Simulation Based Inference for SNe Ia cosmology

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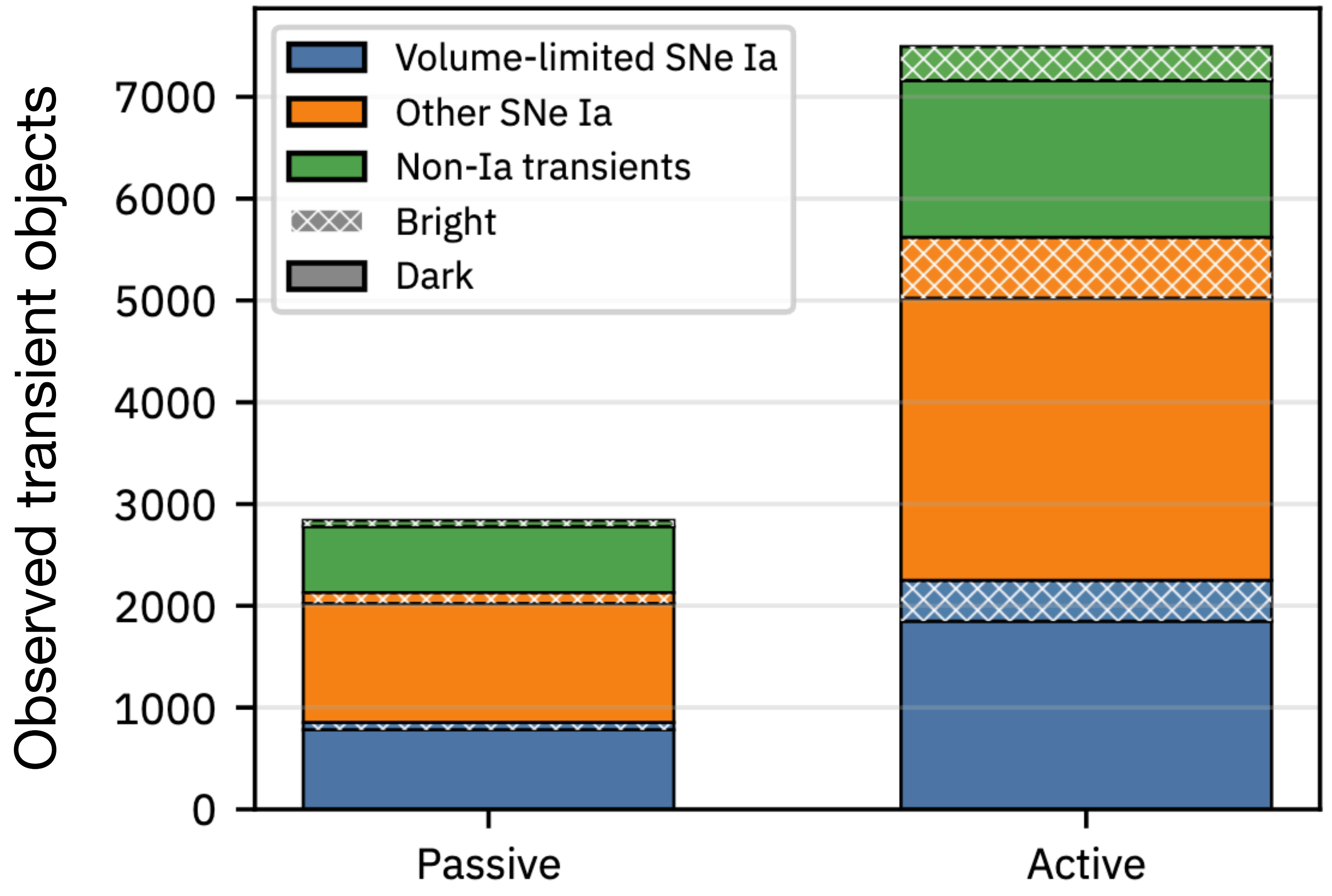
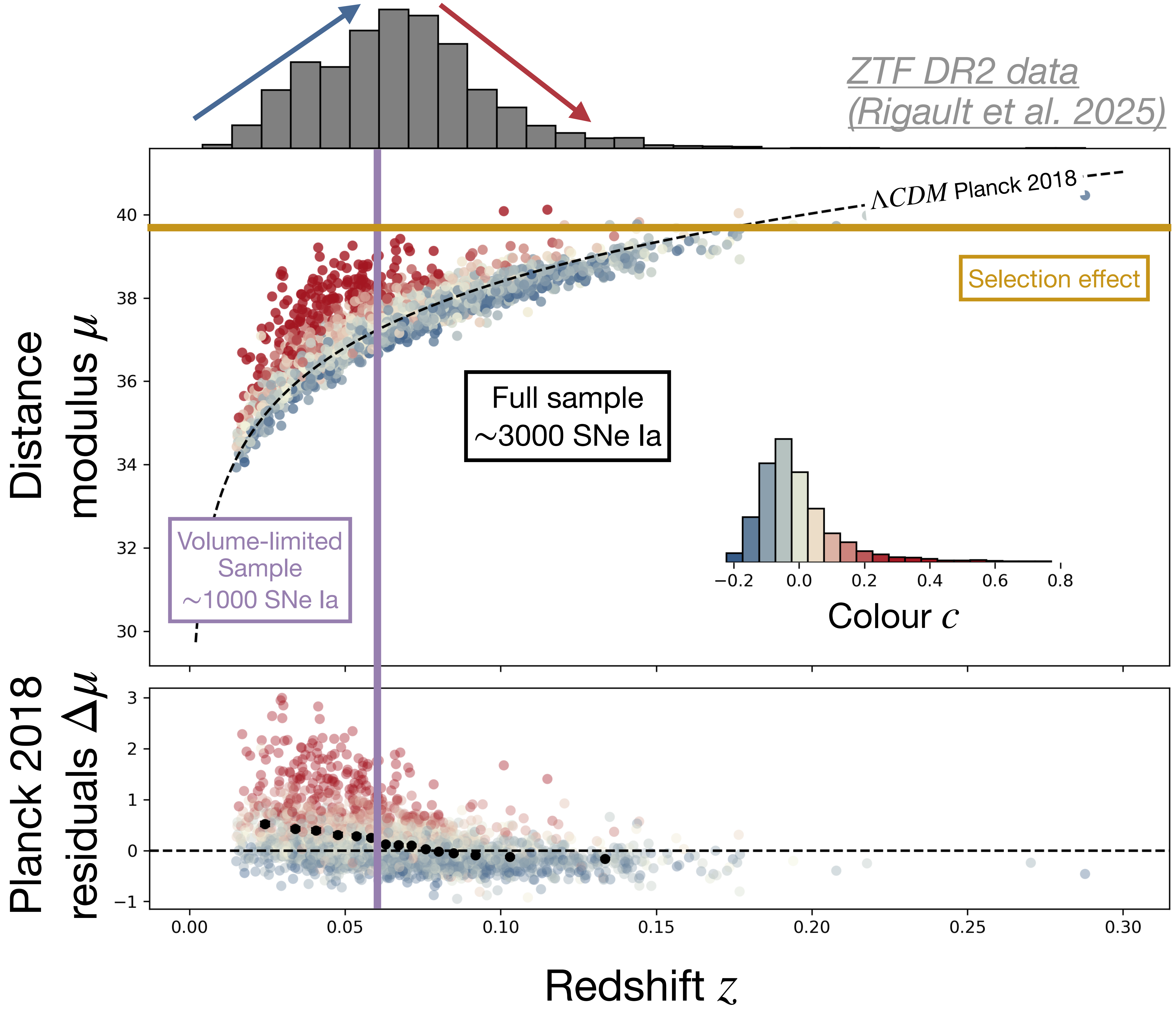
Type Ia SuperNovae

Truong et al. 2026



Up to 7000 spectro SNe Ia each year
~ 100 000 in 10 years !
→Millions of photo SNe Ia

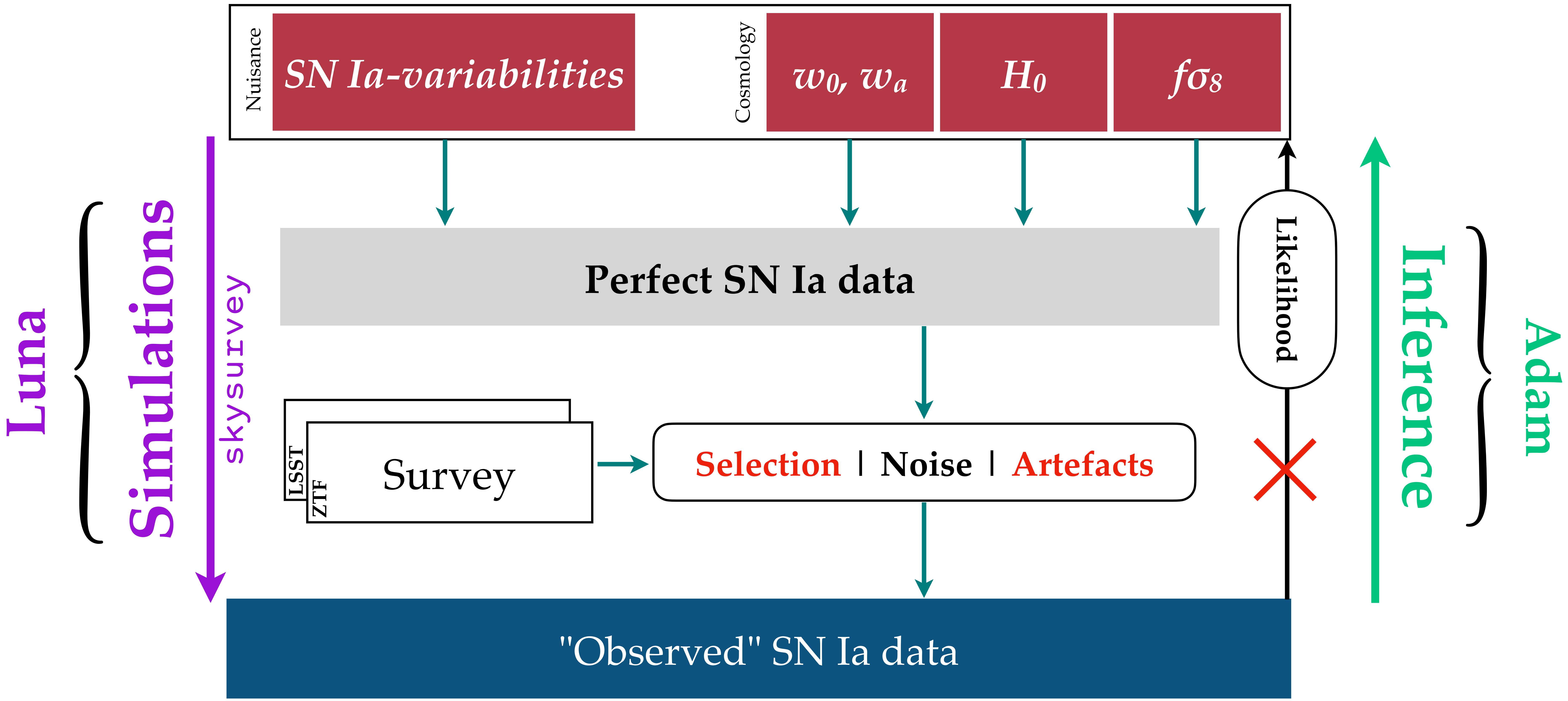
ZTF DR2 data (Rigault et al. 2025)



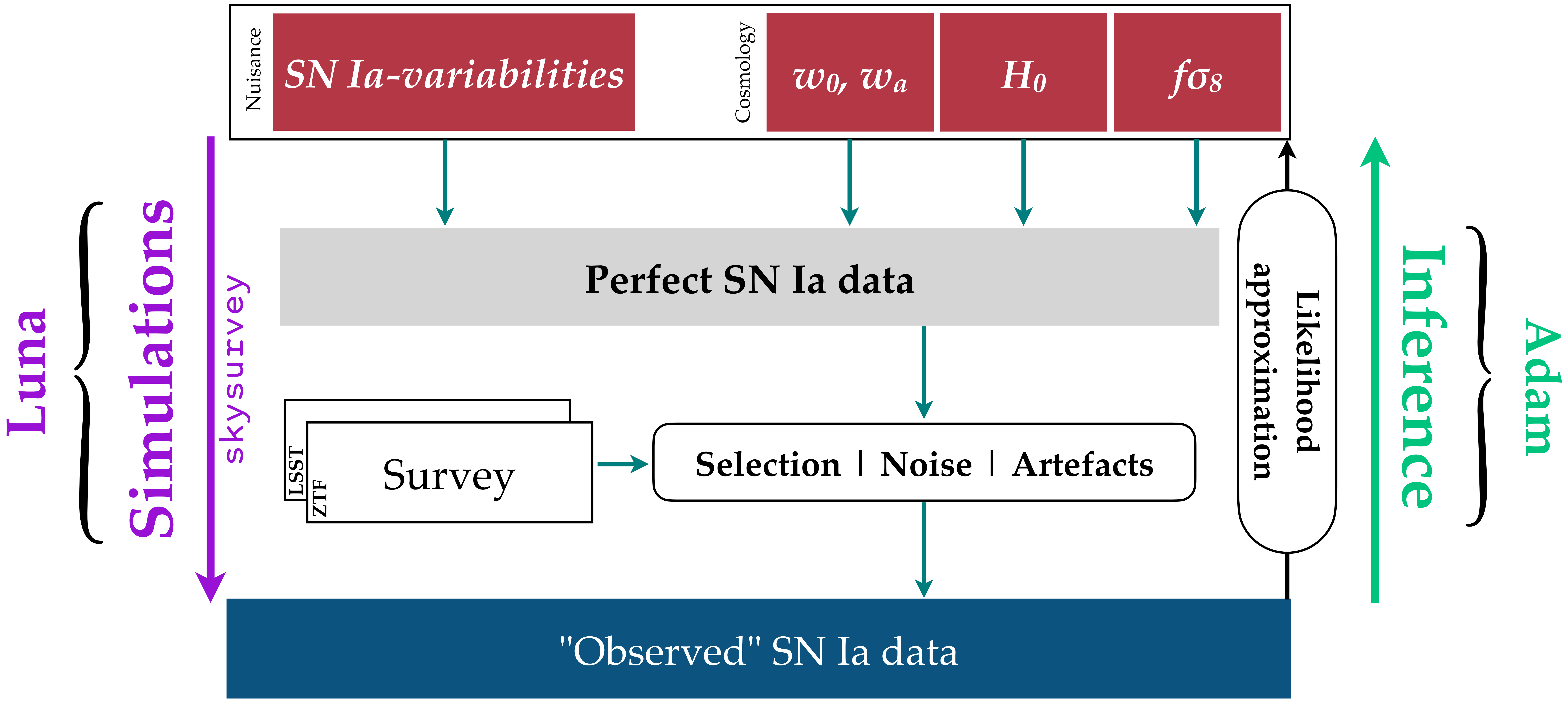
SNe Ia standardisation

Standardisation : $M = M_0 + {\color{blue}\beta} c - {\color{orange}\alpha} x_1 + {\color{red}\gamma} p$

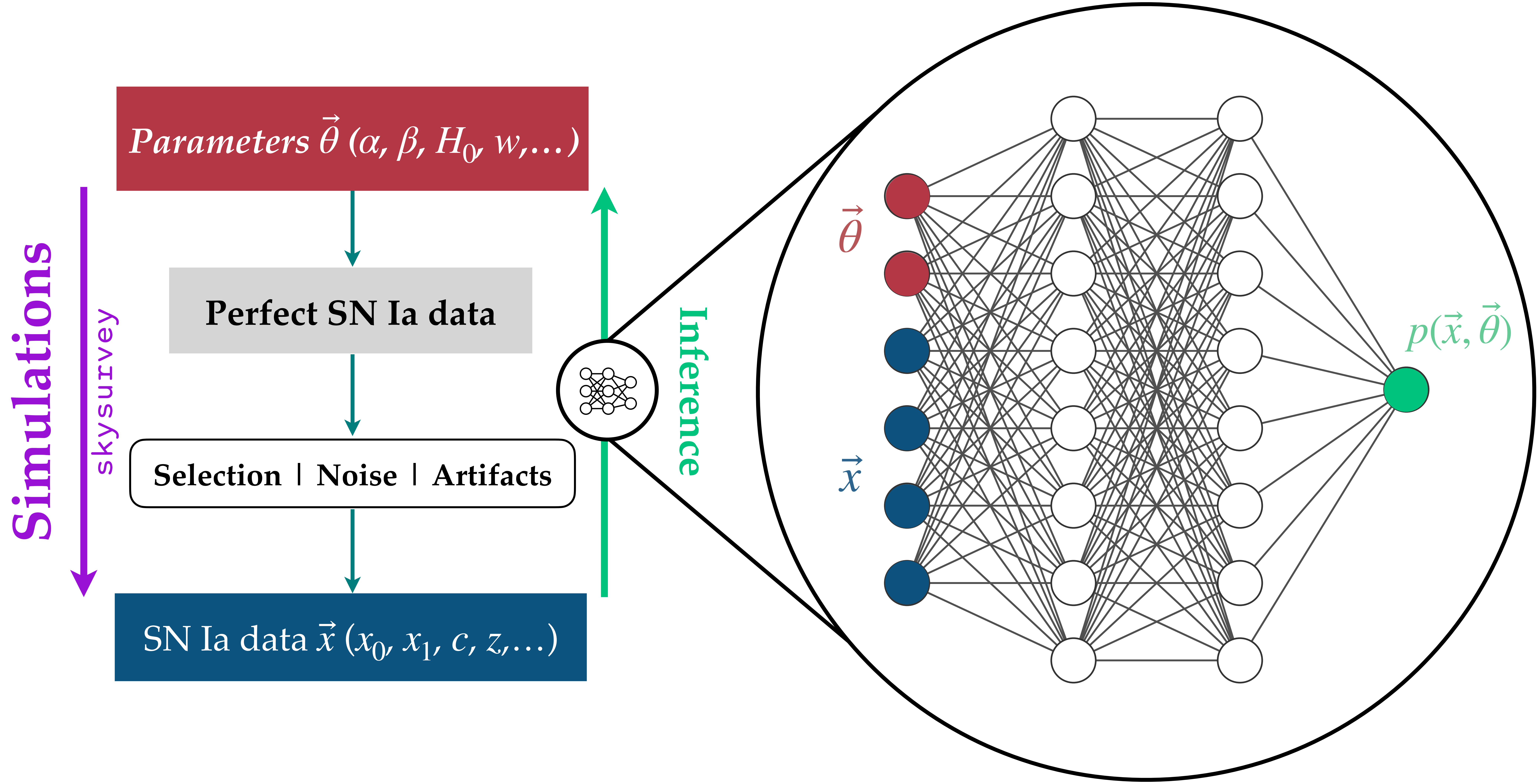
Simulation based inference (SBI)



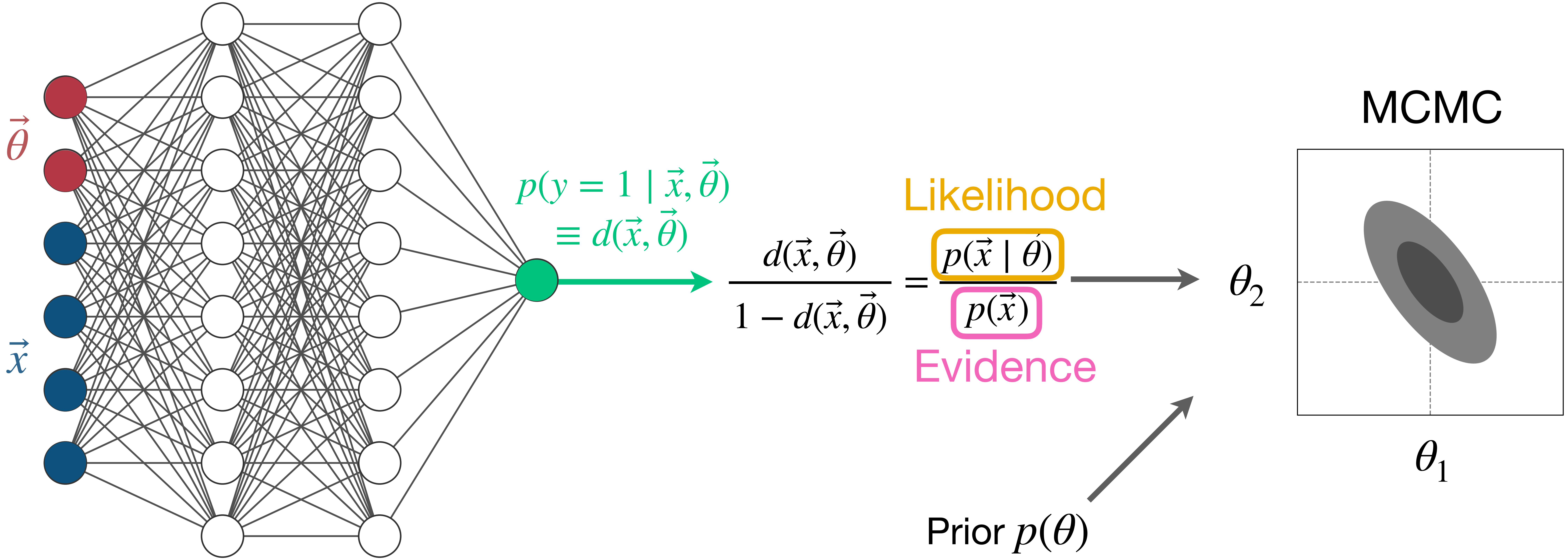
Simulation based inference (SBI)



Neural Ratio Estimator



Neural Ratio Estimator

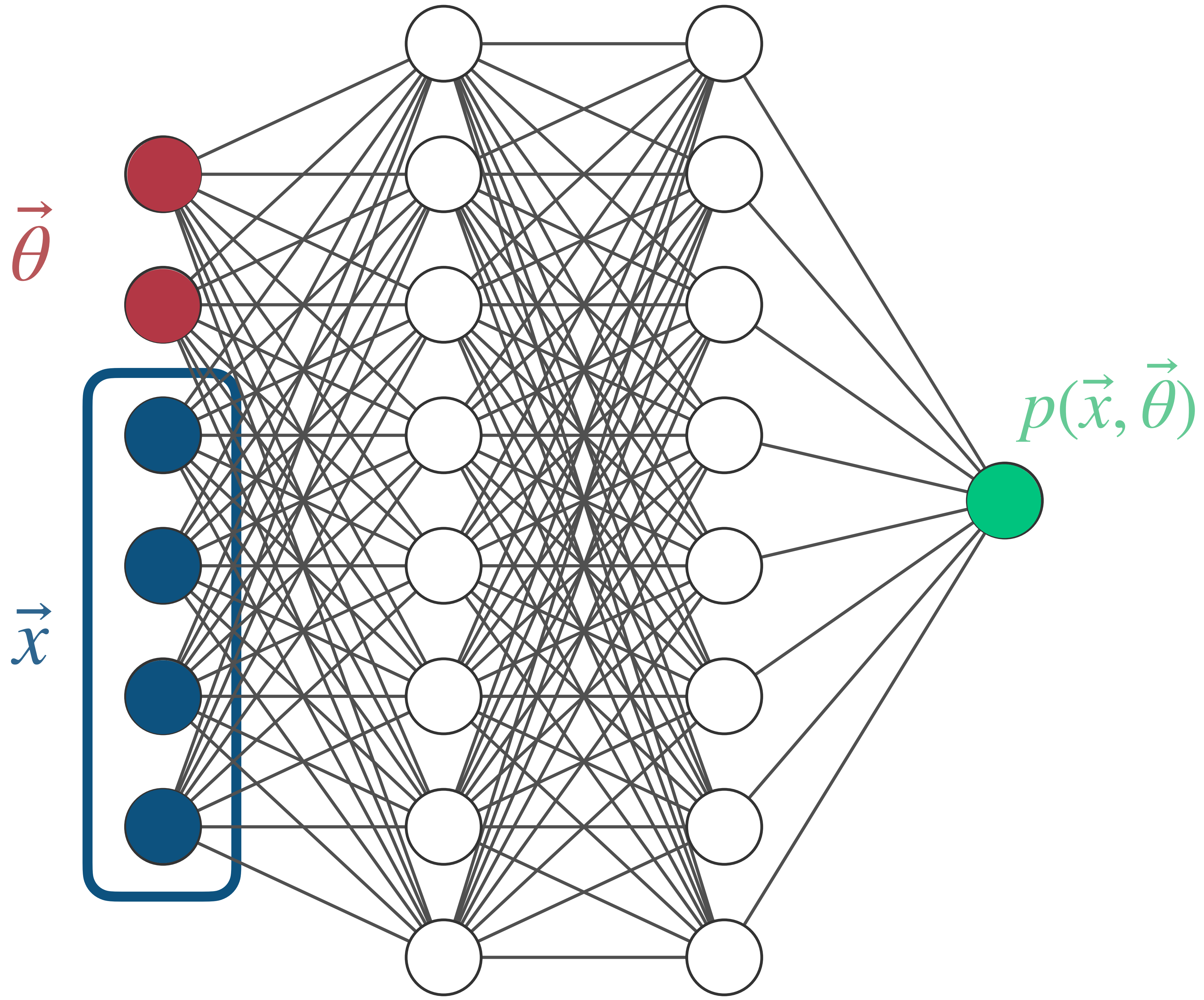


Neural Ratio Estimator

100 000+ SNe Ia

$\times 4+$ observables $(x_0, x_1, c, z, \ldots)$

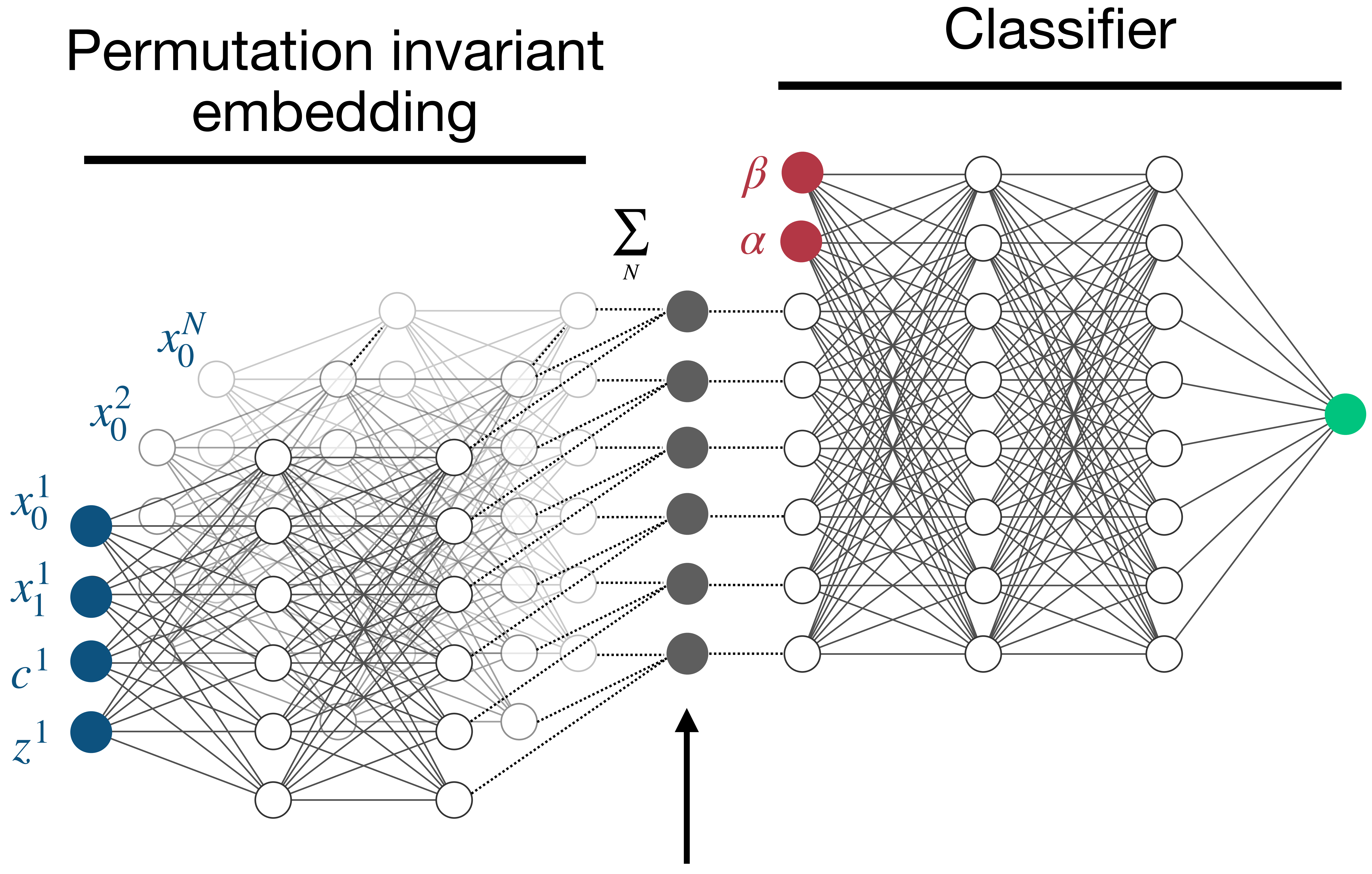
= minimum <u>400 000</u> input neurons !



But :

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

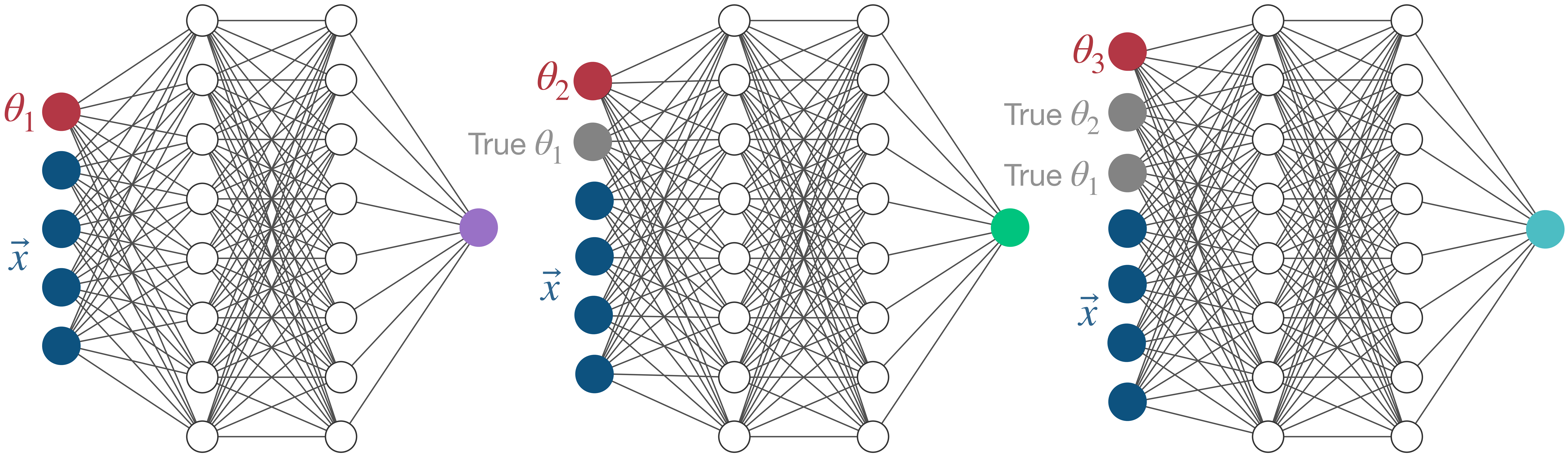
Deepset Zaheer et al. (2018)



Complex information encoded into a small size vector (400000 → 64)

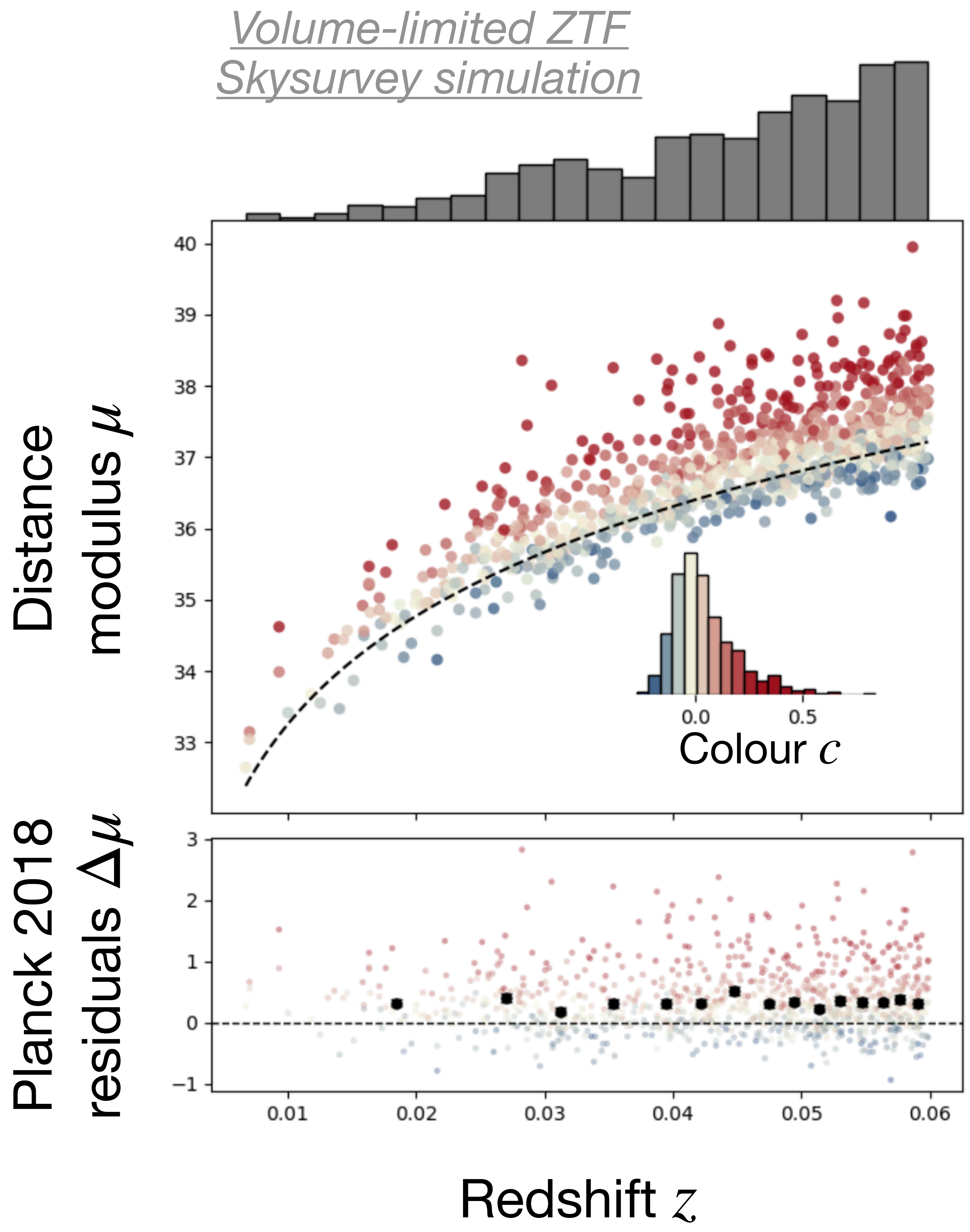
Autoregression Karchev and Trotta (2024)

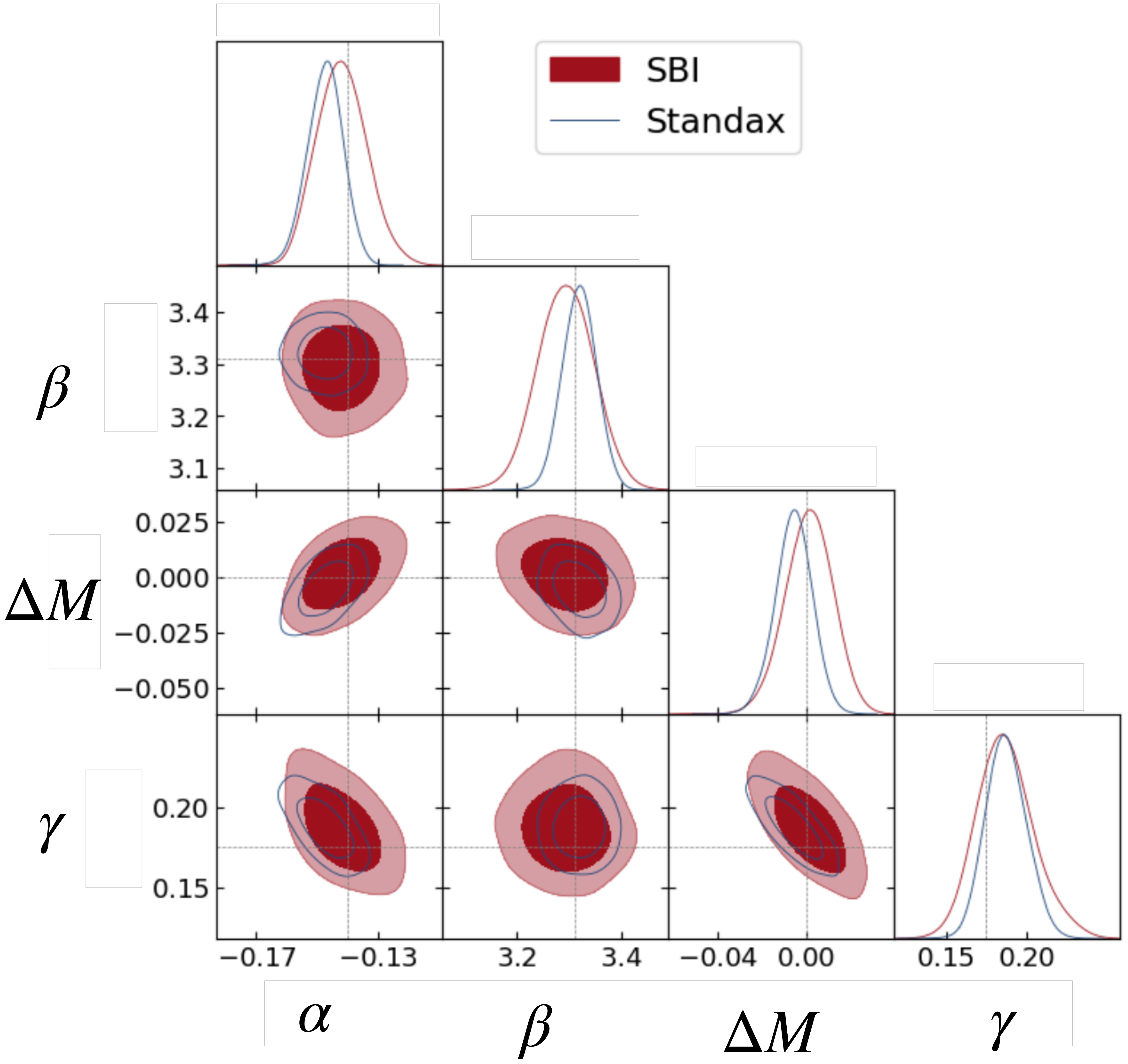
Use joint posteriors to help the network learn difficult parameters.



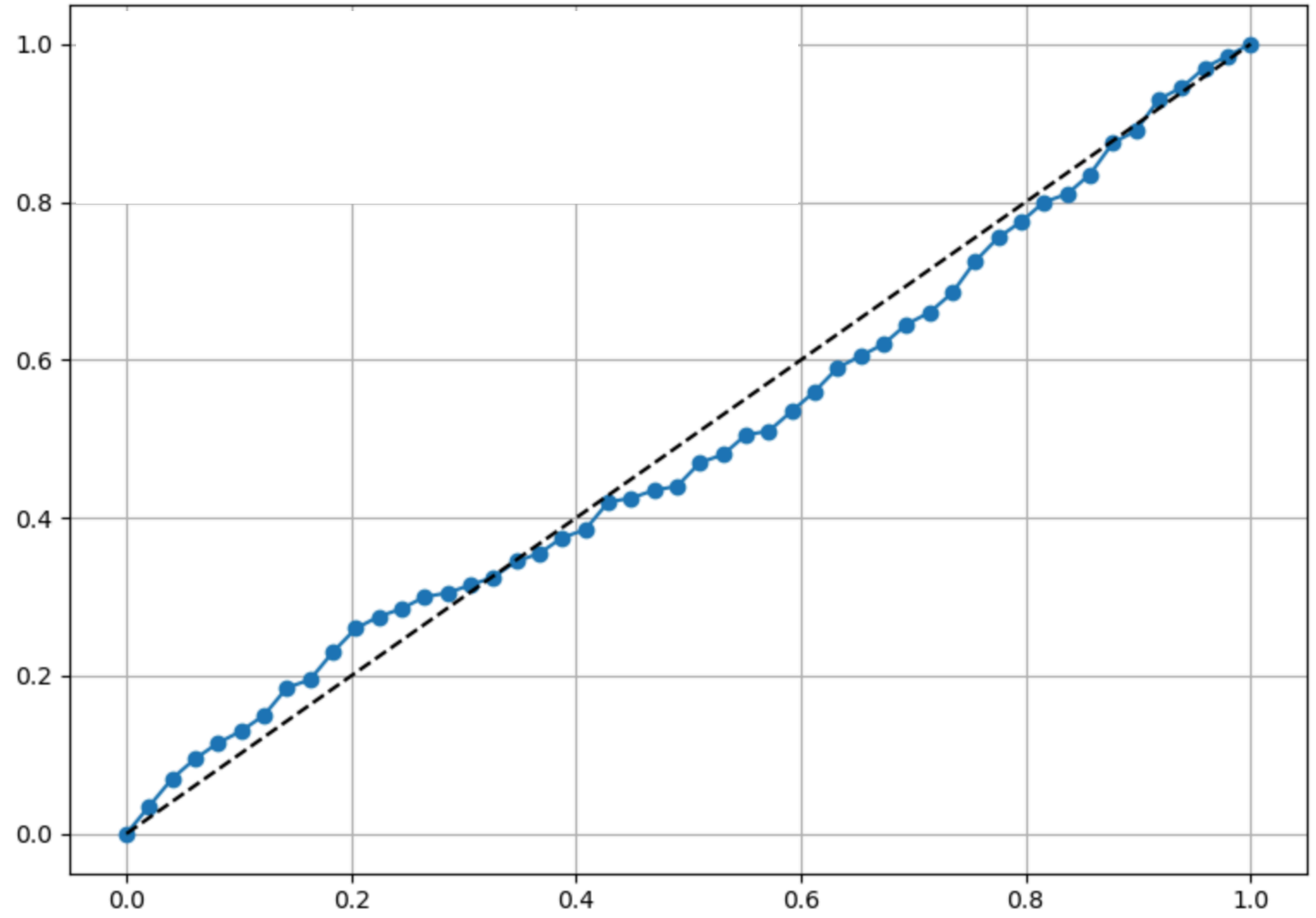
$$p(\theta \mid x) \propto p(\theta_1 \mid x) \cdot p(\theta_2 \mid x, \theta_1) \cdot p(\theta_3 \mid x, \theta_1, \theta_2)$$

Preliminary results: standardisation





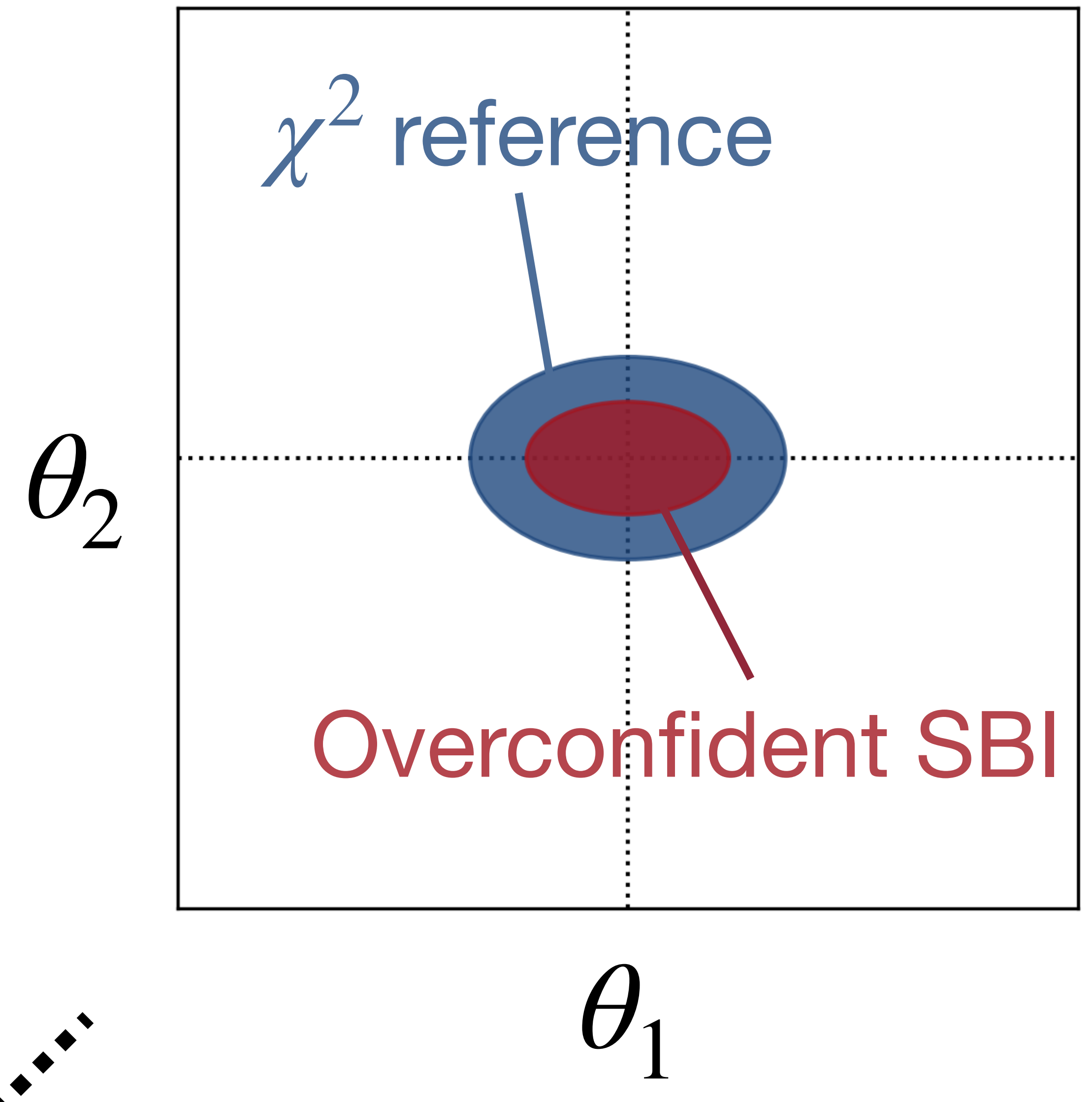
Coverage test [Lemos et al. (2023)]



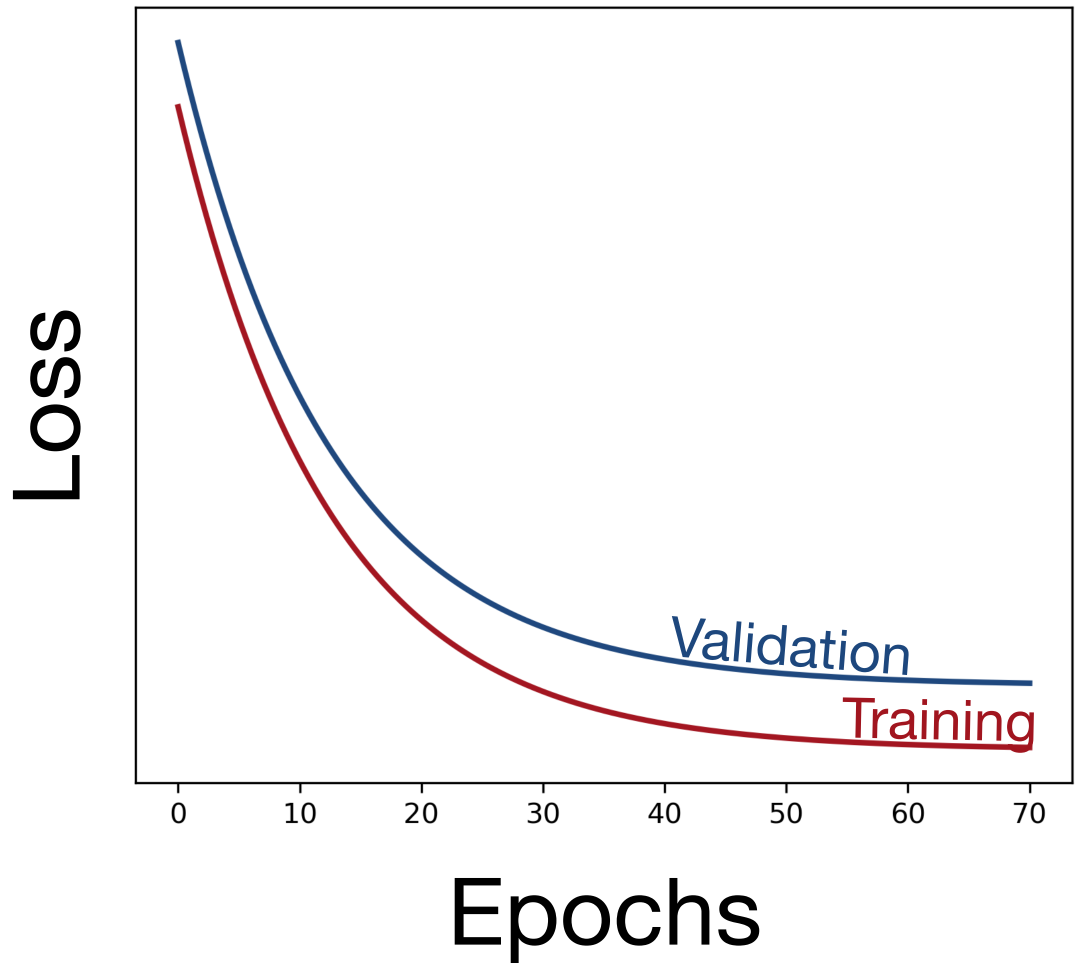
Coverage (from sampling)

Credibility (from posterior size)

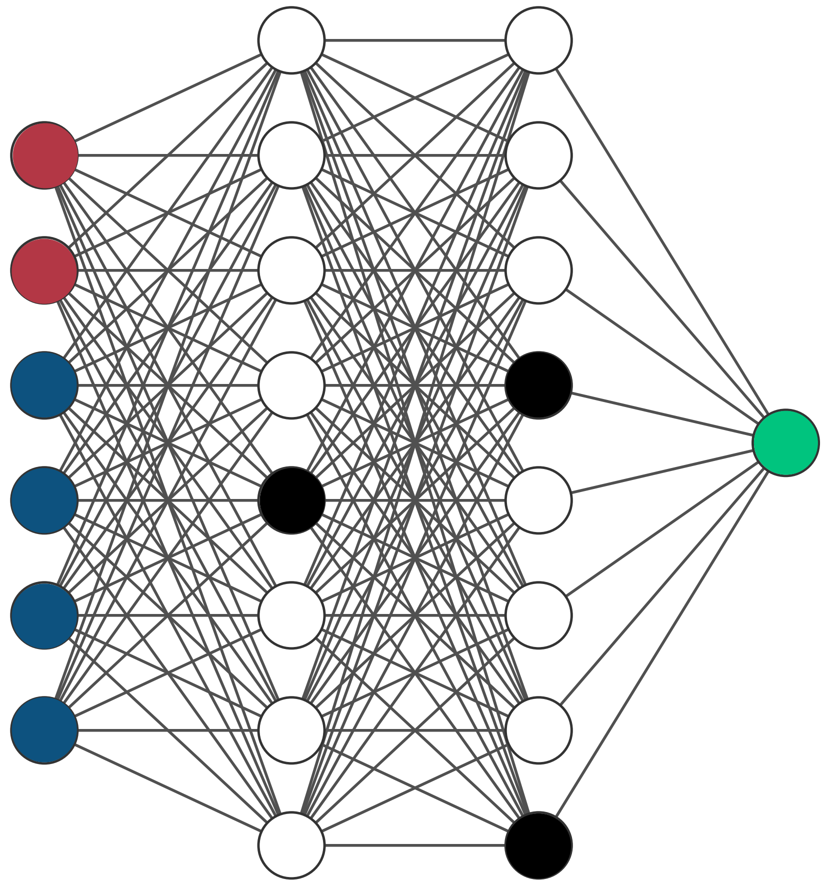
Regularisation



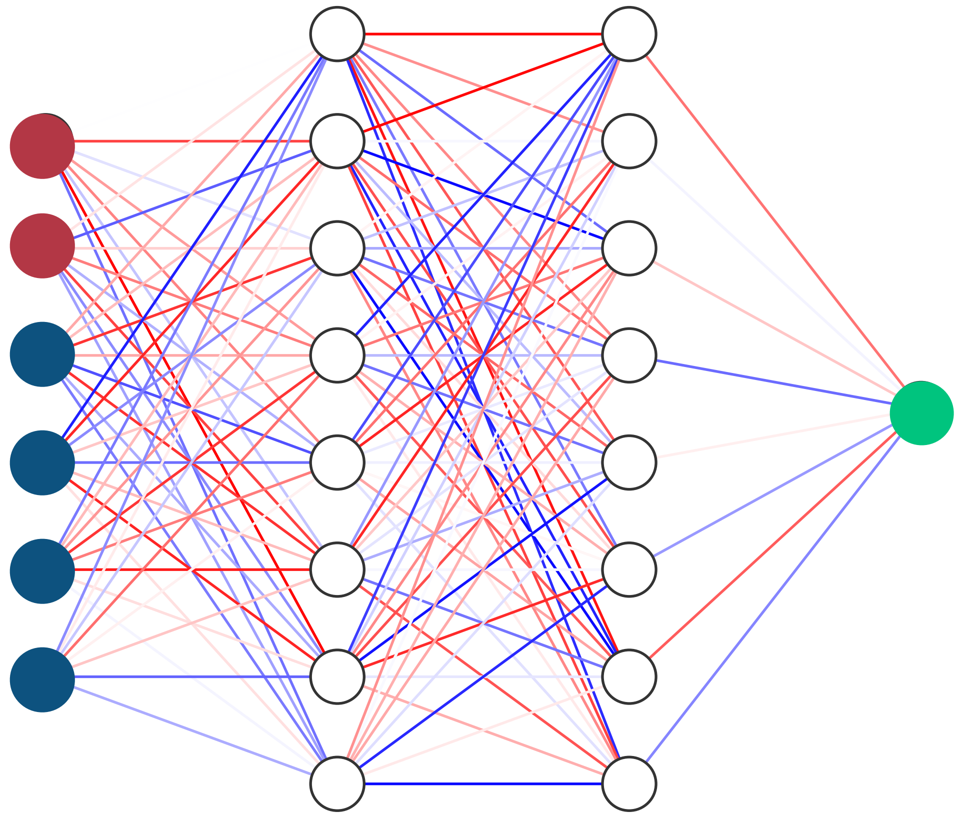
Early stopping



Dropout

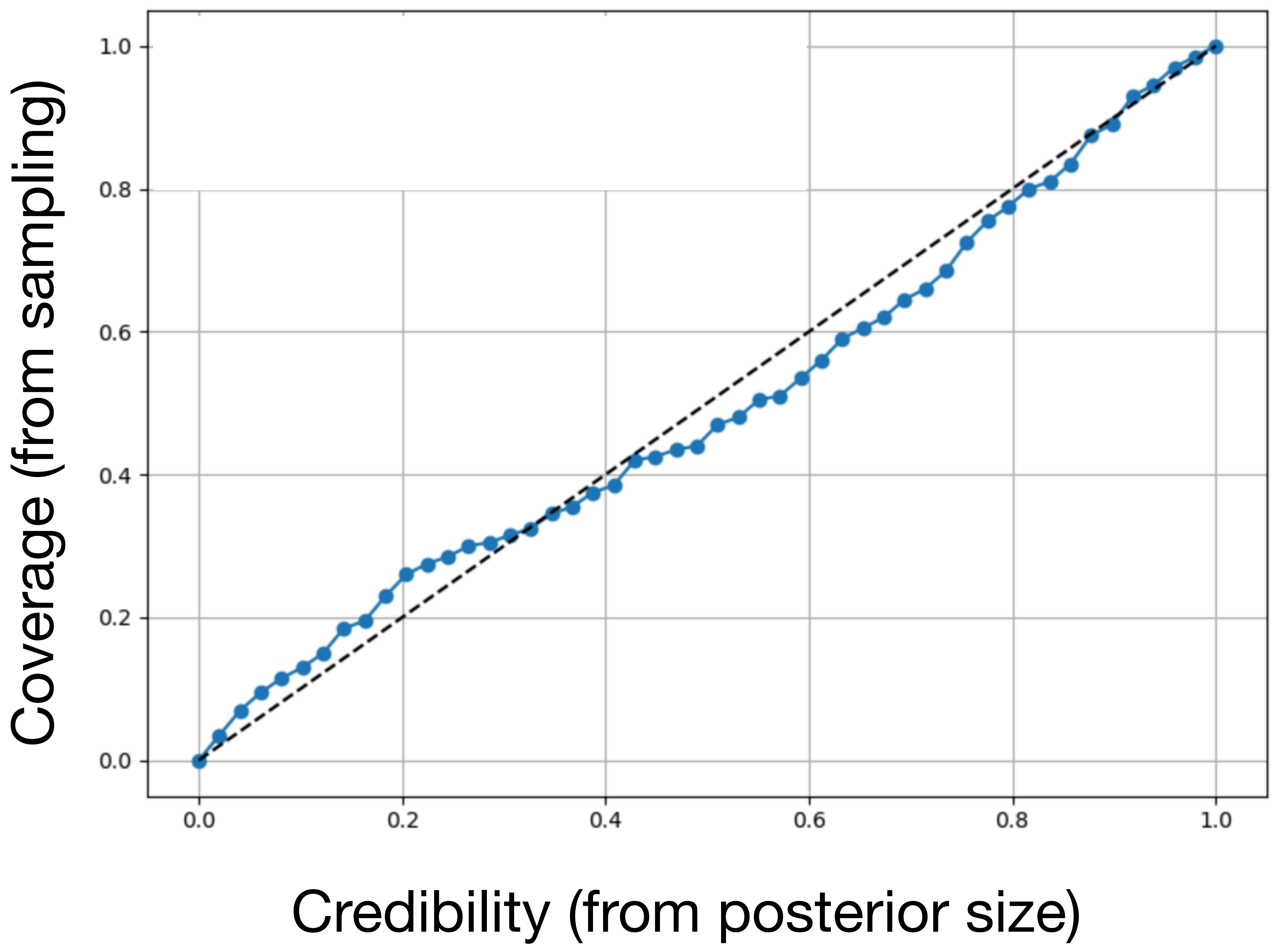


Weight decay

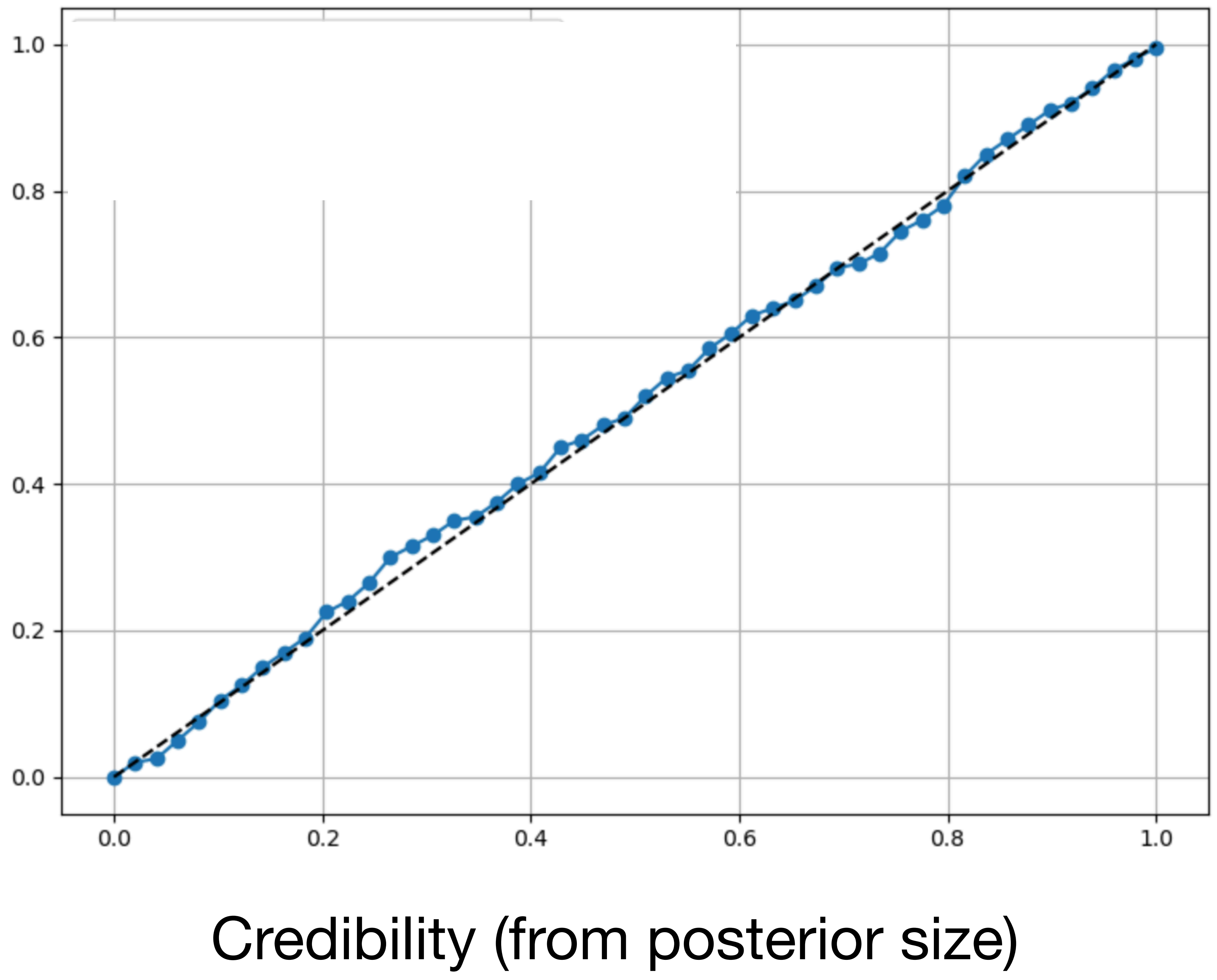


Coverage test

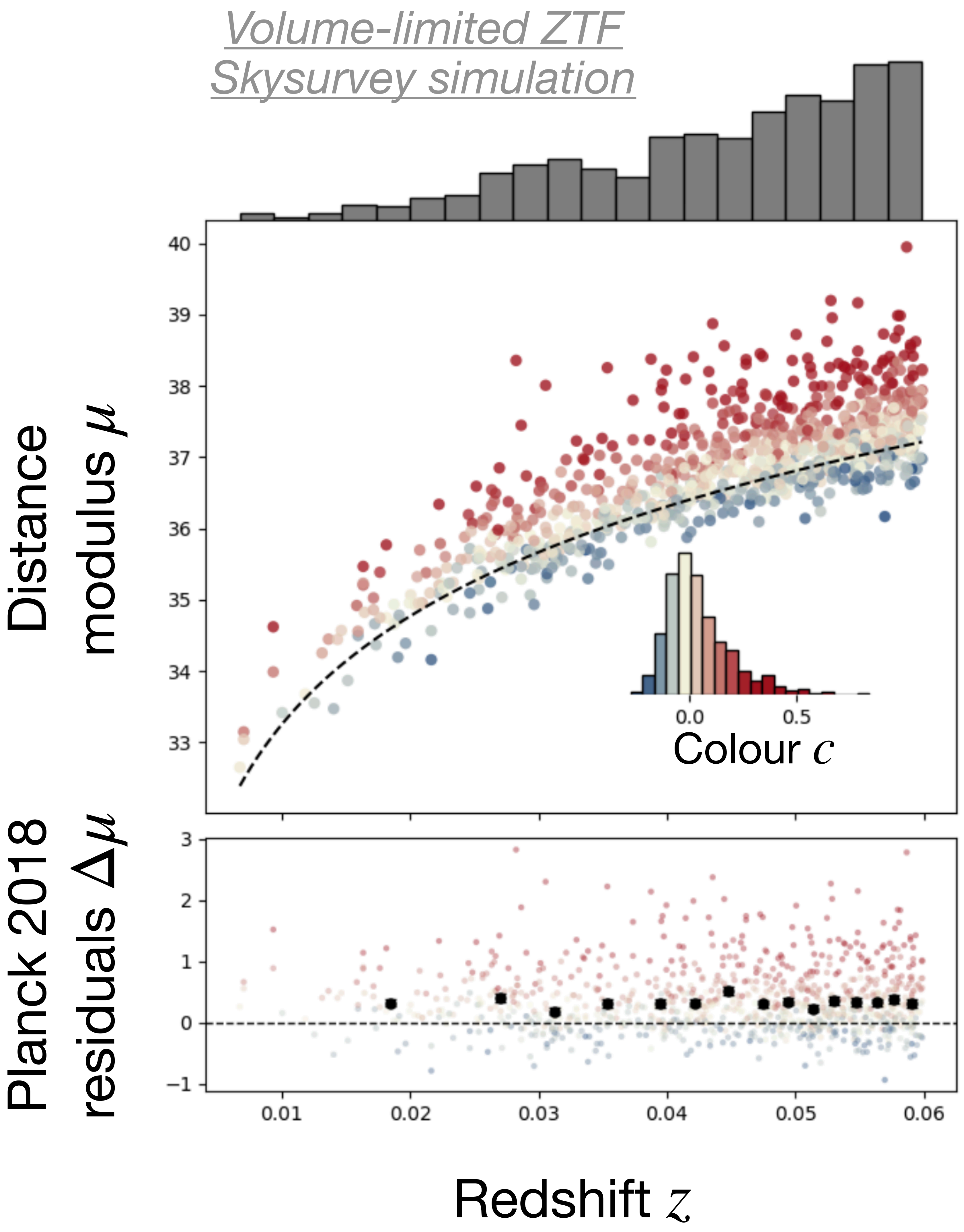
Before regularisation

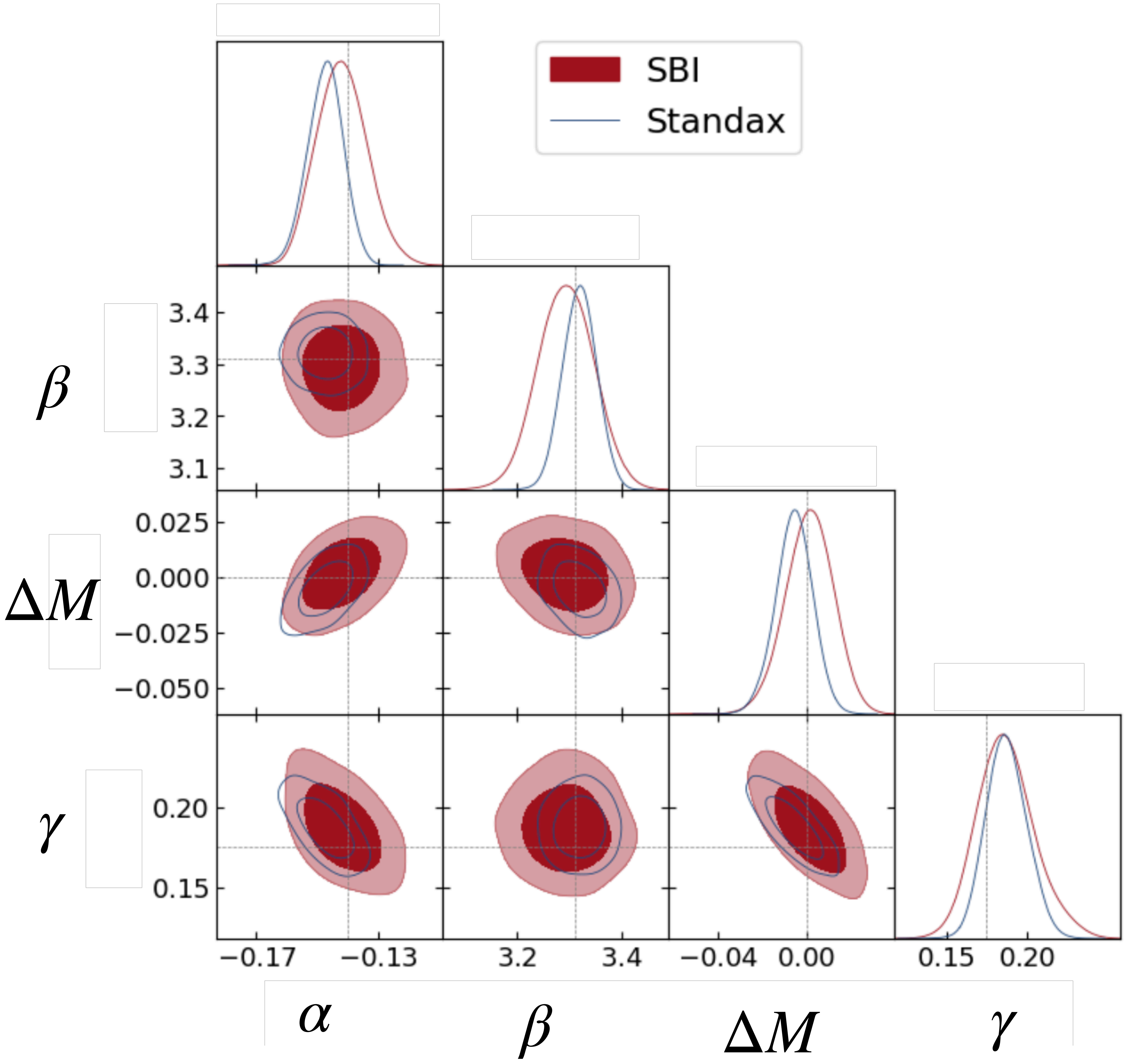


After regularisation

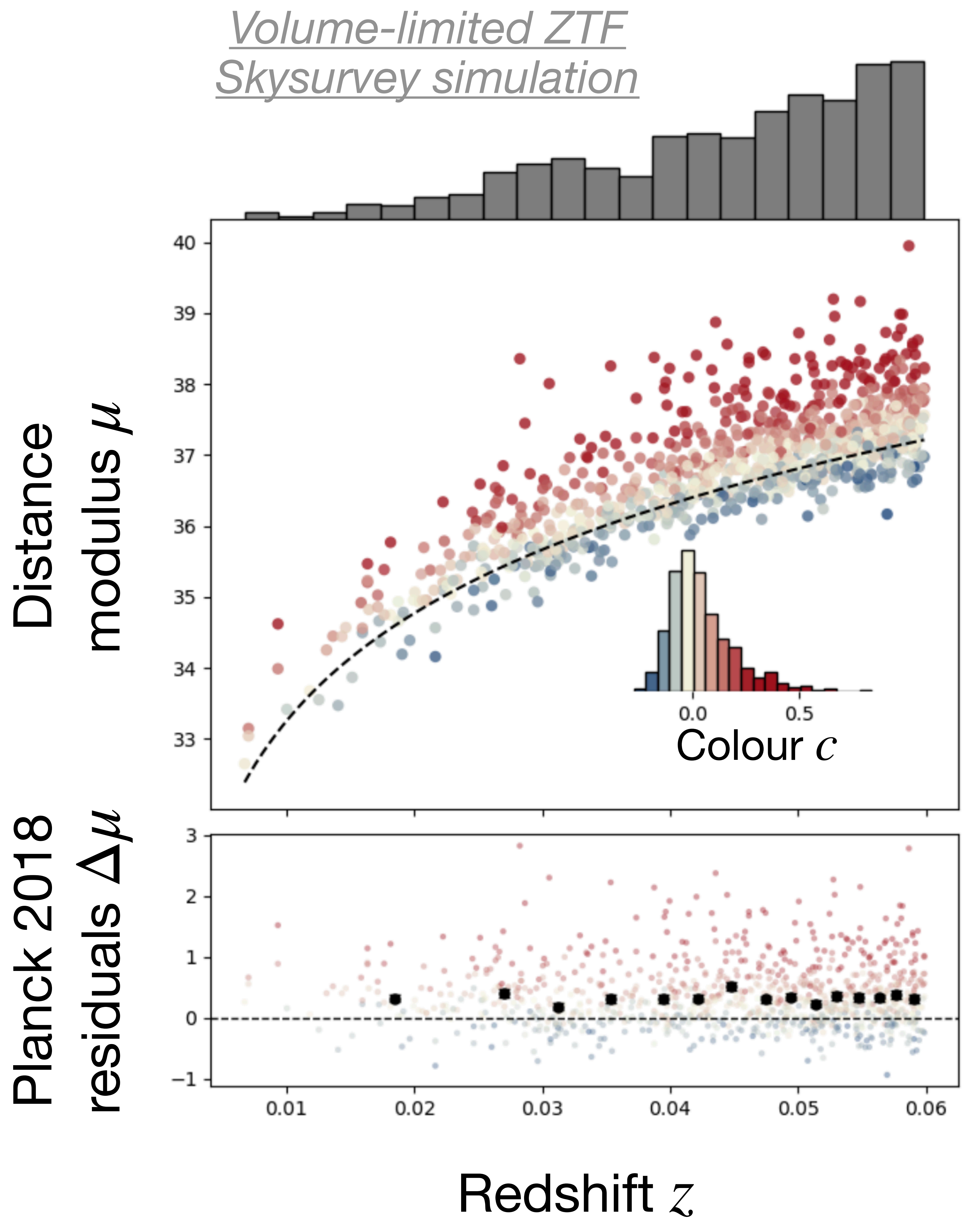


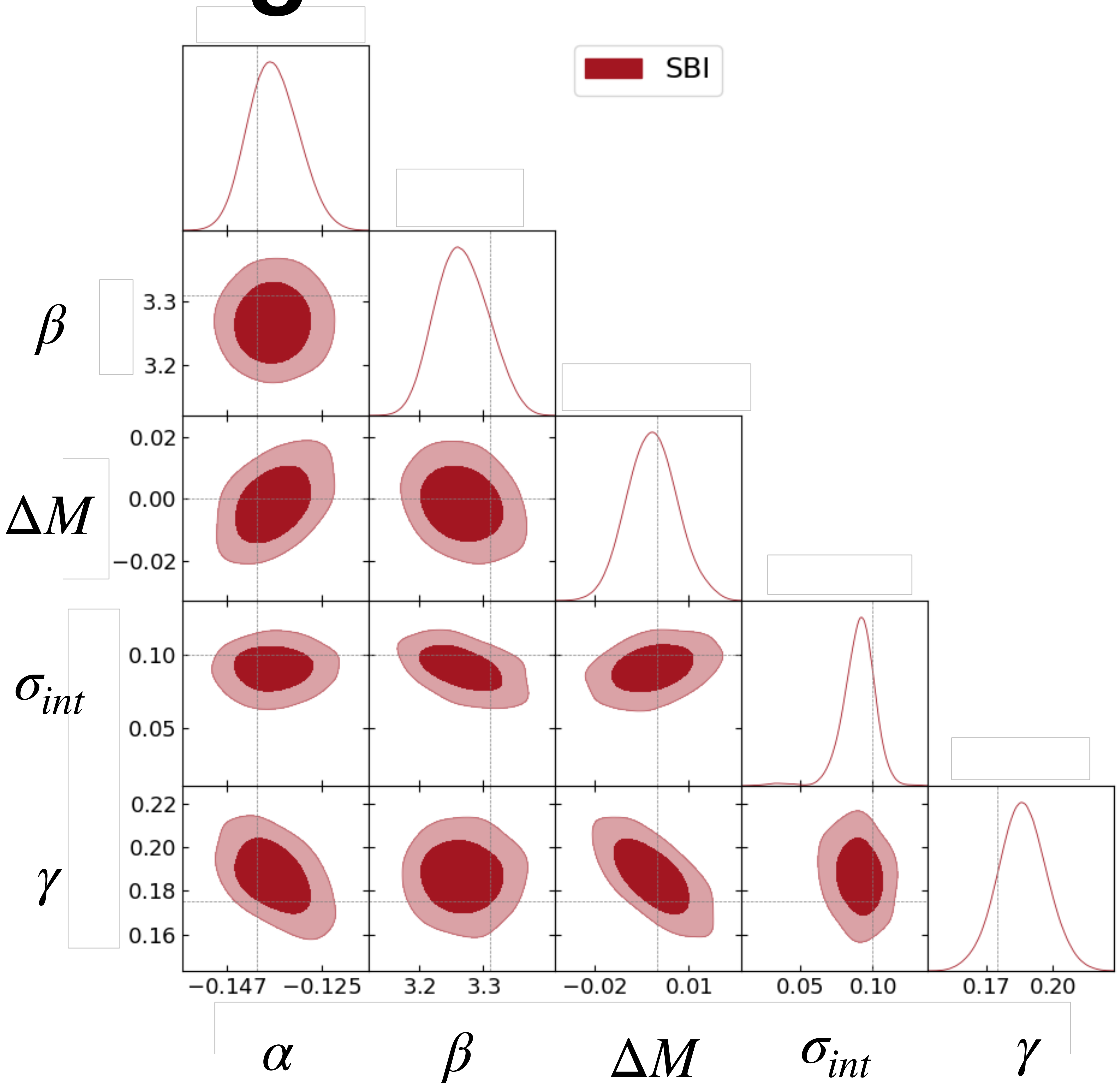
Preliminary results: standardisation



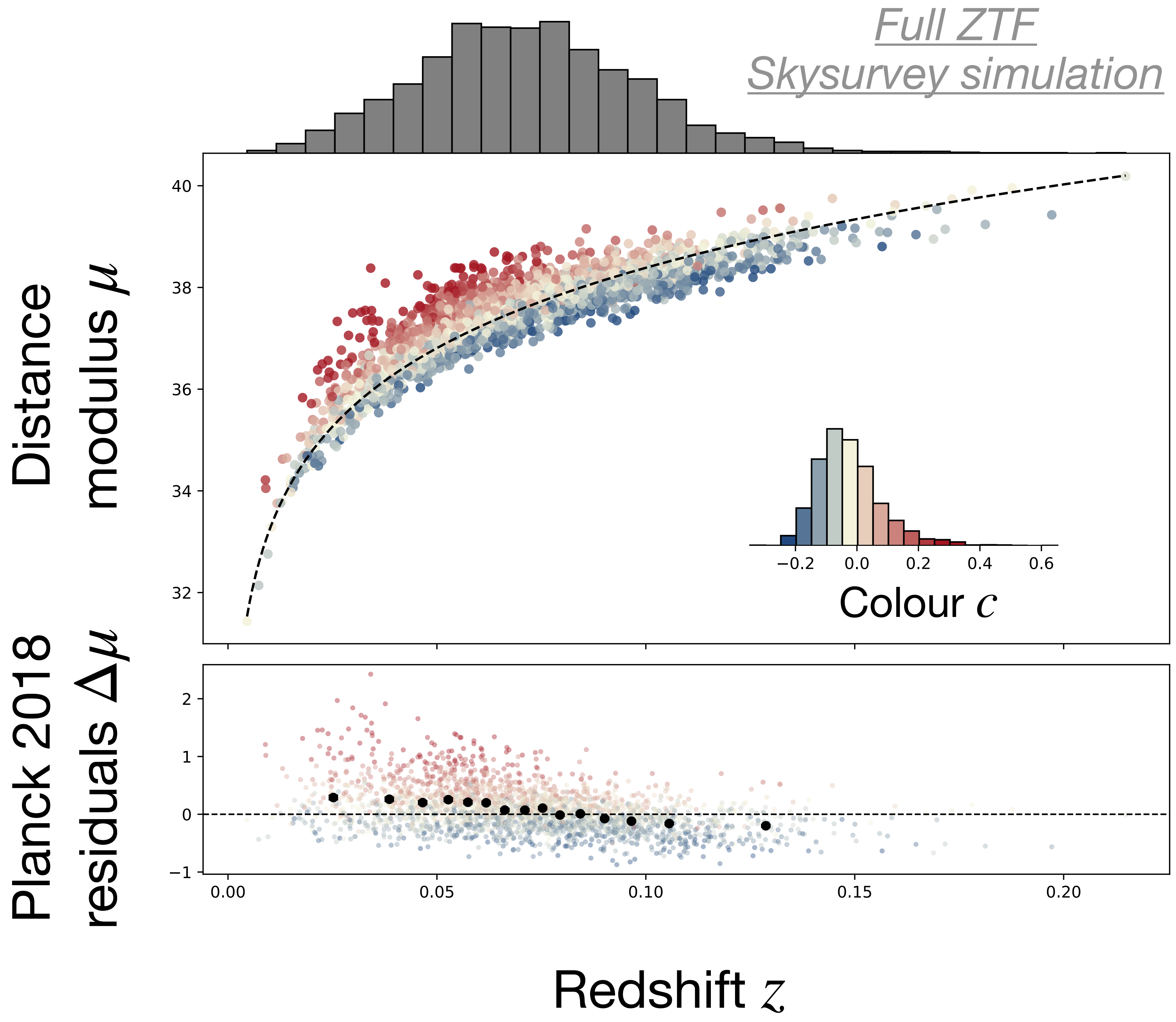


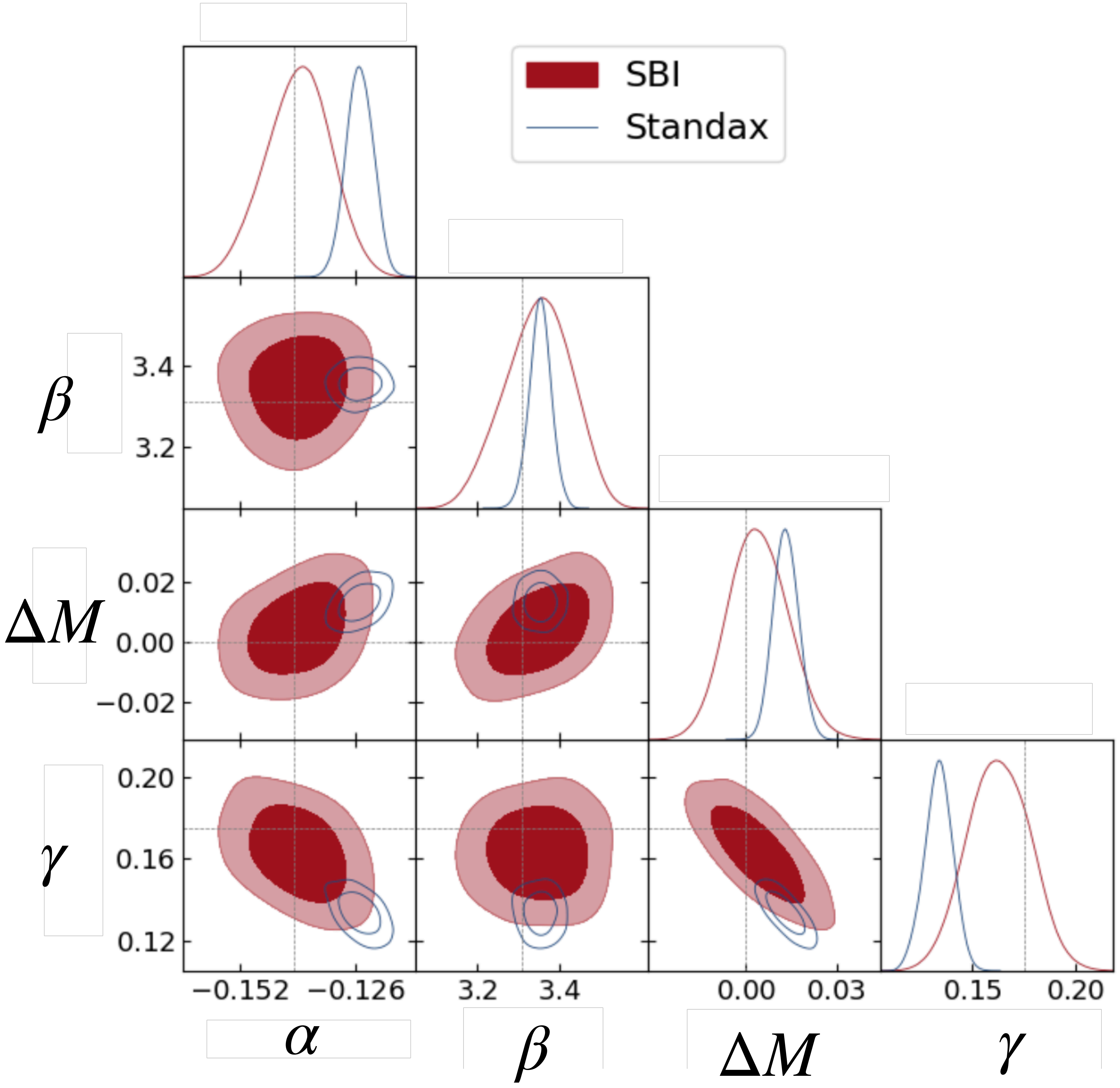
Preliminary results: fitting intrinsic scatter



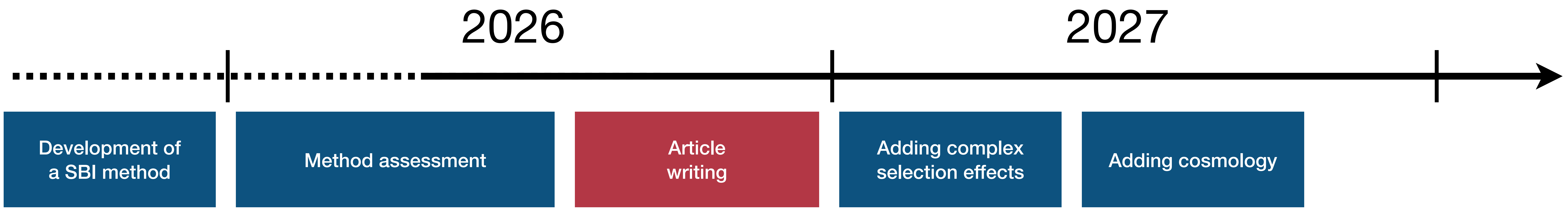


Preliminary results: adding malmquist bias





Conclusions and perspectives



Key Project : DESC SNIa pipeline validation

SLACK : #desc-snia-cosmology-collab

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

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