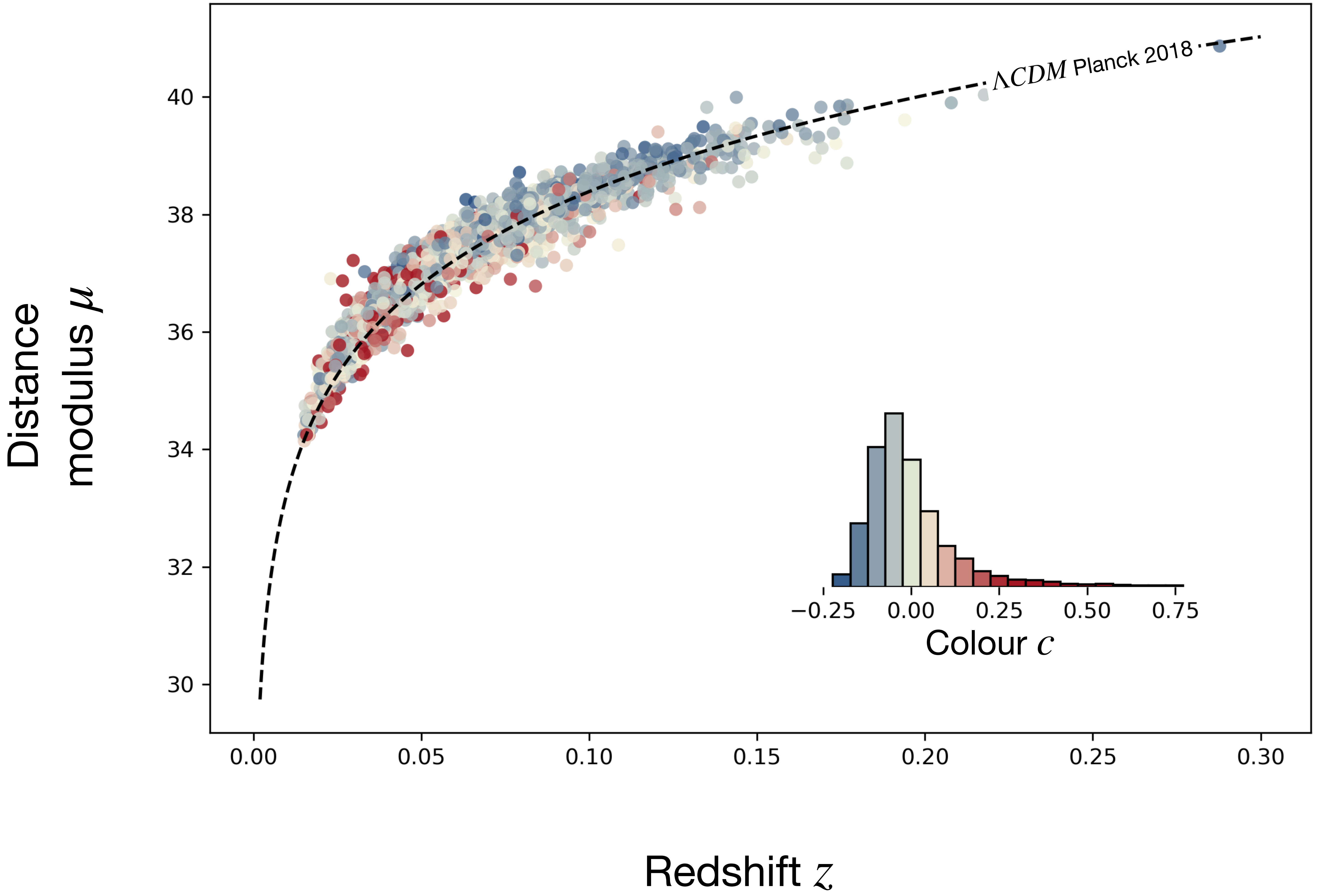
SNe Ia standardisation

Inspired by Madeleine Ginolin



SNe Ia standardisation

Inspired by Madeleine Ginolin



SNe Ia standardisation

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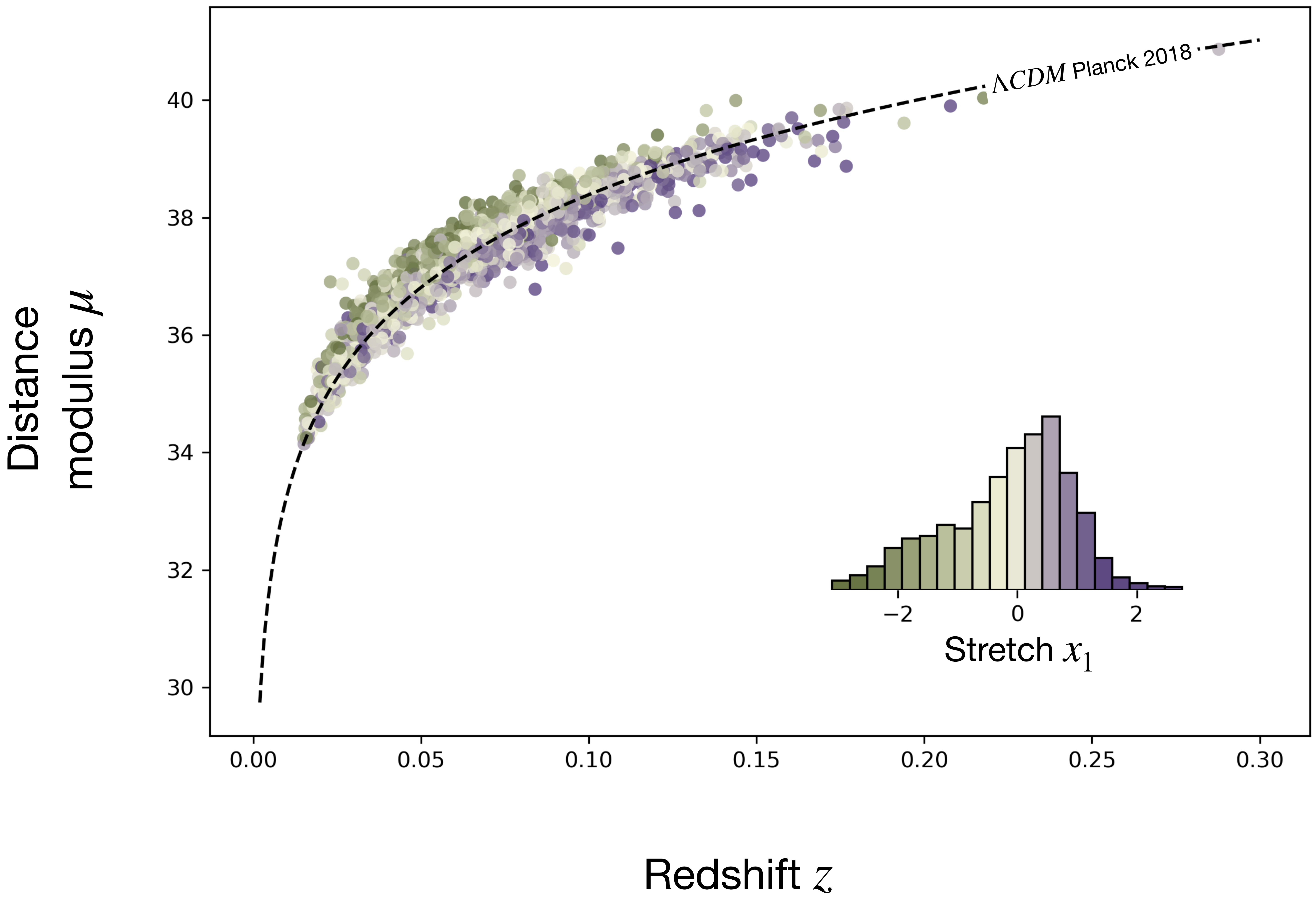

SNe Ia standardisation

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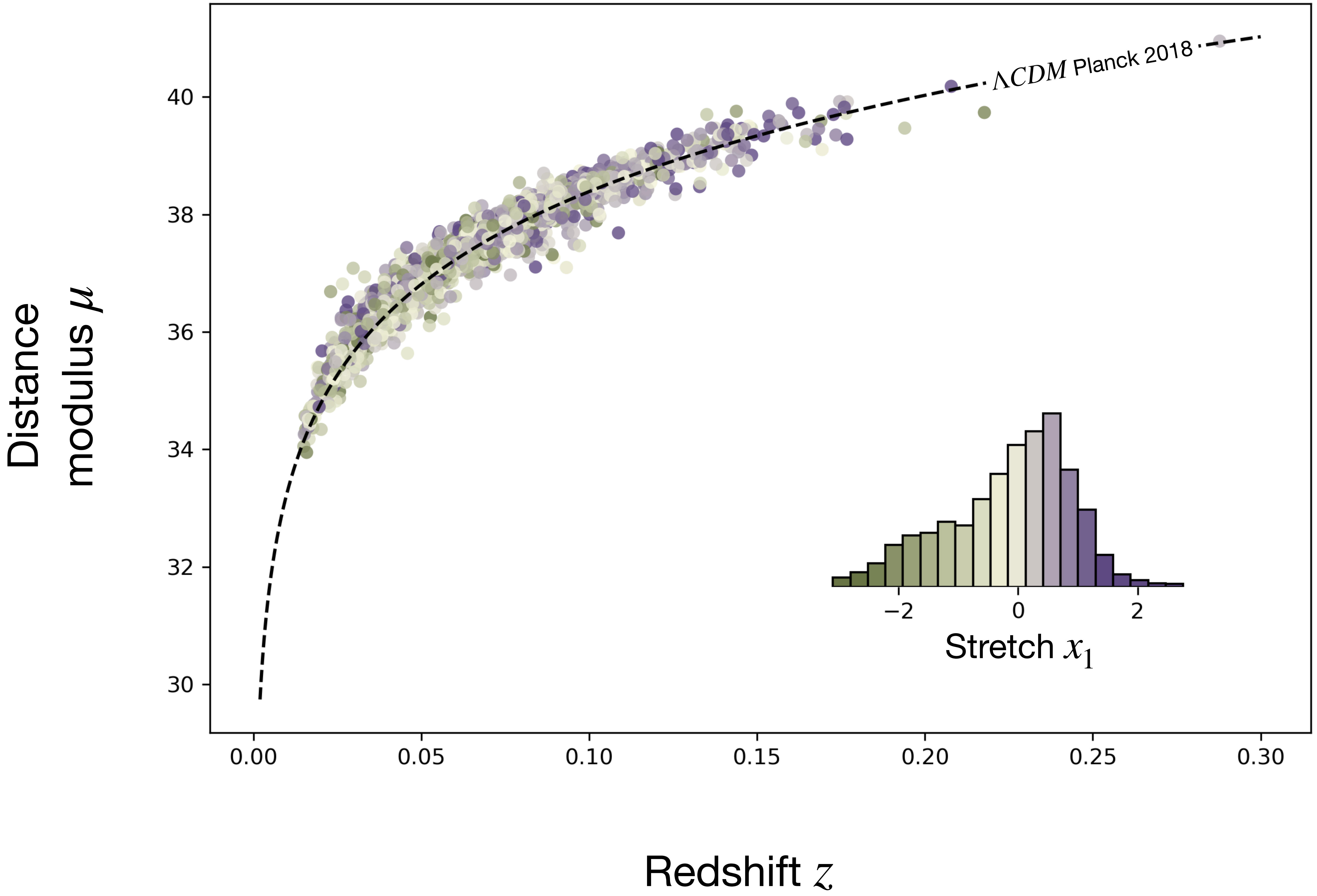
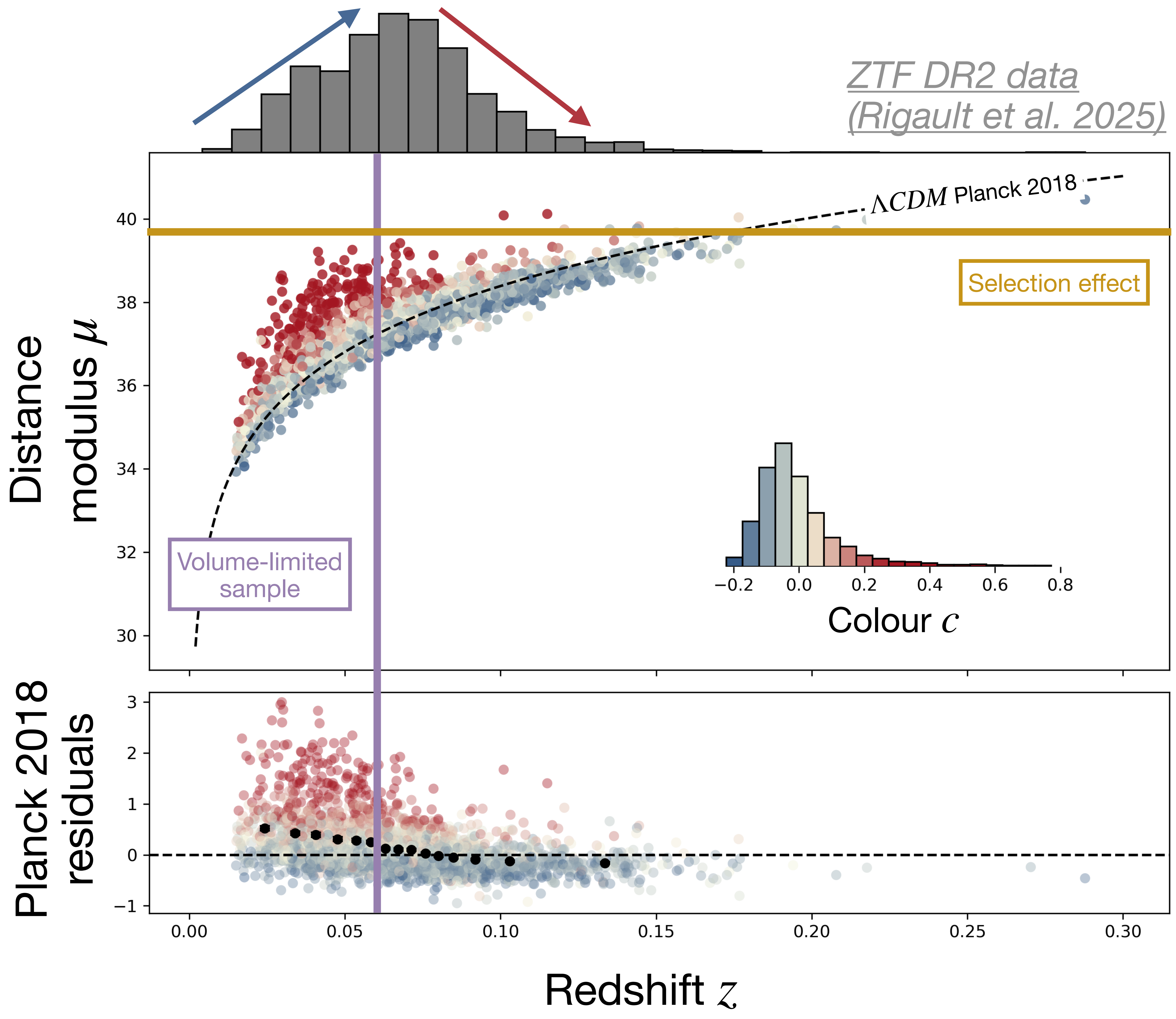
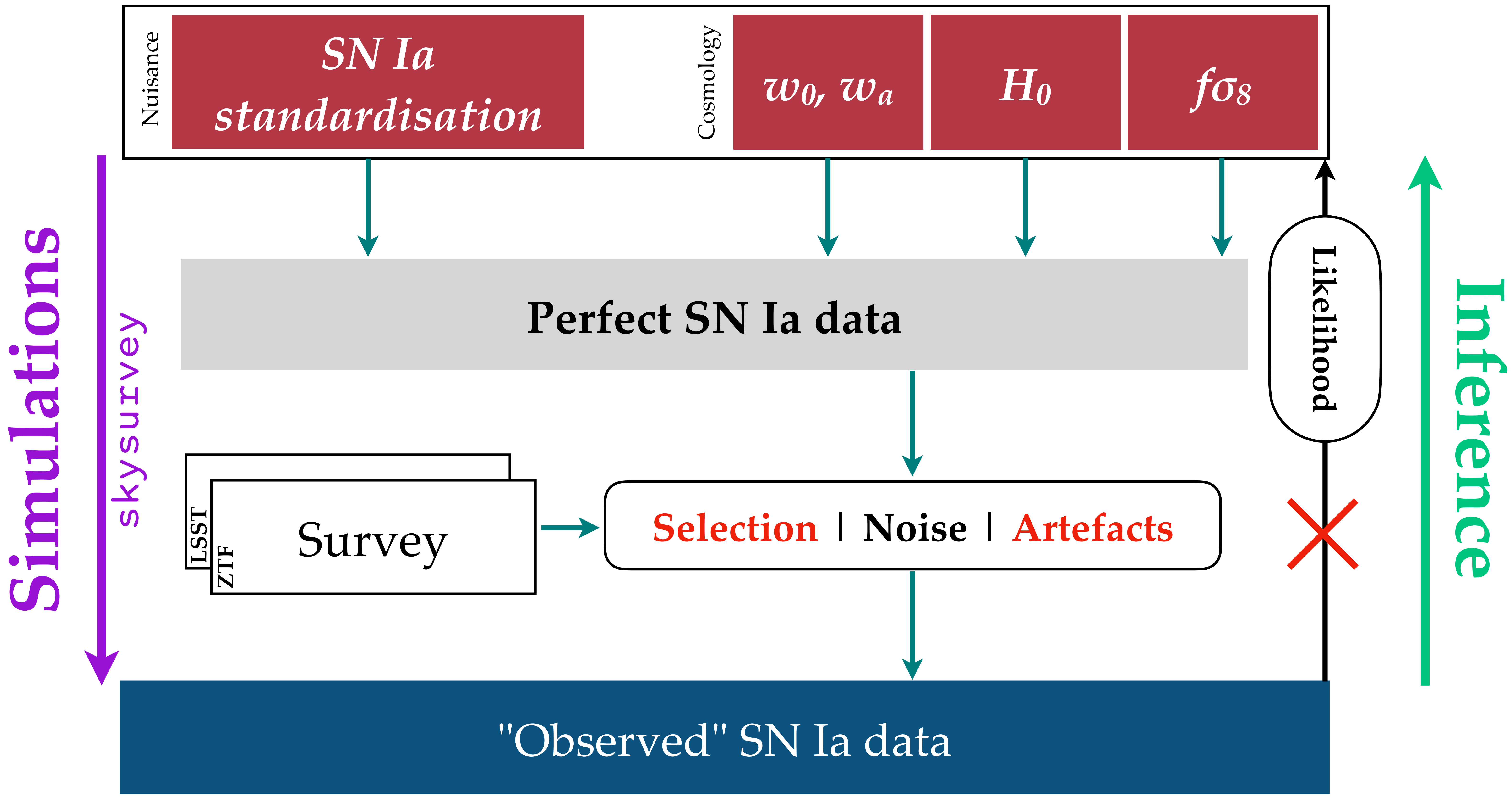


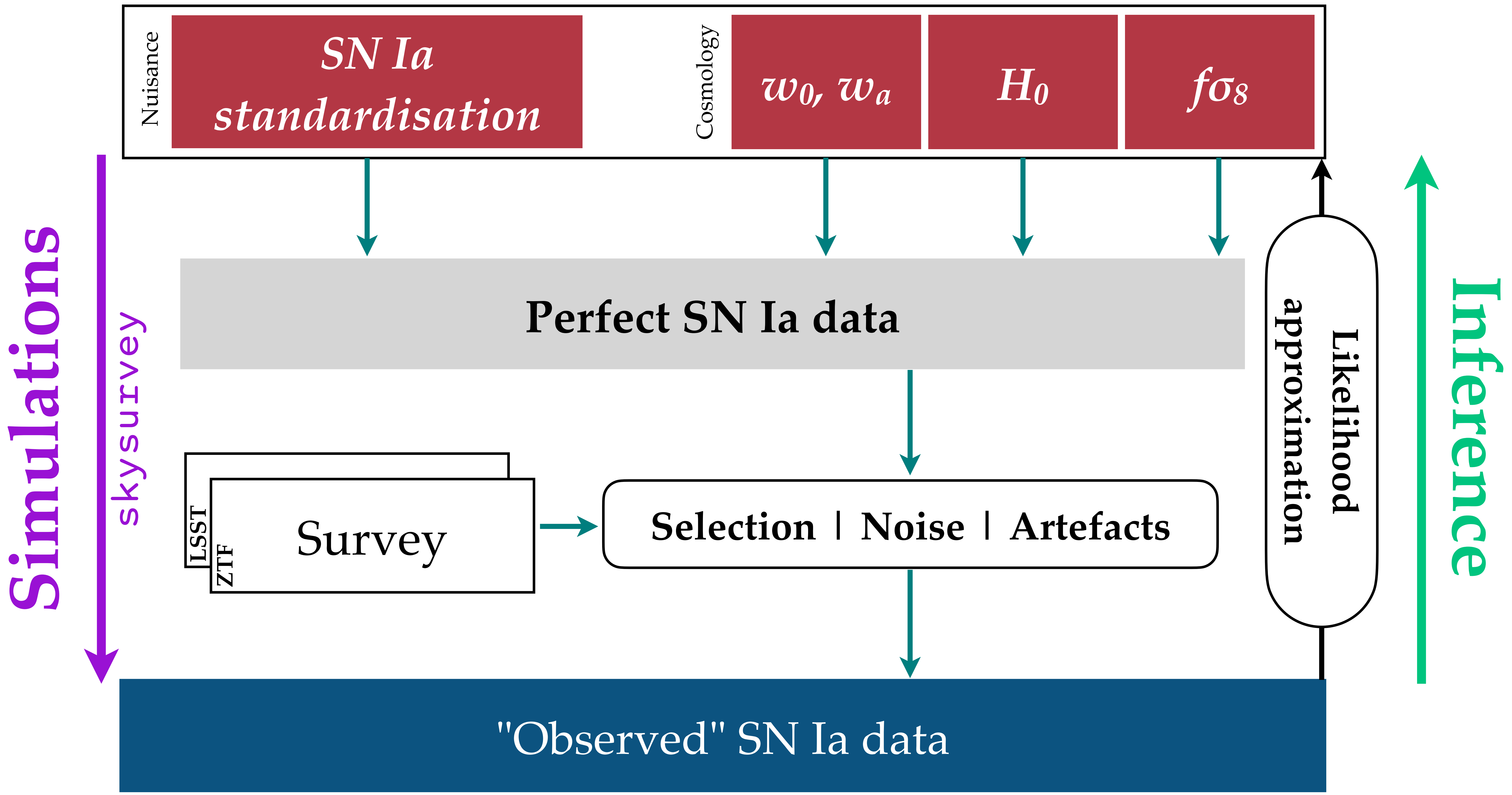
Selection effects



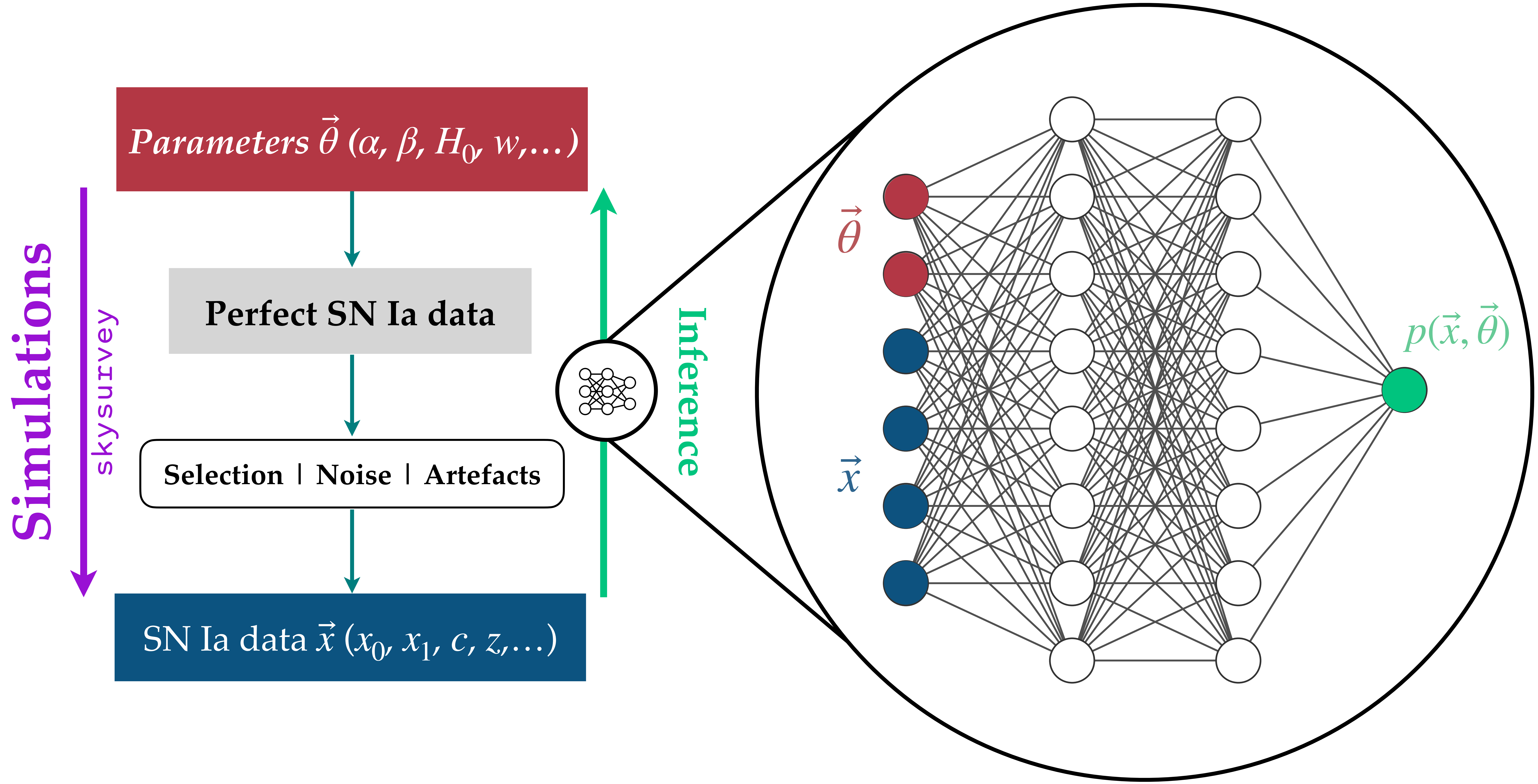
Simulation/inference asymmetry



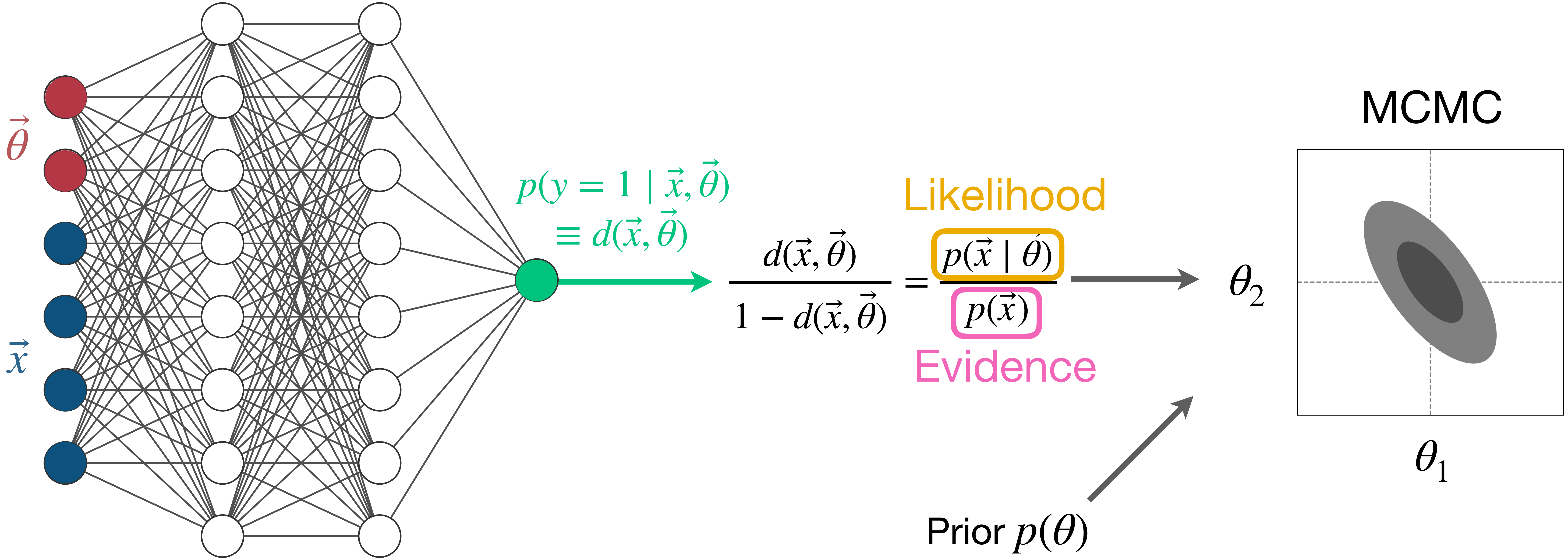
Simulation based inference (SBI)



Neural Ratio Estimator



Neural Ratio Estimator

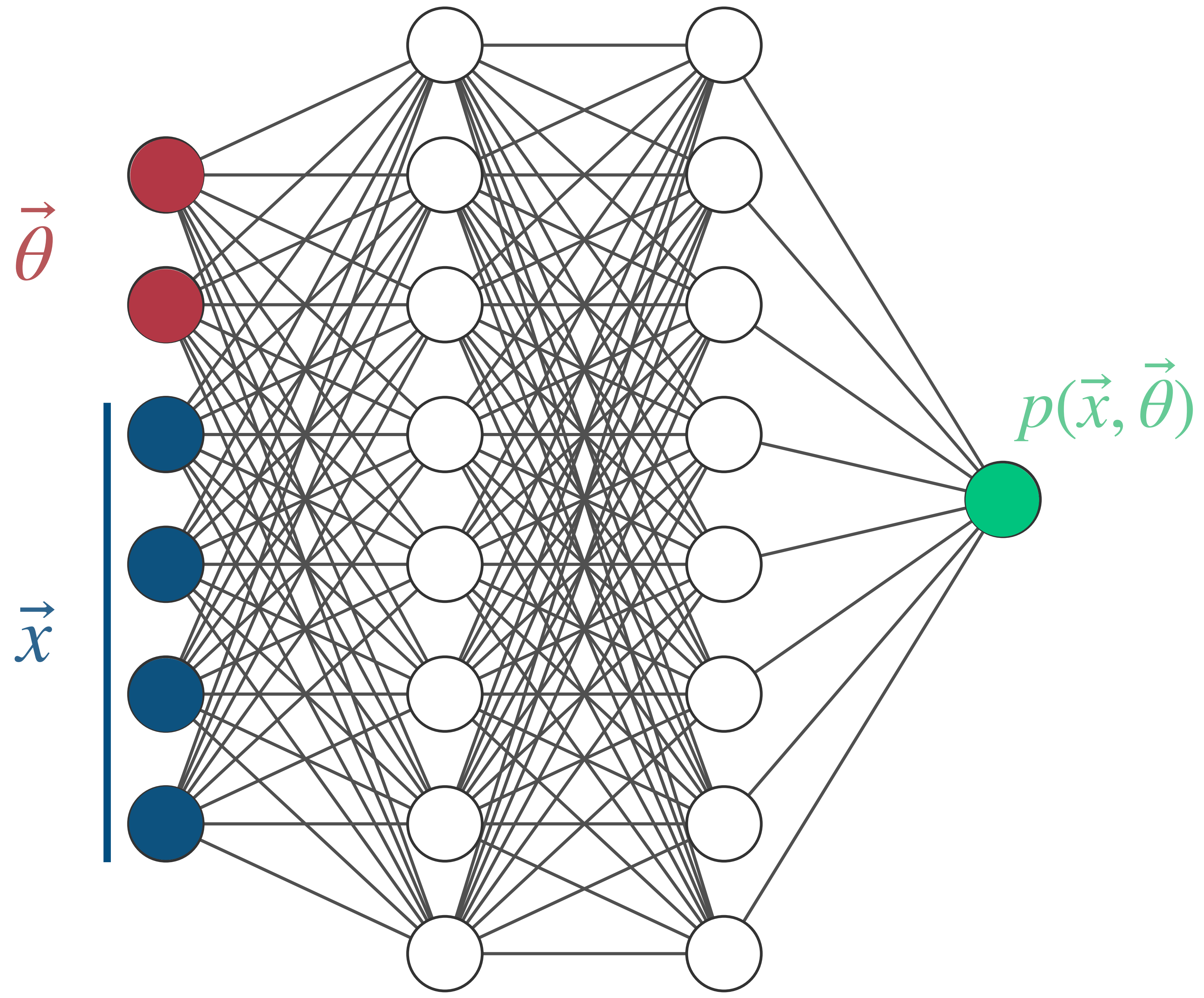


Neural Ratio Estimator

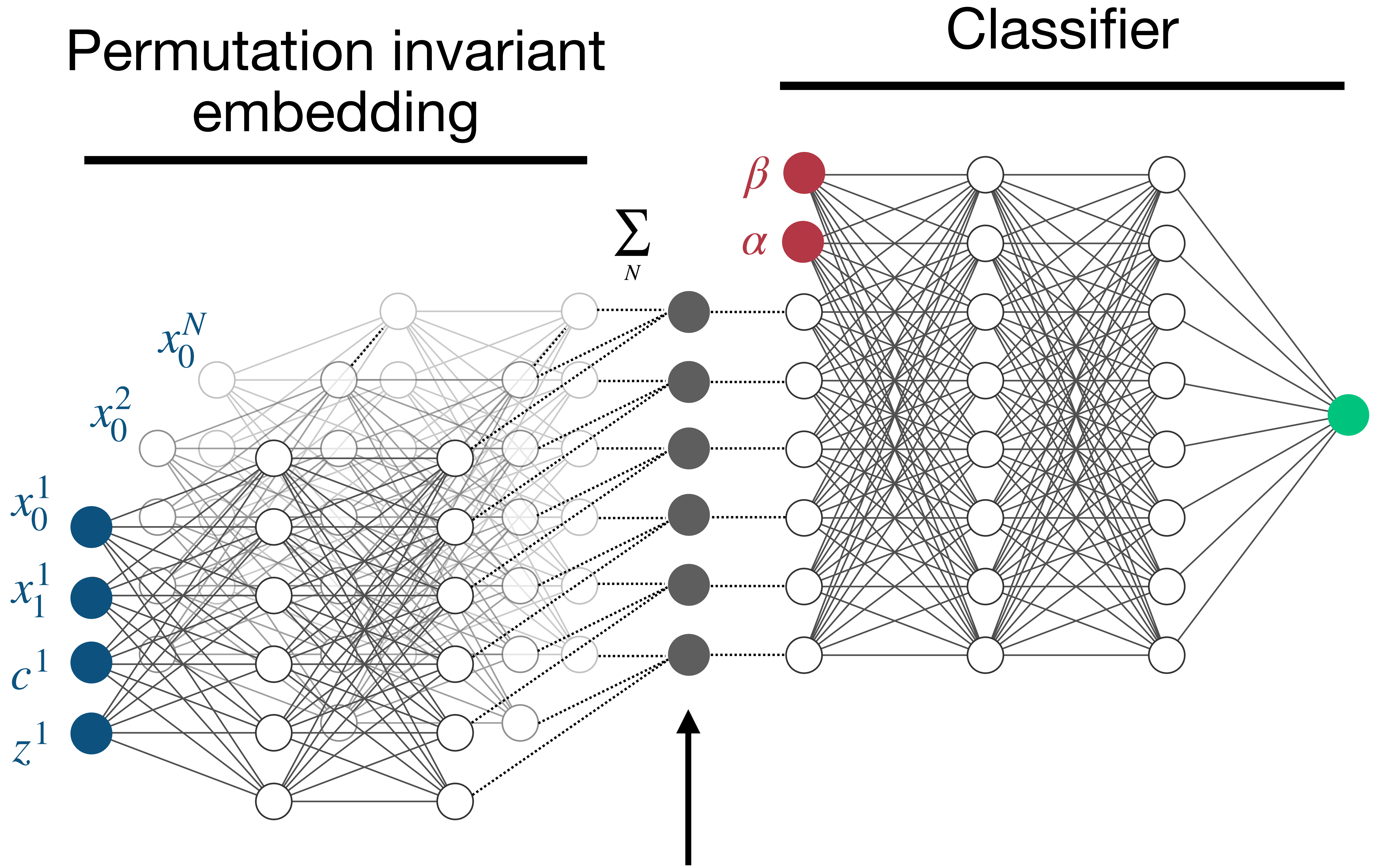
ZTF DR3 = 10 000+ SNe Ia $\times$ 10+ observables $=$ 100 000+ input data neurons $\vec{x}$

Problem :

- Supernovae can be given in any order
- Sample size can vary



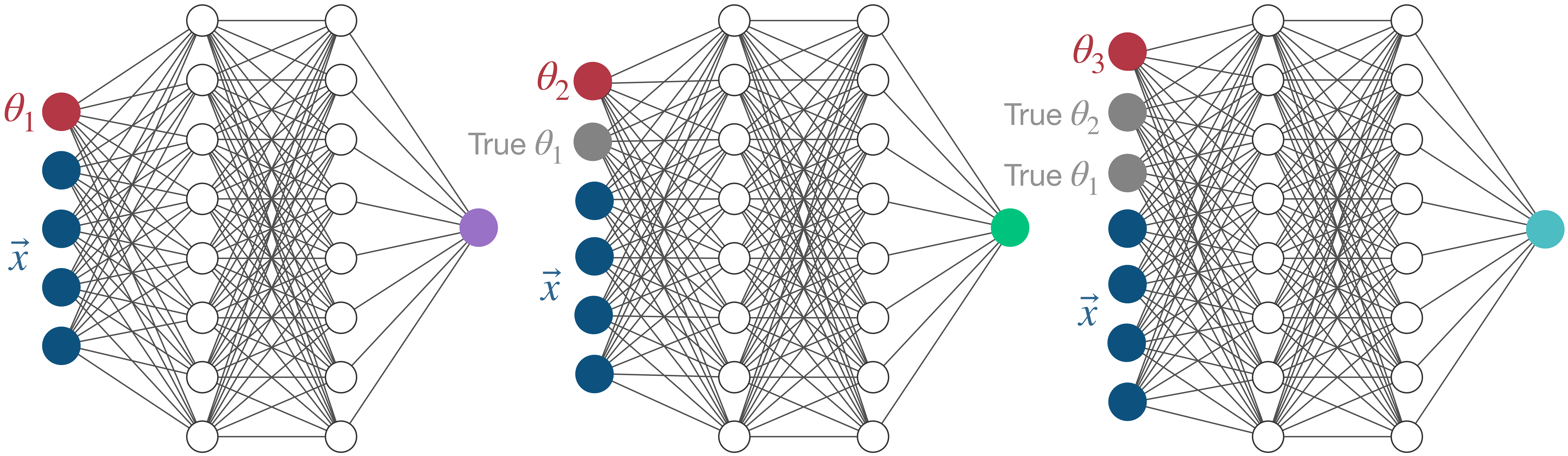
Deepset Zaheer et al. (2018)



Complex information encoded into a small size vector (100 000 → 64)

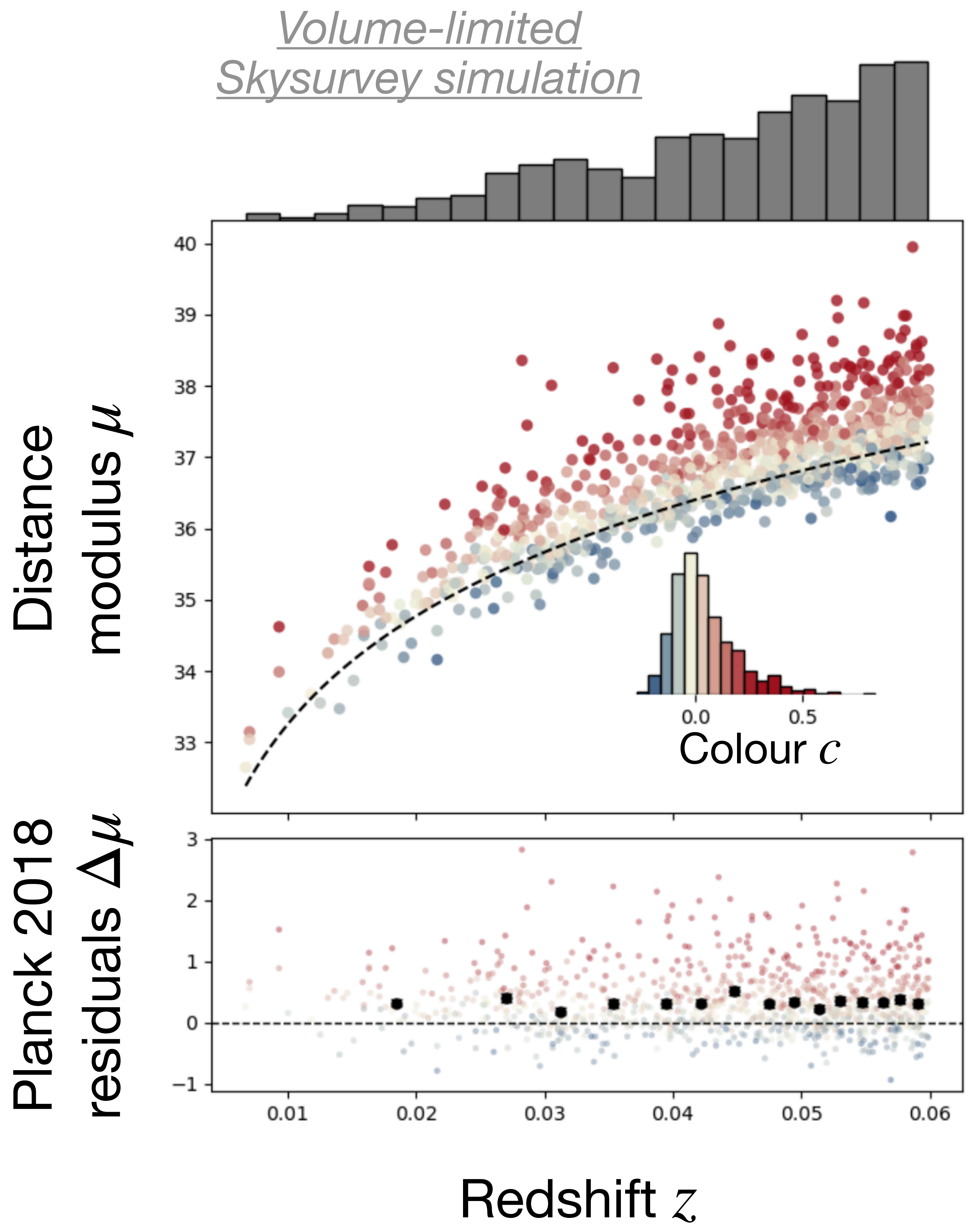
Autoregression Karchev and Trotta (2024)

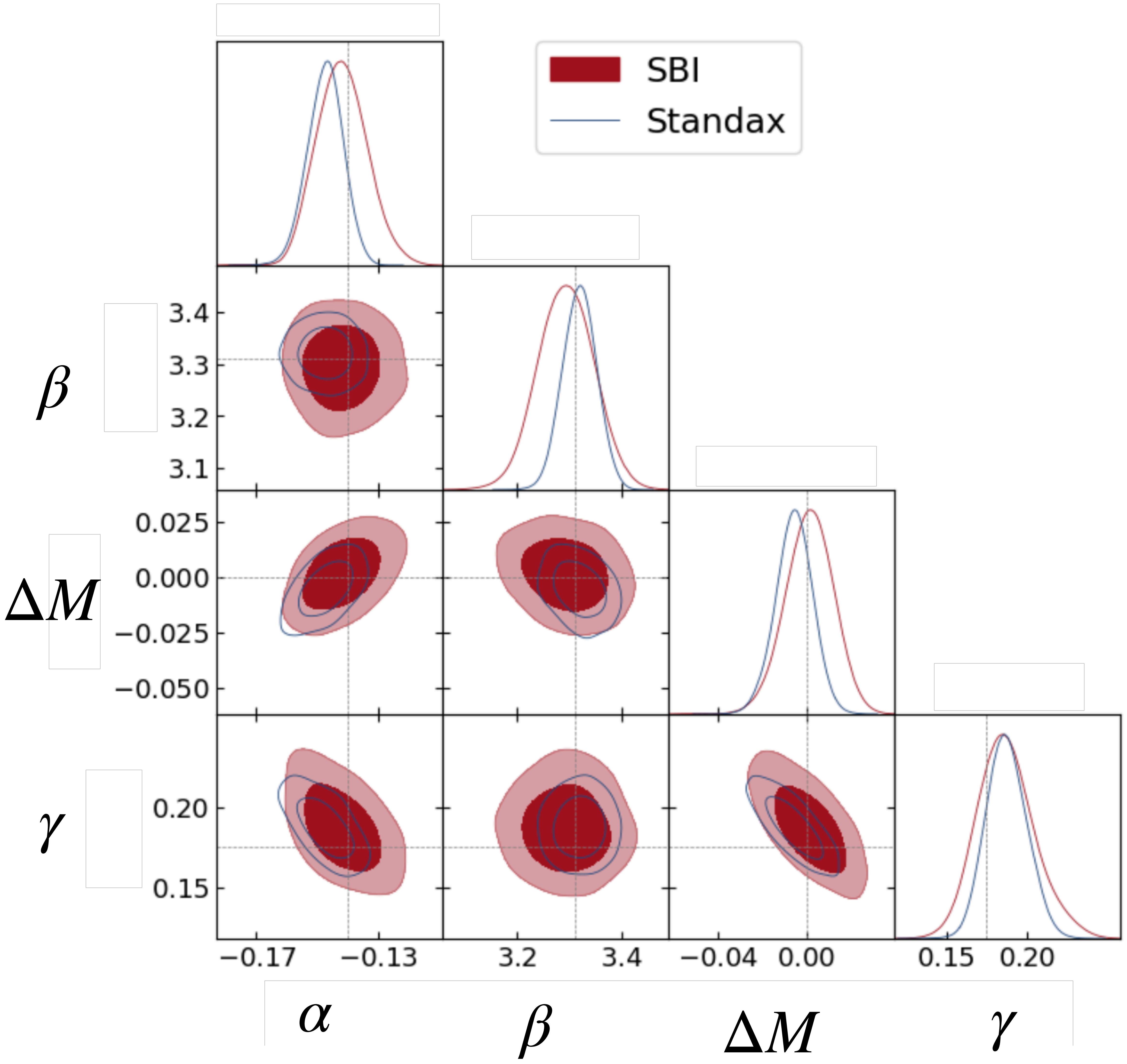
Use joint posteriors to help the network learn difficult parameters.



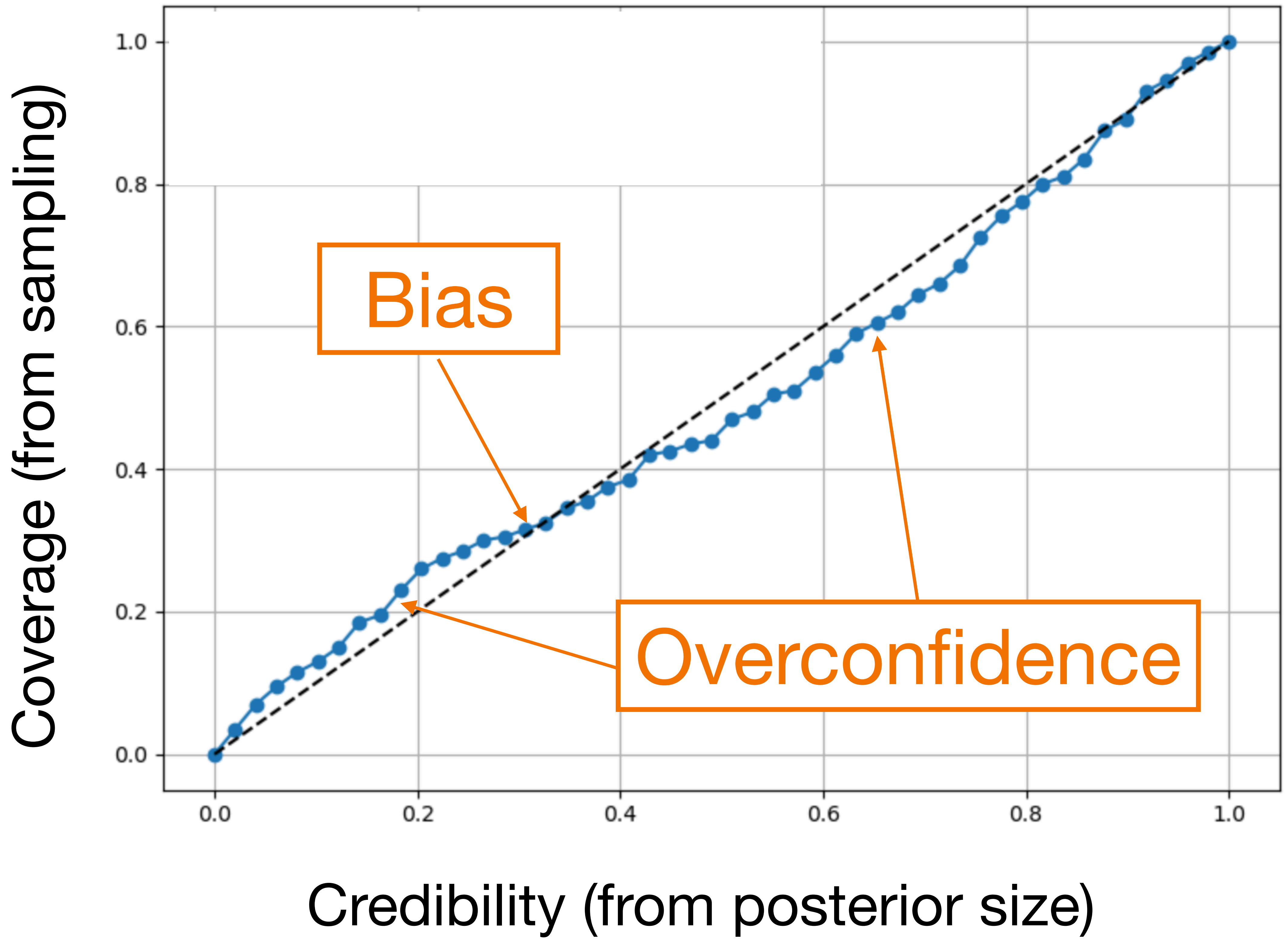
$$p(\theta \mid x) \propto p(\theta_1 \mid x) \cdot p(\theta_2 \mid x, \theta_1) \cdot p(\theta_3 \mid x, \theta_1, \theta_2)$$

Preliminary results: standardisation





Coverage test Lemos et al. (2023)



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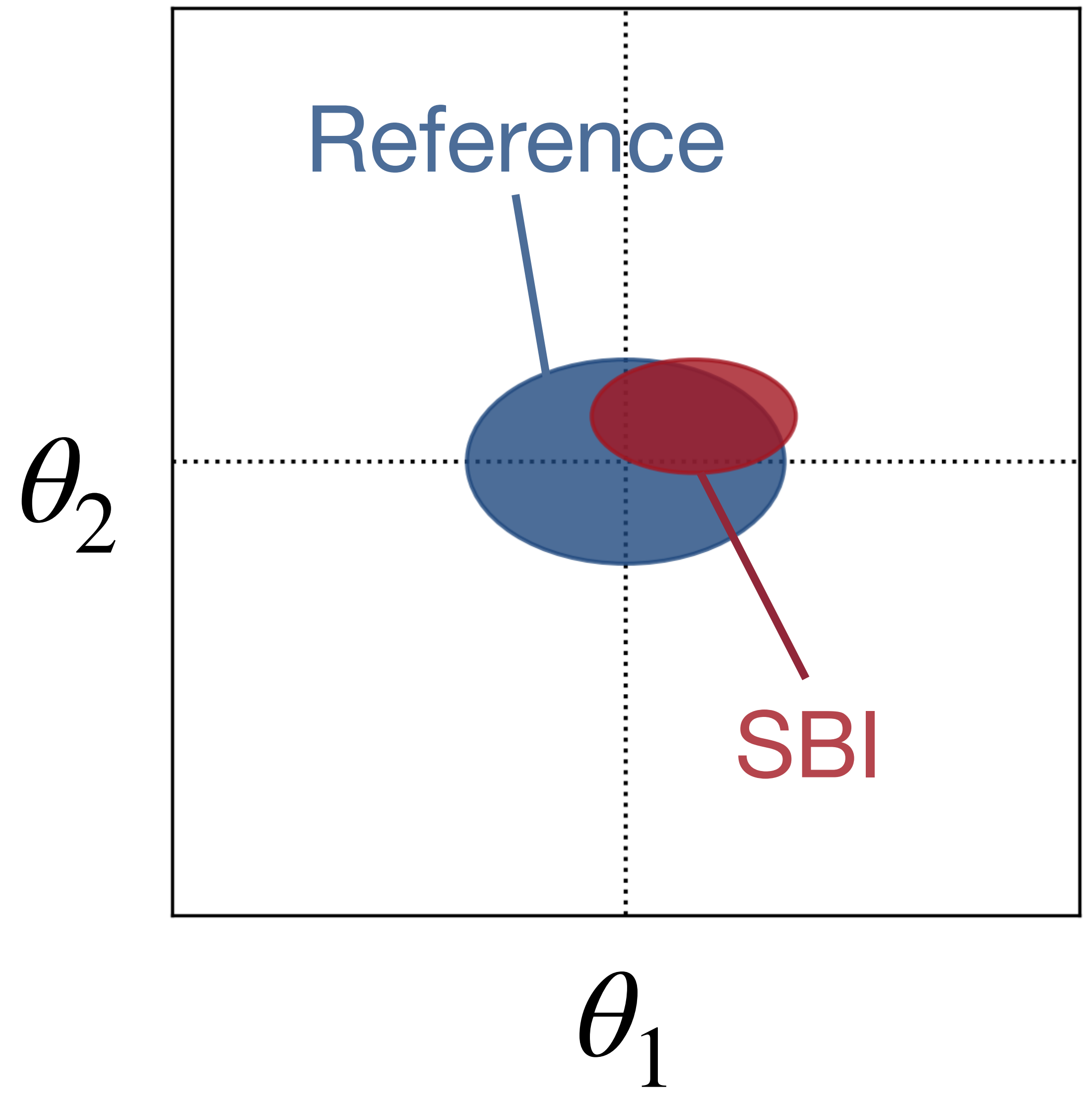
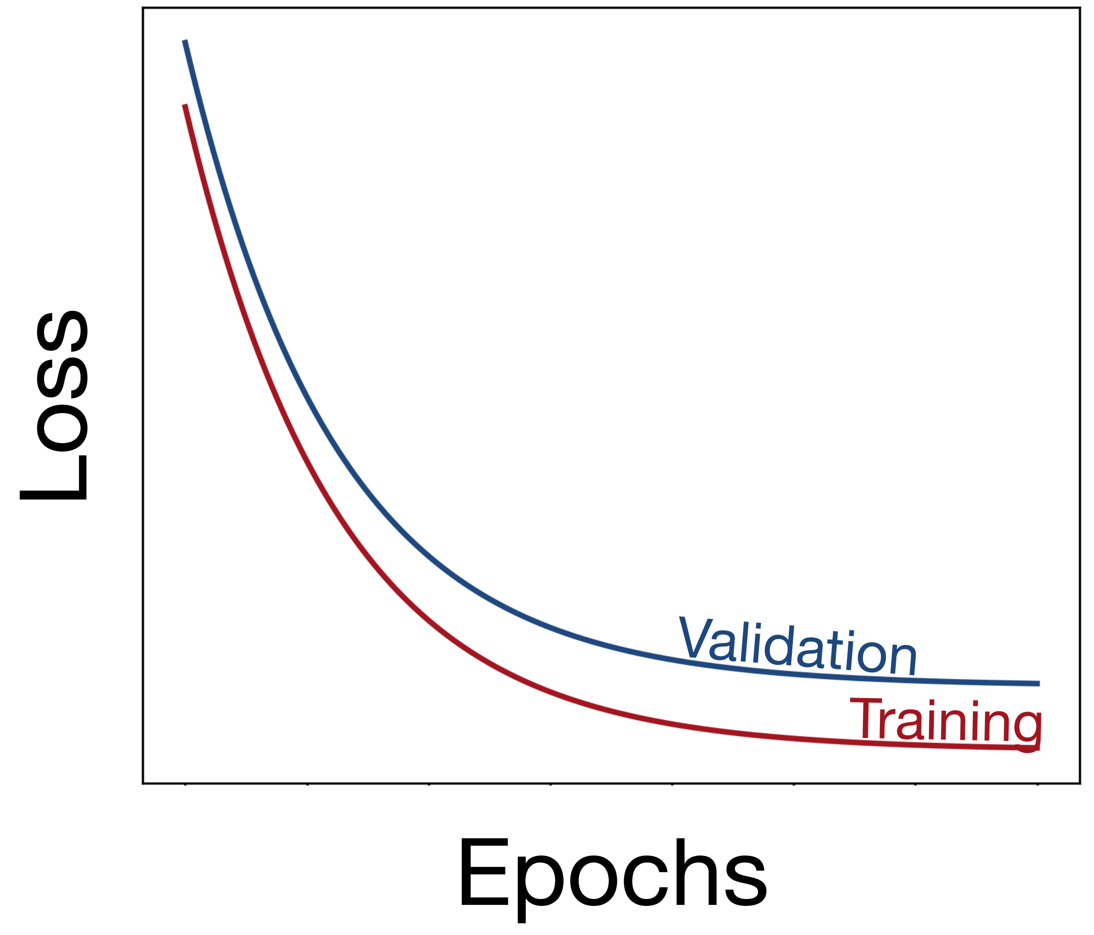
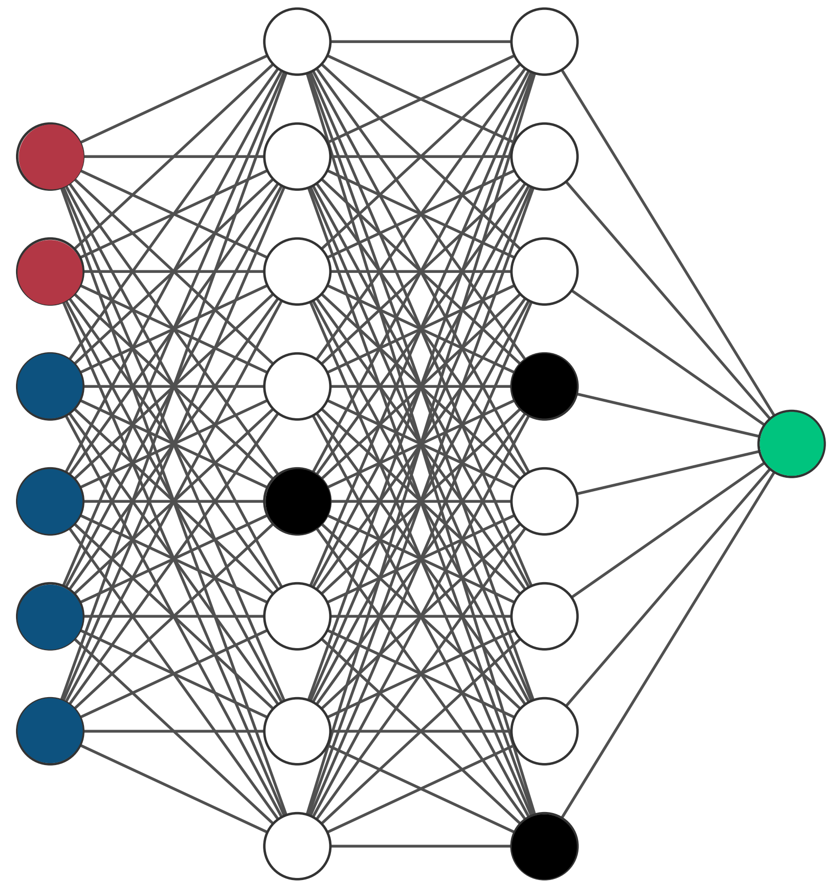


Regularisation

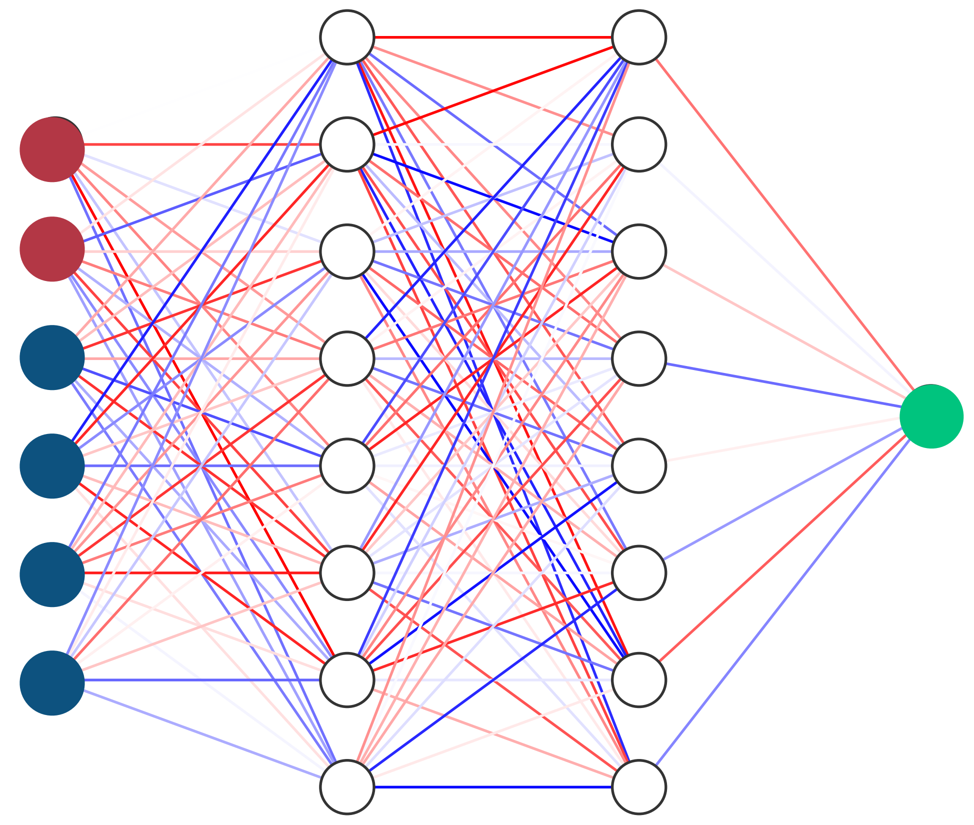
Early stopping



Dropout

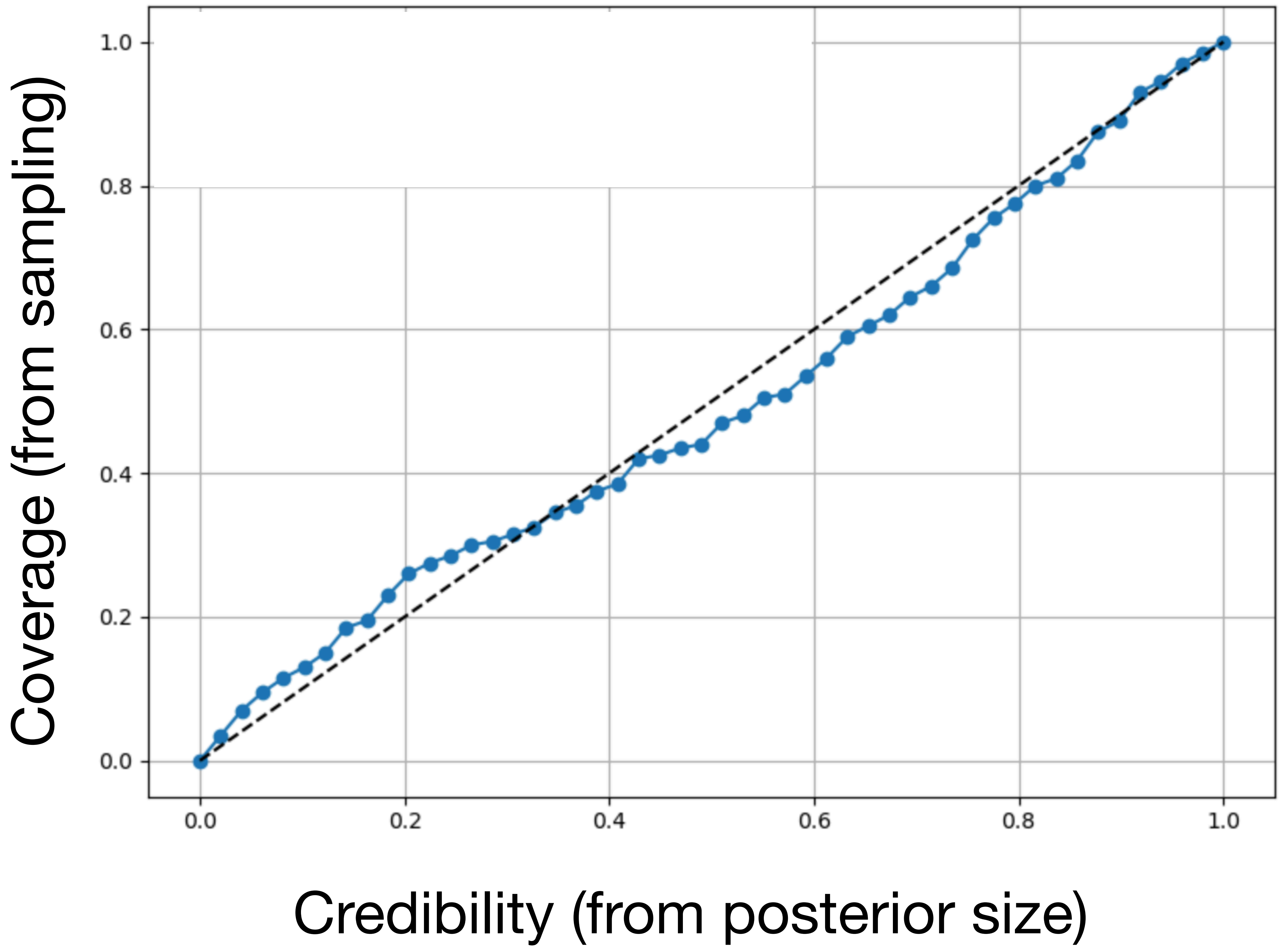


Weight decay

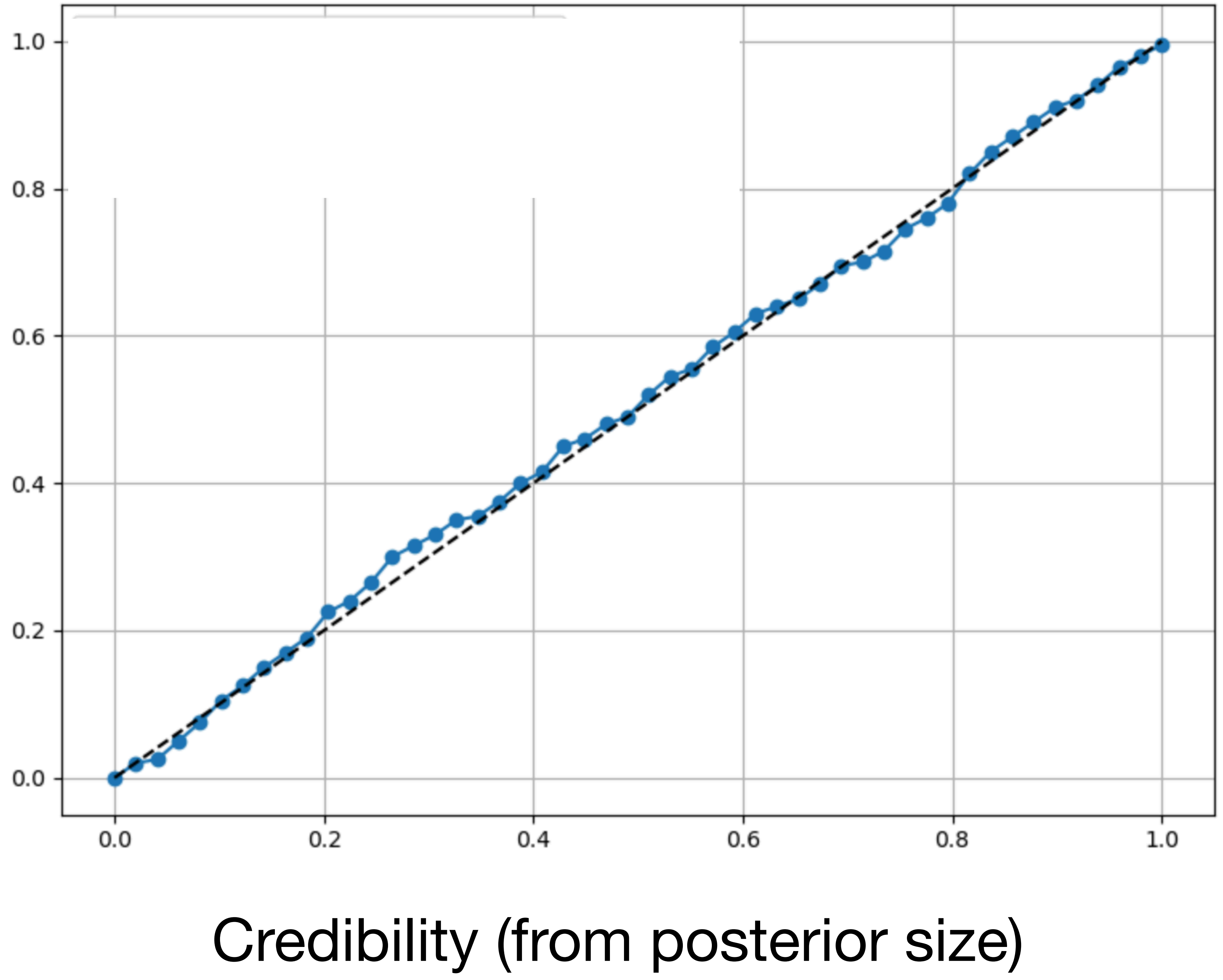


Coverage test

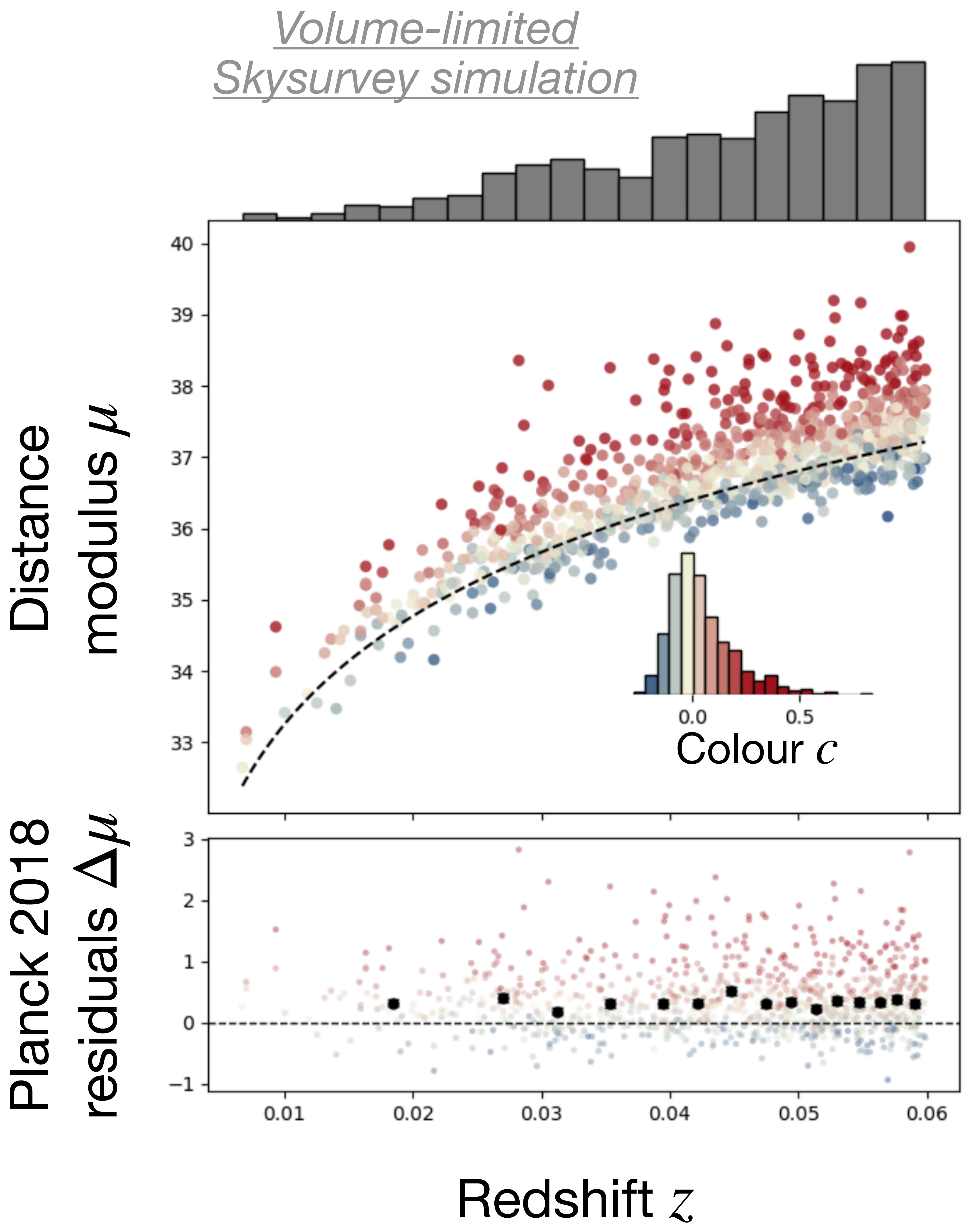
Before regularisation

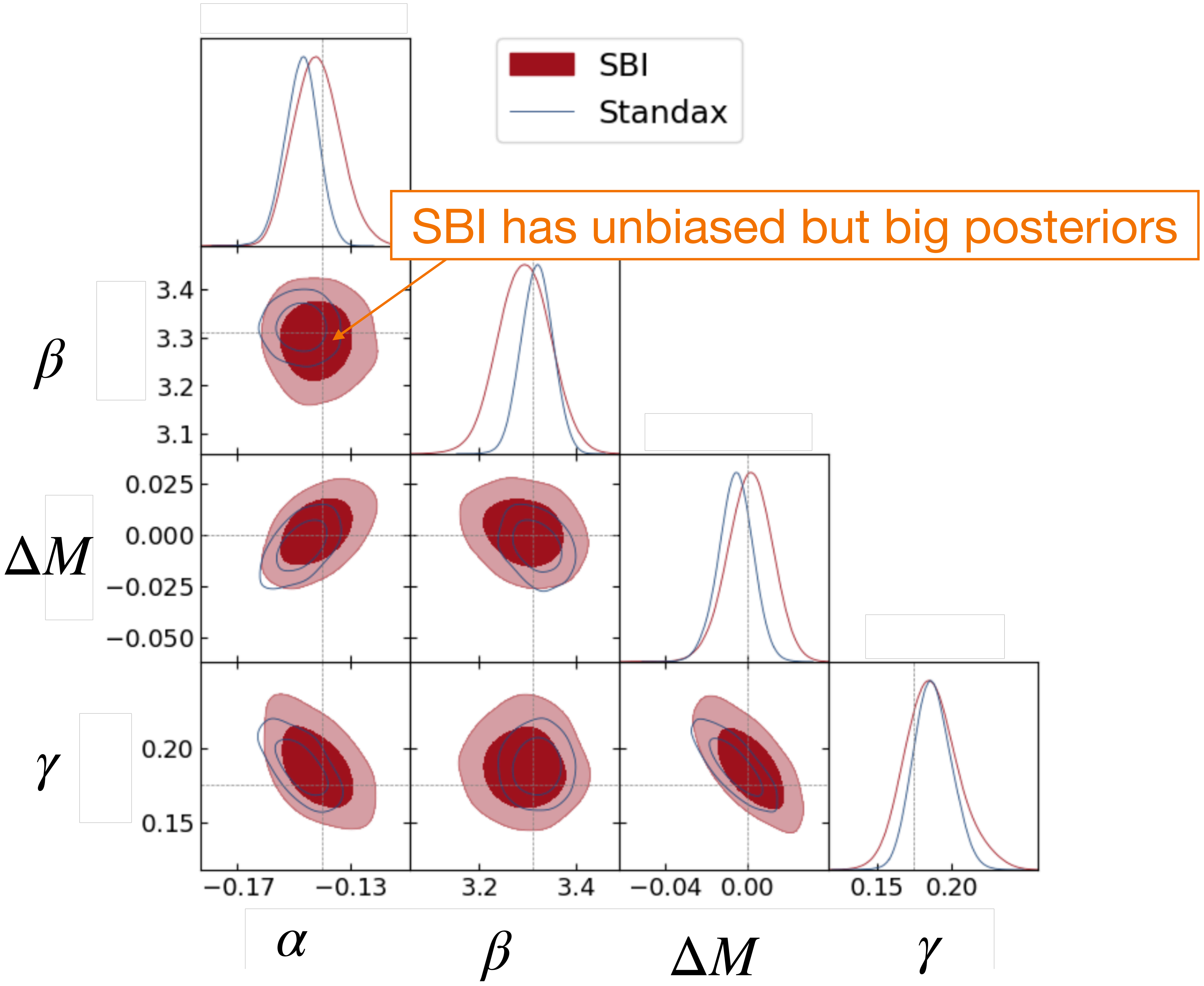


After regularisation

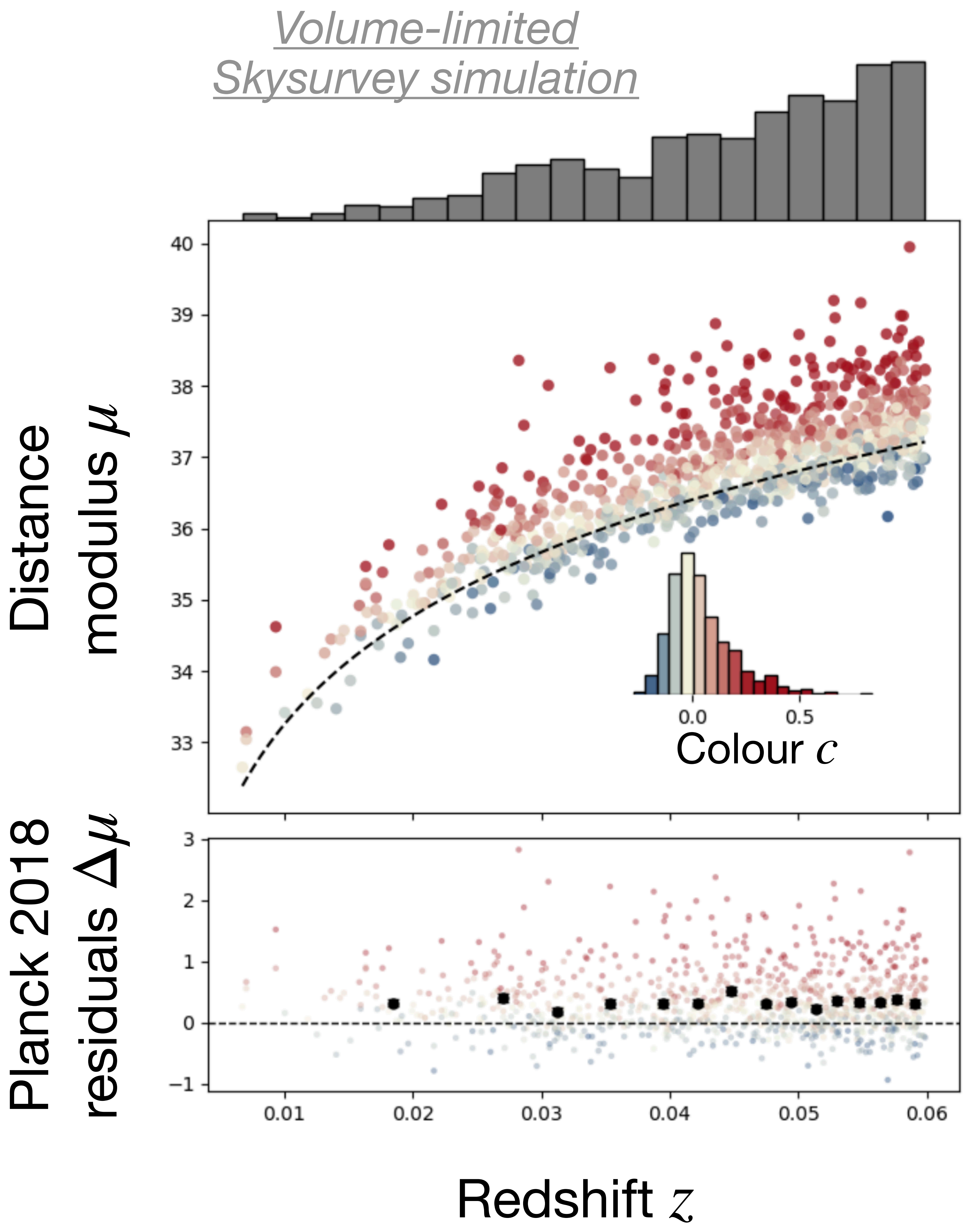


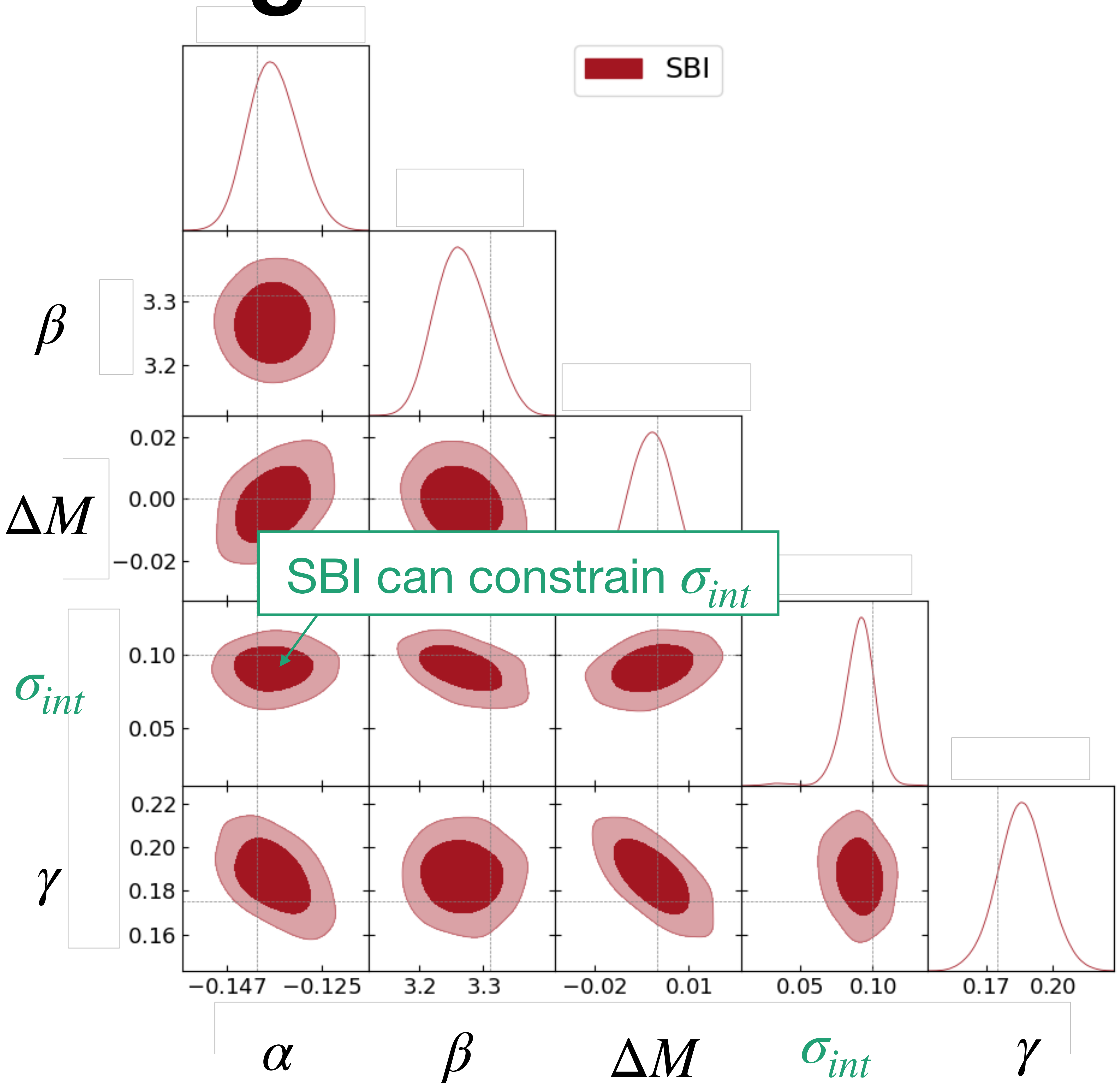
Preliminary results: standardisation



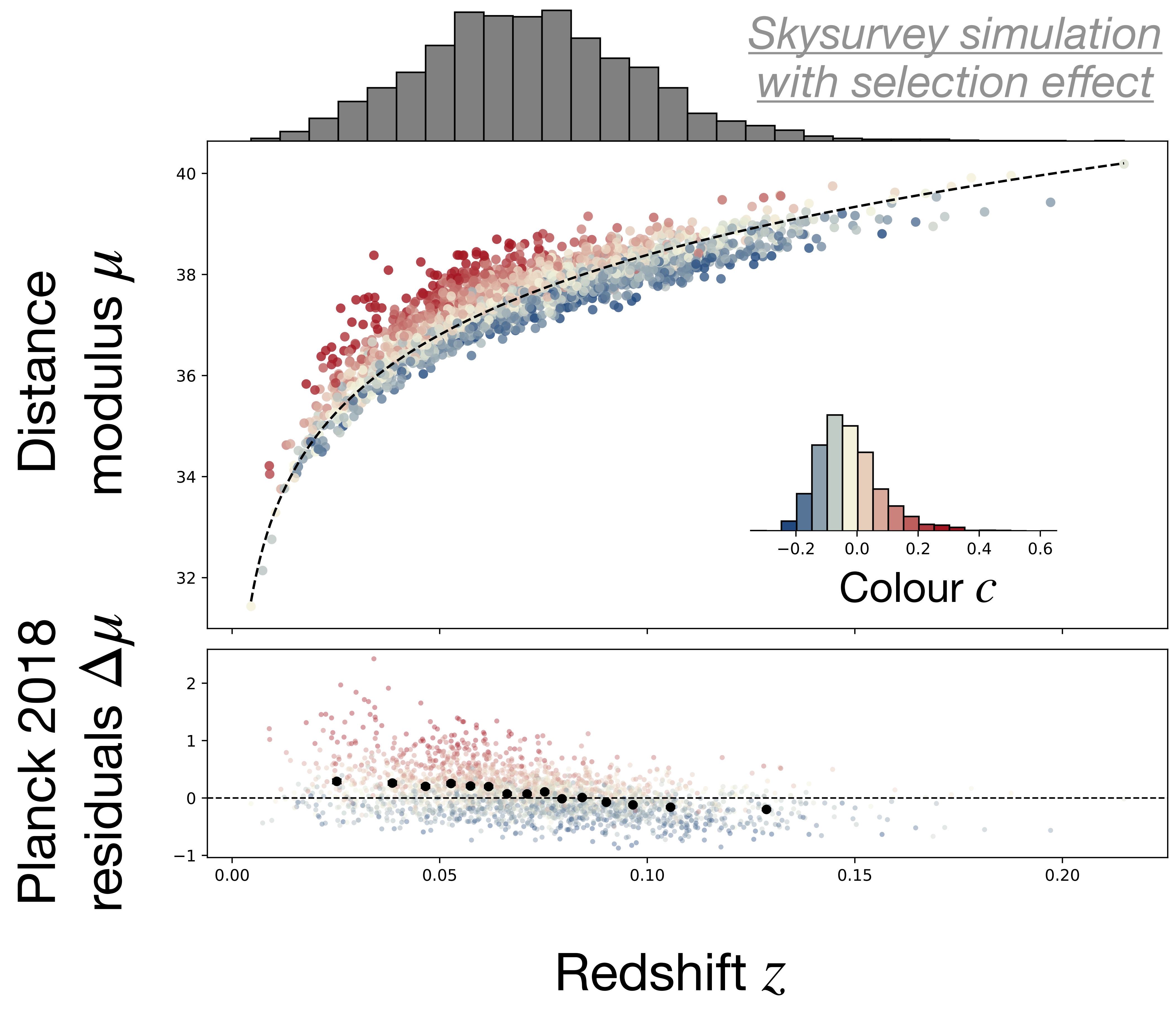


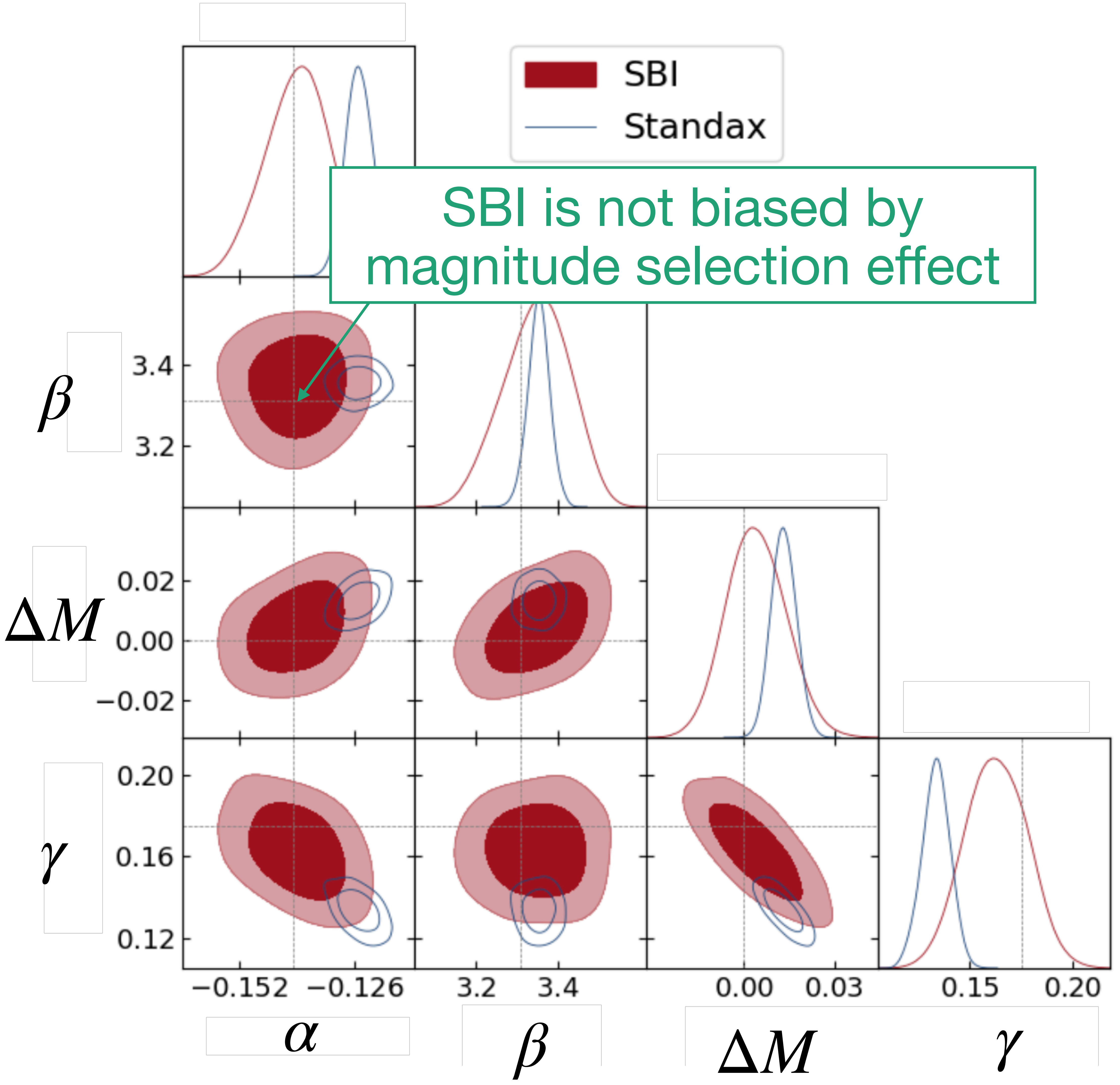
Preliminary results: fitting intrinsic scatter



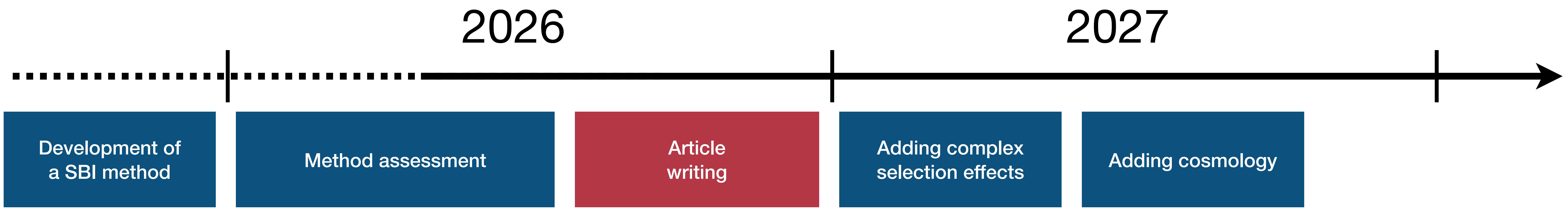


Preliminary results: adding selection effect





Conclusions and perspectives



Annexes

Likelihood proof

We have a classification problem with two classes :

$y = 1$: the parameters in input correspond to the data also in input, sampled from $p(x, \theta)$

$y = 0$: the parameters in input do not correspond to the data in input sampled from $p(x)p(\theta)$

The neural network outputs $p(y = 1 \mid x, \theta)$, the probability that the sample corresponds to the parameters in input, and if the priors on the two classes are equal $p(y = 0) = p(y = 1) = 1/2$ we can write the Bayes optimal classifier of binary cross-entropy as :

$$d(x, \theta) = p(y = 1 \mid x, \theta) = \frac{p(x, \theta)}{p(x, \theta) + p(x)p(\theta)}$$

By taking $\dfrac{d(x, \theta)}{1 - d(x, \theta)} = \dfrac{\frac{p(x, \theta)}{p(x, \theta) + p(x)p(\theta)}}{1 - \frac{p(x, \theta)}{p(x, \theta) + p(x)p(\theta)}}$ we get $\dfrac{\frac{p(x, \theta)}{p(x, \theta) + p(x)p(\theta)}}{\frac{p(x)p(\theta)}{p(x, \theta) + p(x)p(\theta)}} = \dfrac{p(x, \theta)}{p(x)p(\theta)} = \dfrac{p(x \mid \theta)}{p(x)} = r(x \mid \theta)$

Joint posterior proof

$$\frac{p(x \mid \theta)}{p(x)} = \frac{p(\theta \mid x)}{p(\theta)} \longrightarrow \frac{p(\theta \mid x)}{p(\theta)} = \frac{p(\theta_1 \mid x)}{p(\theta_1)} \cdot \frac{p(\theta_2 \mid x, \theta_1)}{p(\theta_2)} \cdot \frac{p(\theta_3 \mid x, \theta_1, \theta_2)}{p(\theta_3)}$$

Deepset

Zaheer et al. (2018)

$$f(X) = \rho\left(\sum_{x \in X} \phi(X_i)\right)$$

There exist ϕ and ρ such that

f is permutation invariant

Kessler and Scolnic 2017

BEAMS with Bias Correction (BBC)

Skysurvey simulation

$$\text{Standardisation}: M = (M_0 - \bar{\delta}_{M_0}) + \beta(c - \bar{\delta}_c) - \alpha(x_1 - \bar{\delta}_{x_1}) + \gamma p$$

Problem : the inference in two steps loses part of the covariance between selection effects and cosmological parameters