Turning likelihoods into effective simulators:

Application to **Planck + Stage IV** galaxy surveys and **Dynamical Dark Energy**

Guillermo Franco Abellán

GFA et al. (2024)

and more very soon!

with

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ultra-high precision cosmology...

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- Expensive simulations 😞

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- Intractable noise models
- Expensive simulations
- High-dimensional parameter spaces

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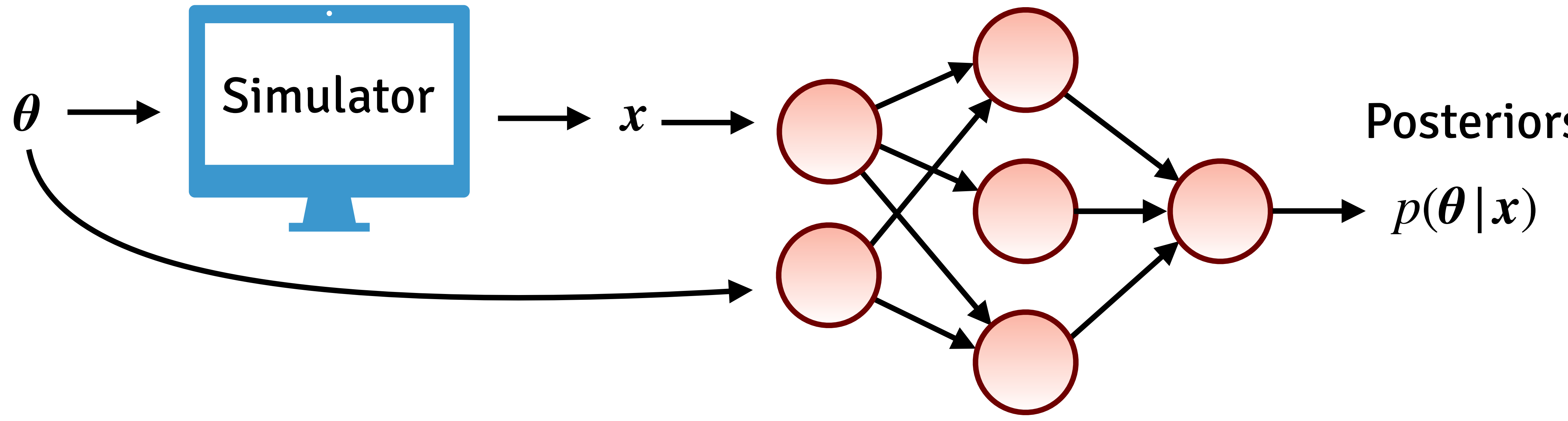

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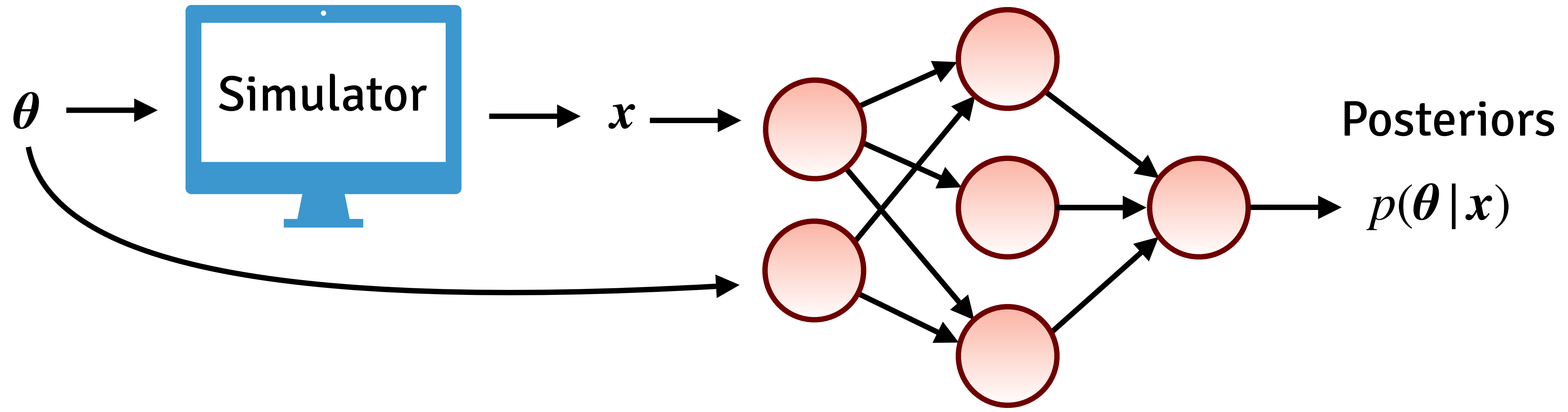

III. Inference: evaluate trained NN at $\mathbf{x} = \mathbf{x}_0$ to get $p(\boldsymbol{\theta} \,|\, \mathbf{x}_0)$

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Strong advantages even for explicit likelihoods

SBI has already been applied to different LSS surveys:

- **BOSS** [Lemos et al. (2023)]
- **DES** [Jeffrey et al. (2024)]
- **KiDS** [von Wietersheim-Kramsta et al. (2024)]
- **HSC** [Novaes et al. (2024)]

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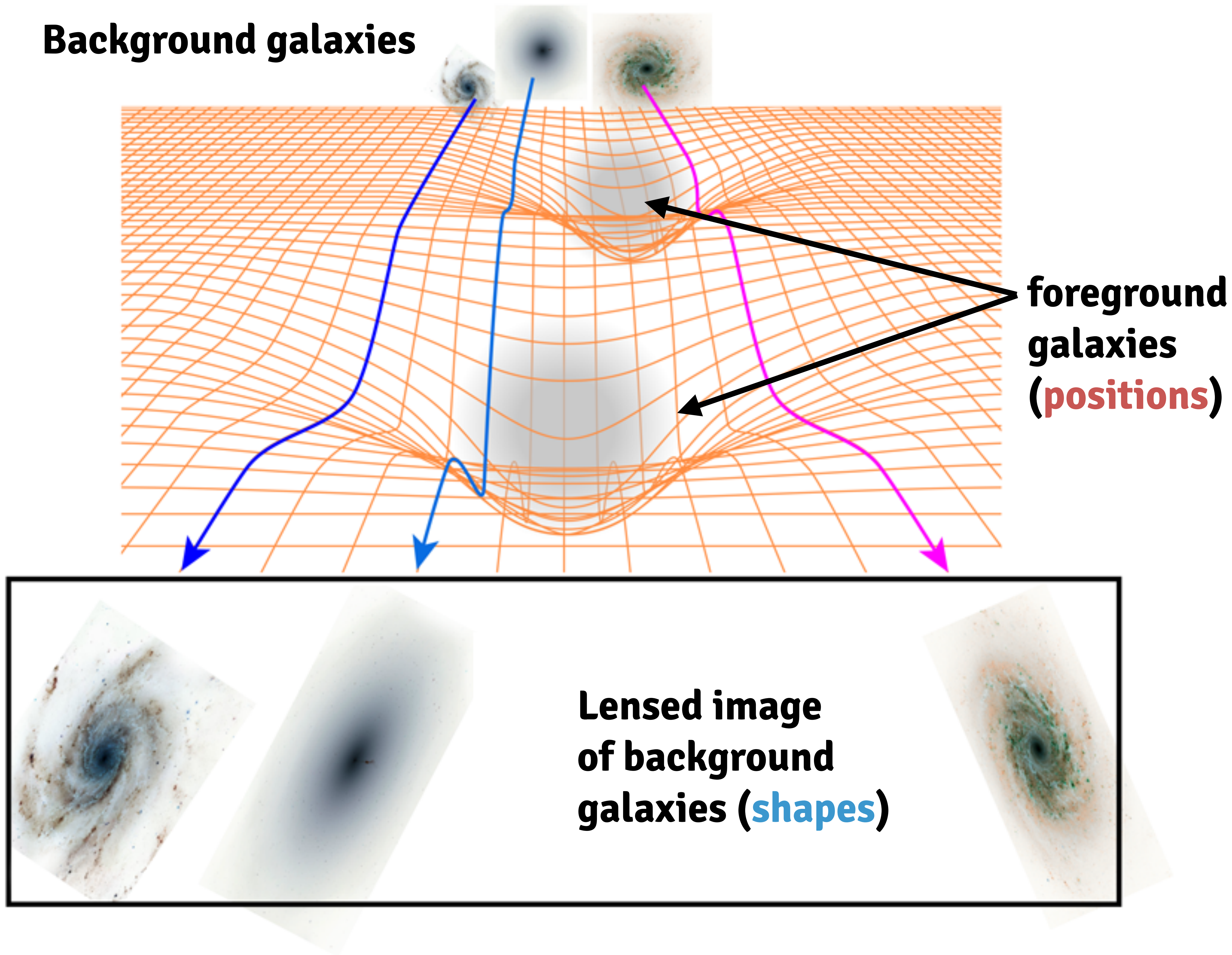
GOAL

Apply SBI to **accelerate parameter inference** from a Stage-IV photometric survey like **Euclid**

MNRE = **M**arginal **N**eural **R**atio **E**stimation

Implemented in Swyft [Miller et al (2020)]

Which are the Euclid primary observables?



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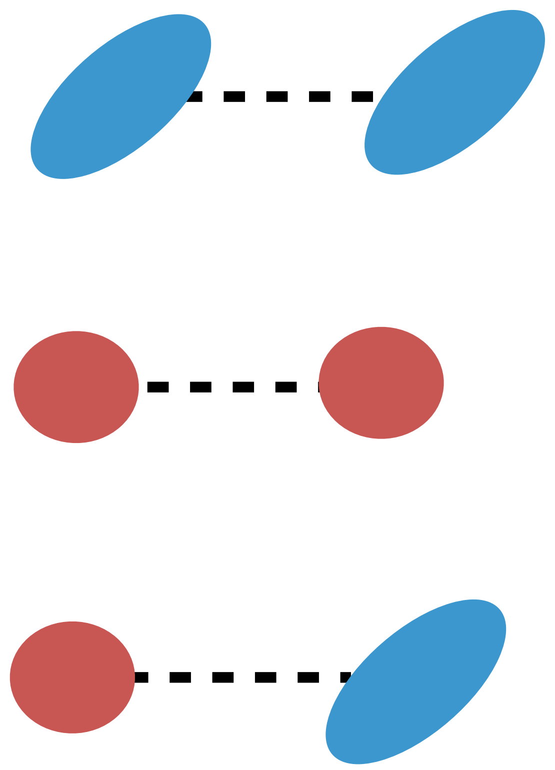
Summarise maps of galaxy positions/shapes using three 2-point statistics **(3x2pt)** measured at 10 tomographic redshift bins

- **Cosmic Shear**
- **Galaxy clustering**
- **Galaxy-Galaxy lensing**



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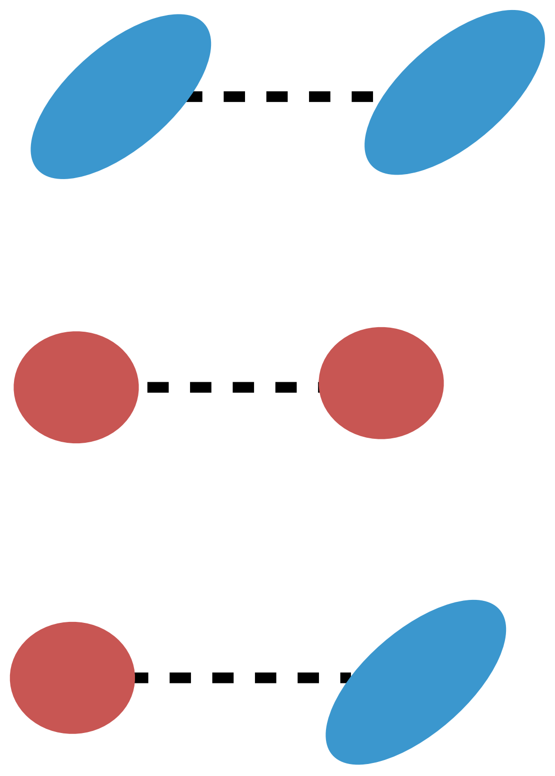

...described by angular power spectra $$C_{ij}^{XY}(\ell) = \int dz\ W_i^X(z) W_j^Y(z)\ P_m(k_\ell, z)$$

SBI analysis of Euclid 3x2pt

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1. Simulator:

We generate 50k realisations of 3x2pt spectra with gaussian noise

$$\hat{C}_{ij}^{AB}(\ell) = C_{ij}^{AB}(\ell) + n_{ij}^{AB}(\ell)$$

$n_{ij}^{AB}(\ell) \leftarrow \mathcal{N}(0,\mathbf{C})$

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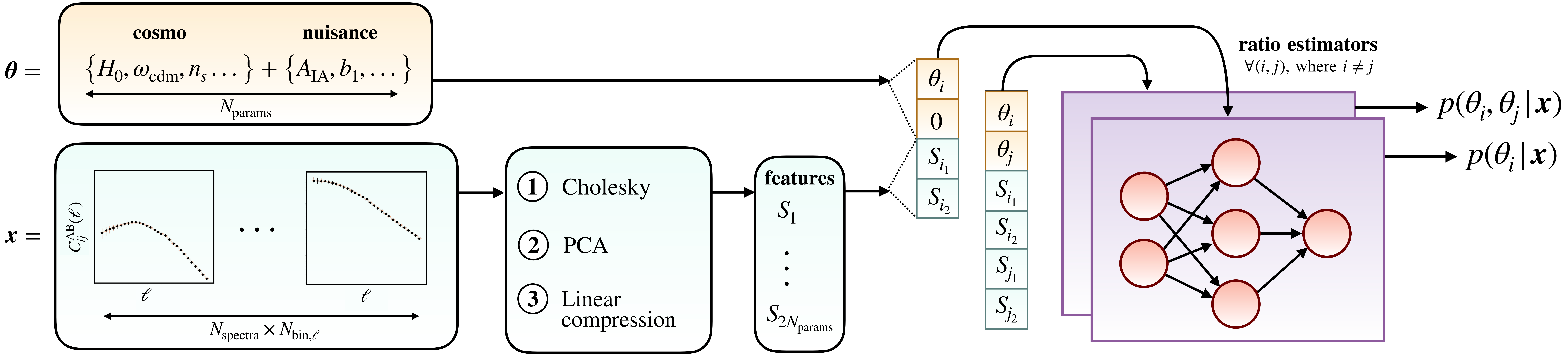
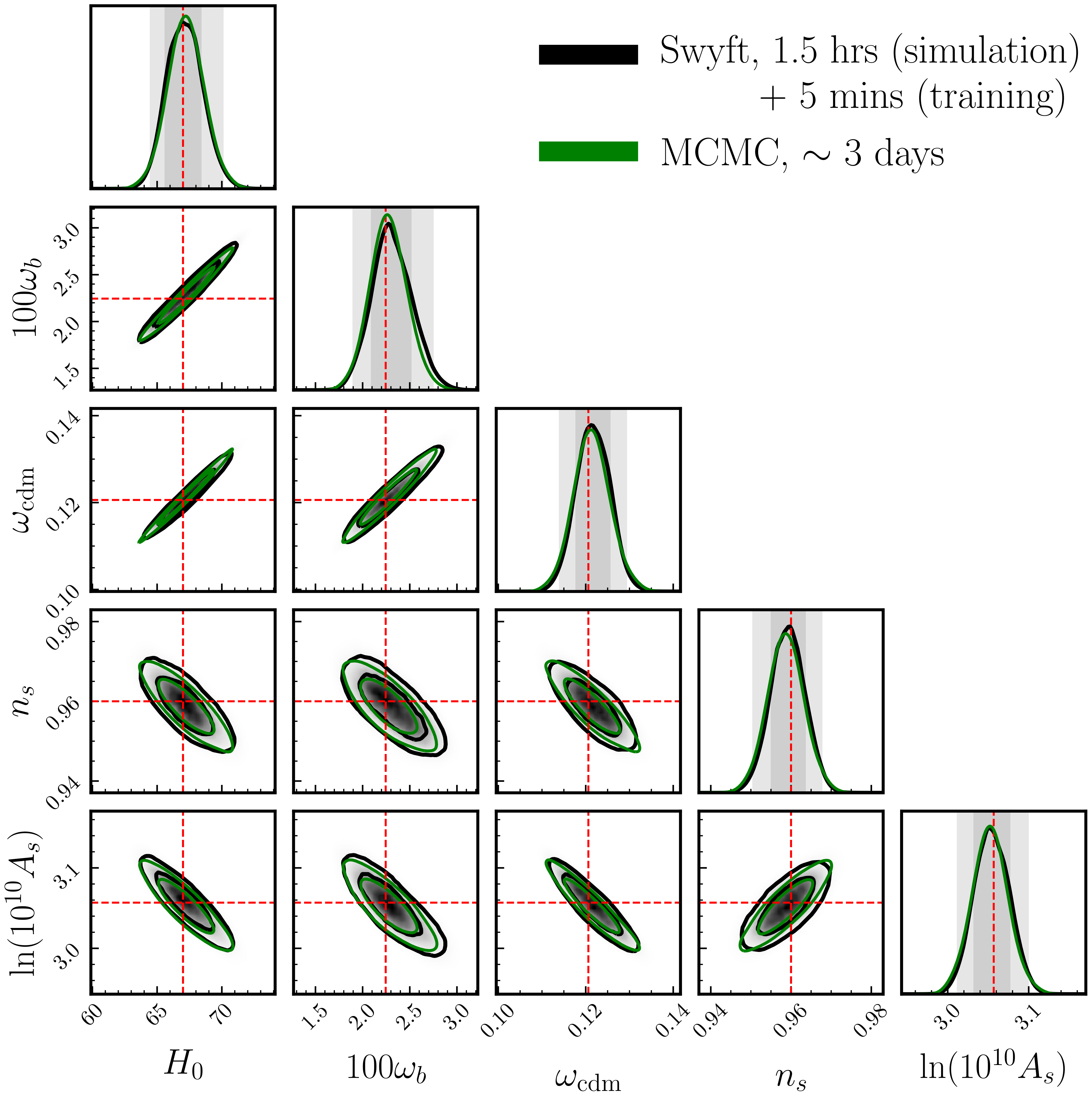
2. Network: We pre-compress spectra into param-specific features using PCA



Forecast ΛCDM posteriors



GFA et al. (2024)

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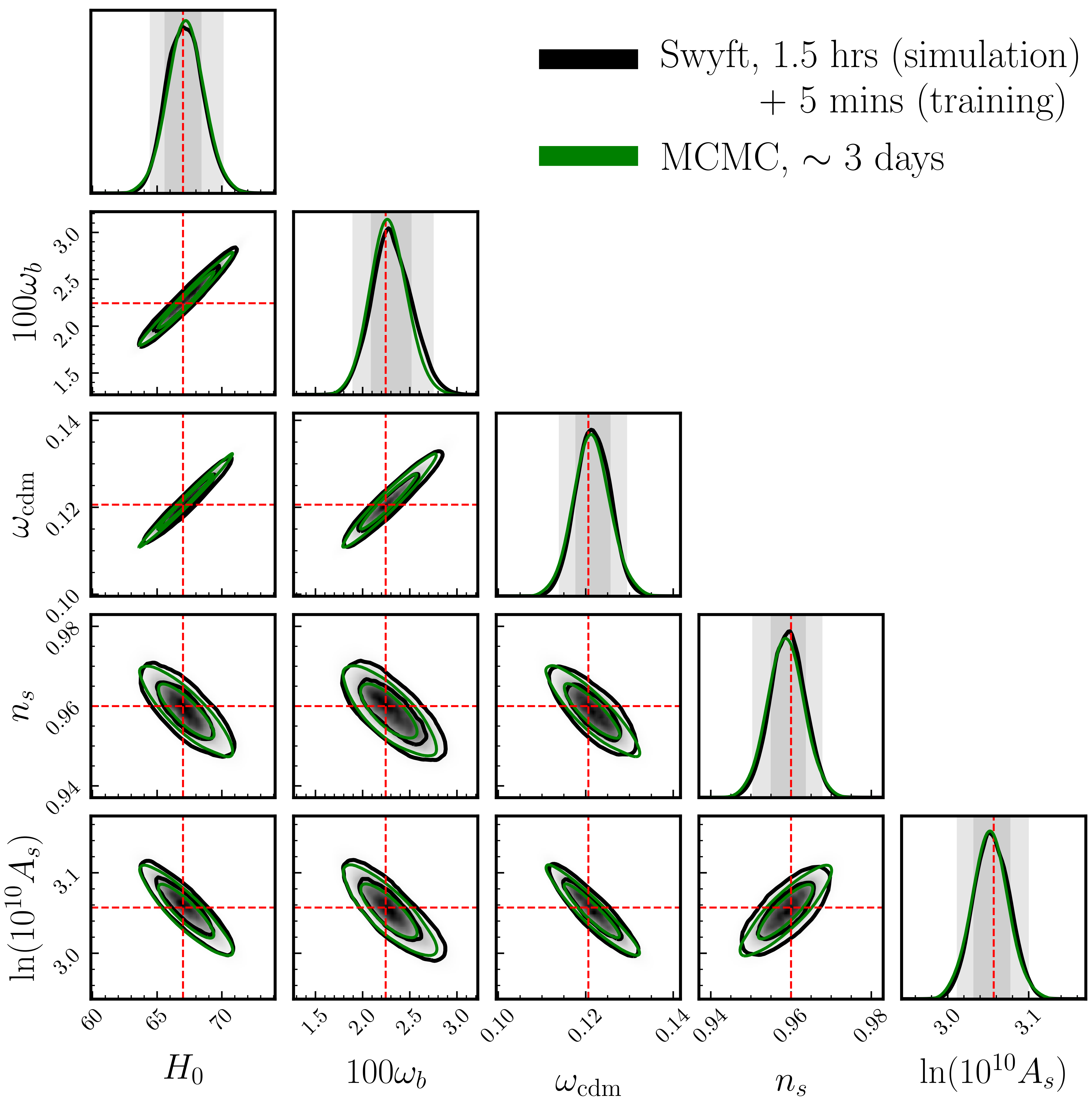

SBI and MCMC are in excellent agreement!

GFA et al. (2024)

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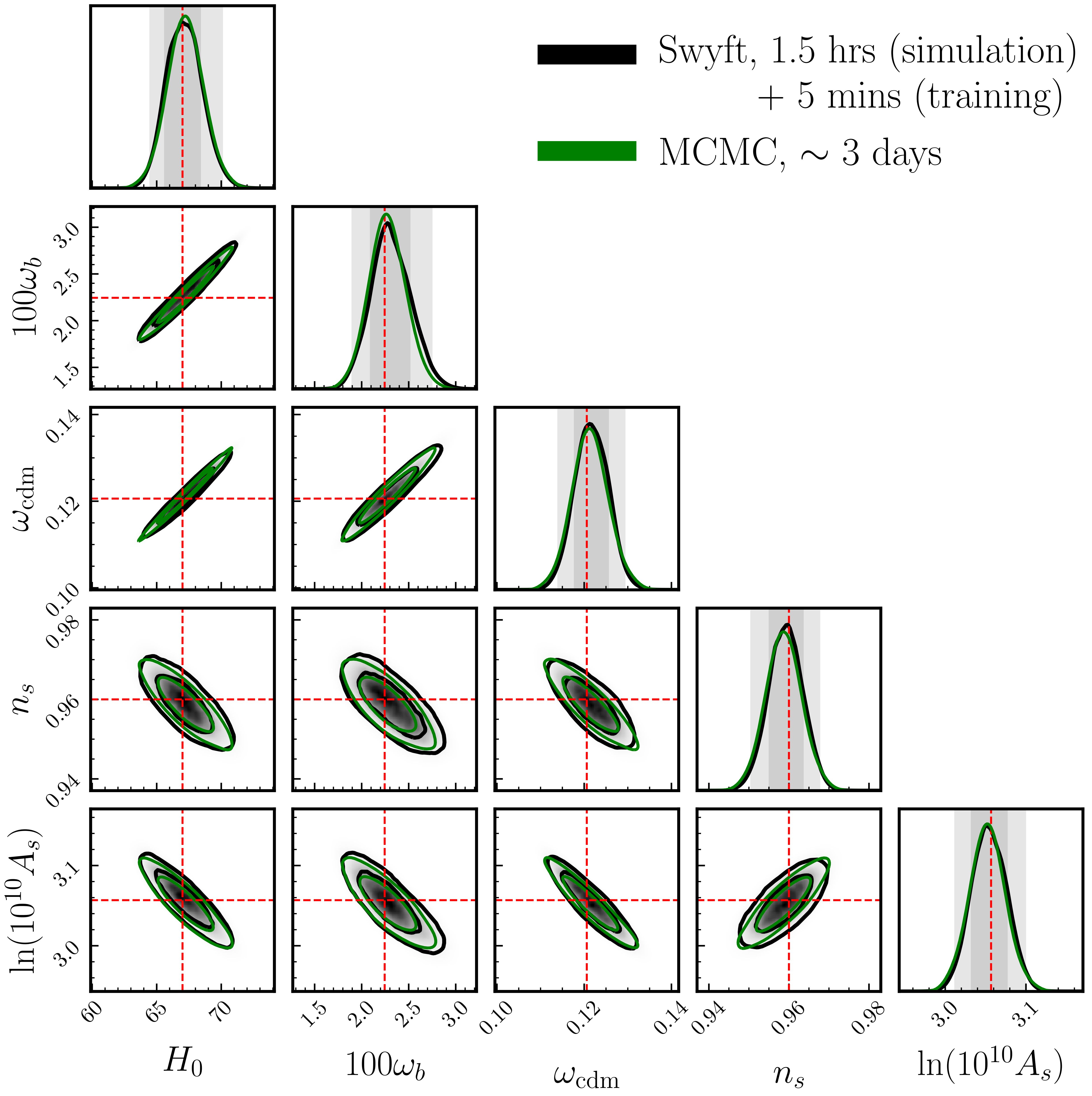

Dramatic reduction in CPU time!

SBI and MCMC are in excellent agreement!

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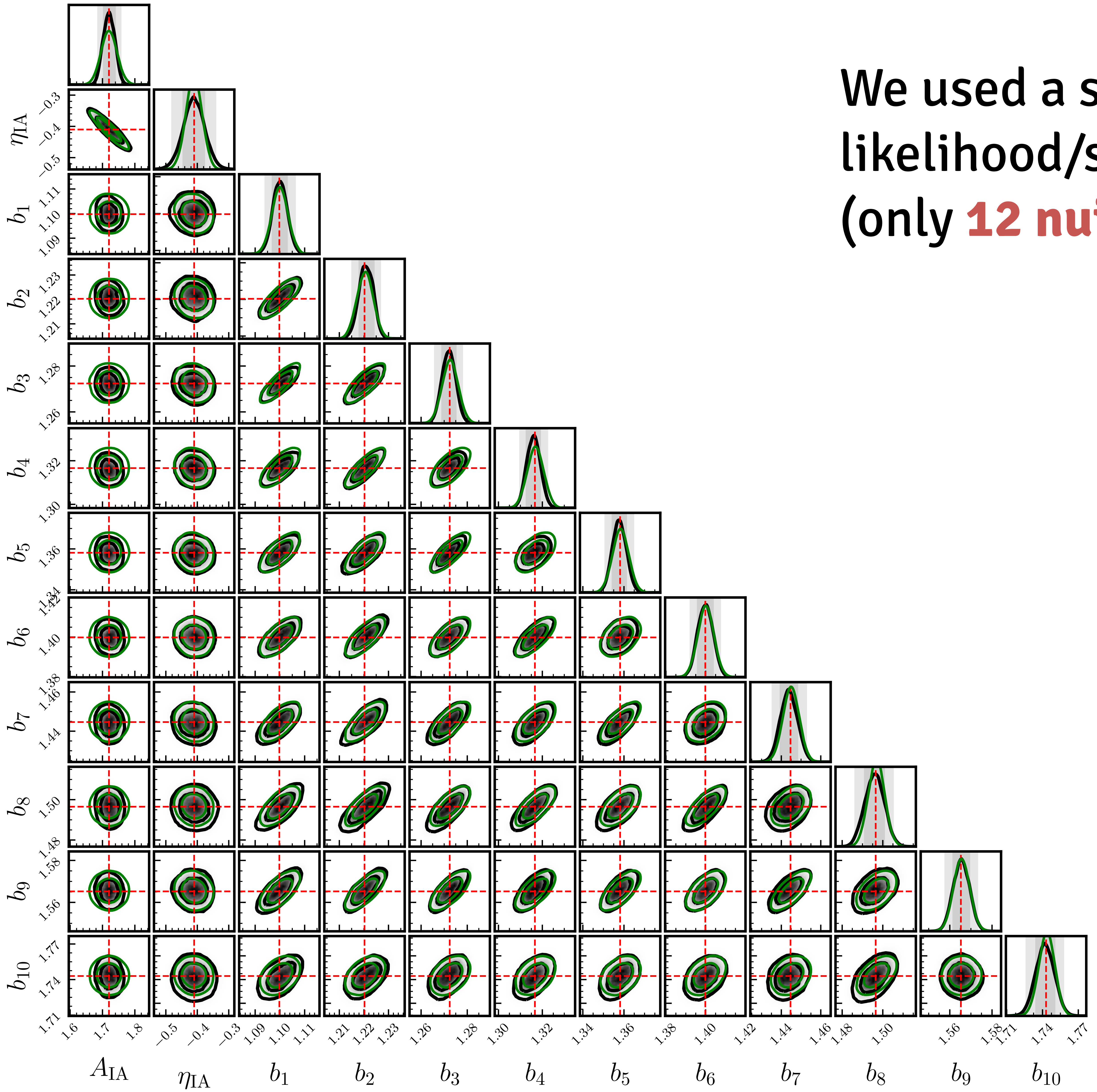
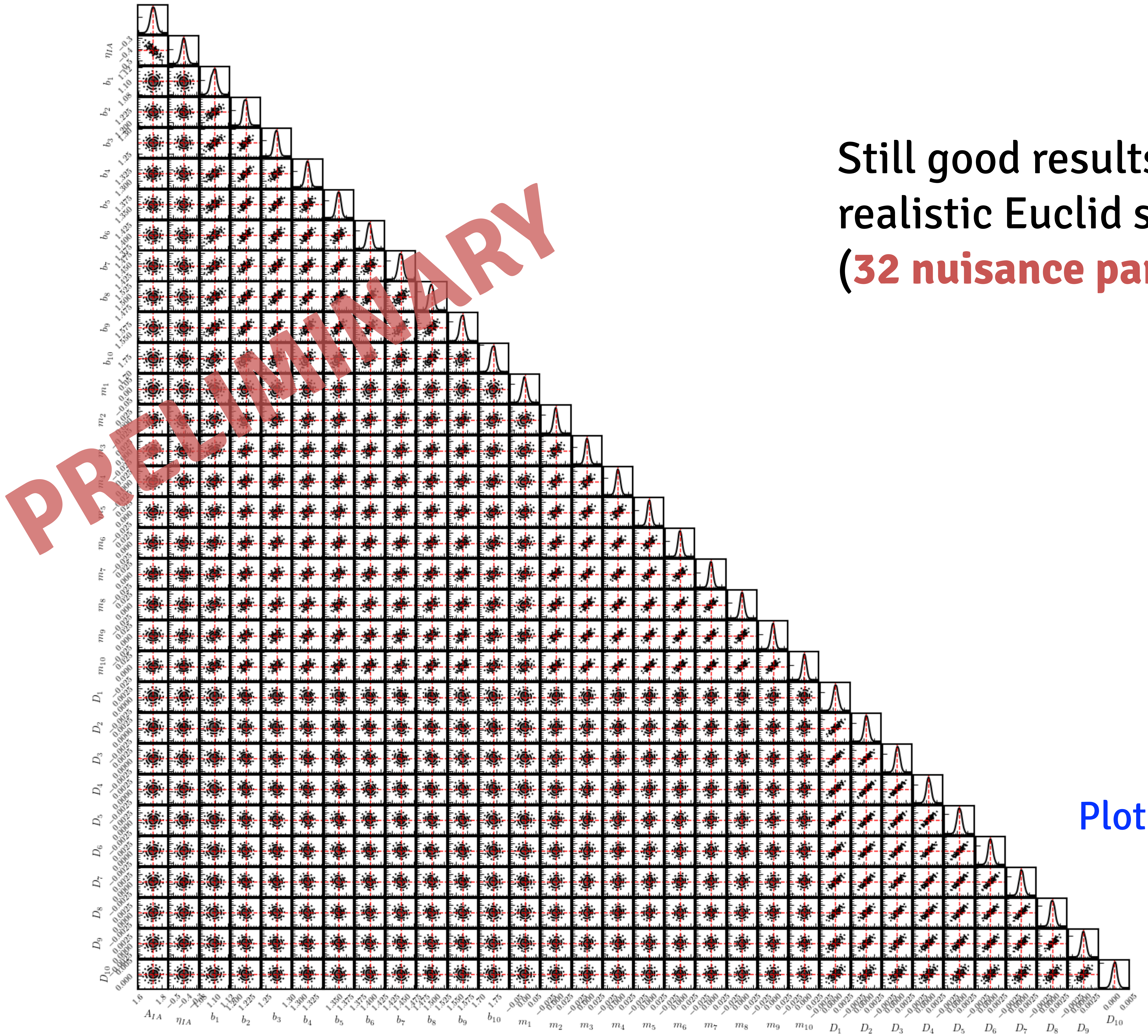


We used a simplified Euclid likelihood/simulator
(only **12 nuisance parameters**)

[GFA et al. (2024)]



Still good results with a more realistic Euclid simulator (**32 nuisance parameters**)

Plot by Alexandra Wernersson

What about combining different cosmological probes?

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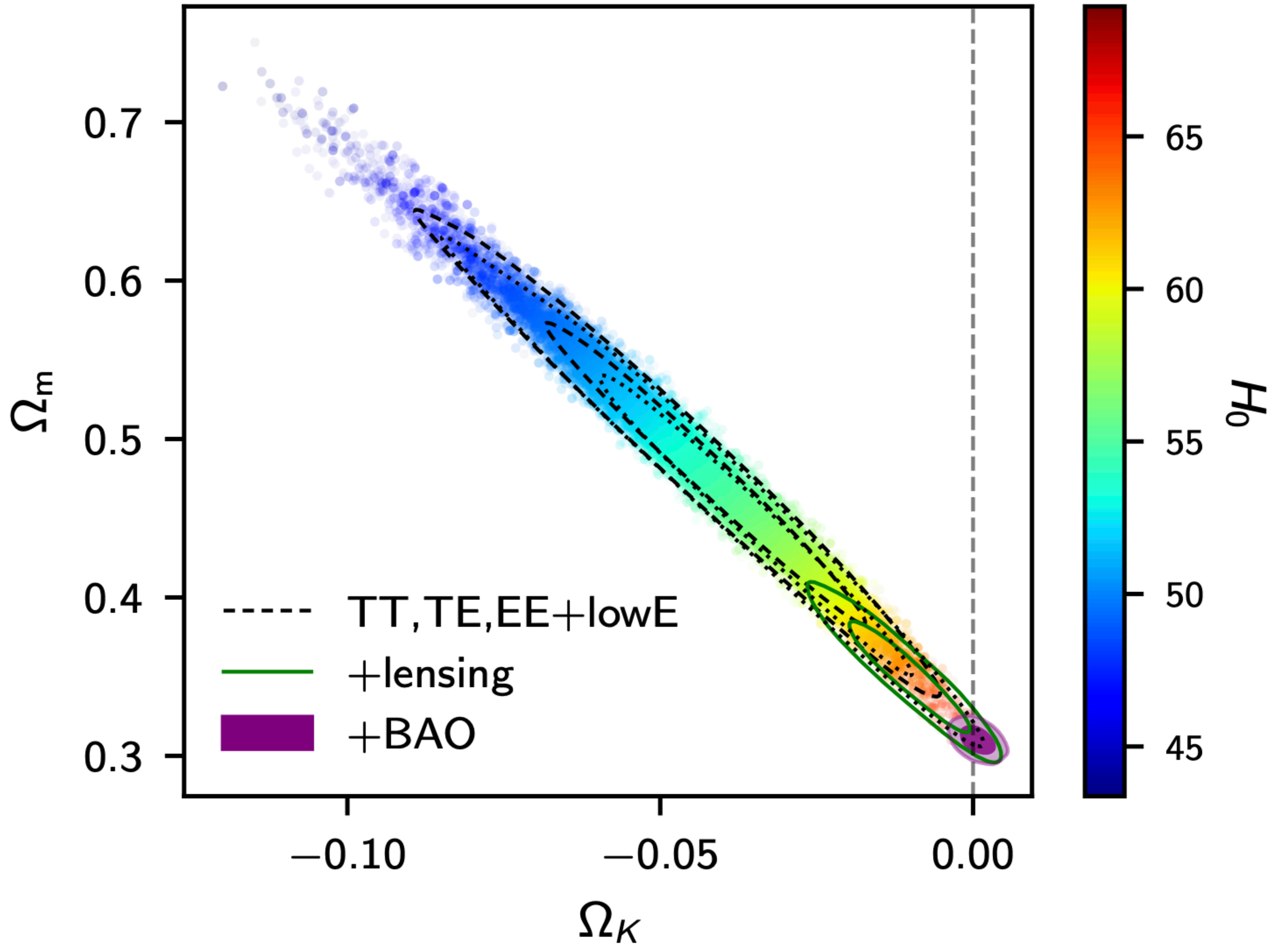
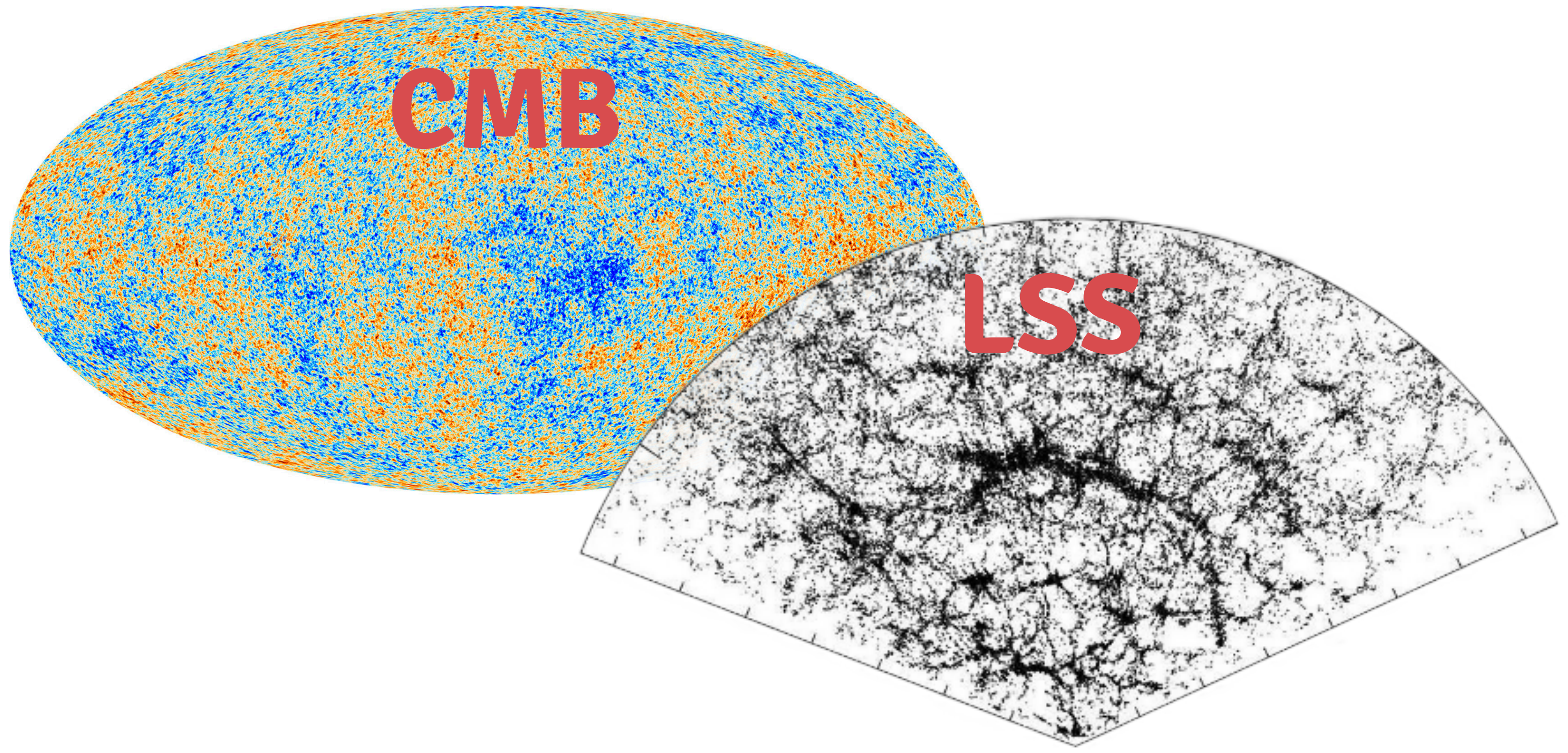
Canonical example:

Planck 2018 Results. VI.



Joint analyses of CMB & LSS



Very complementary
(high-z vs. low-z, linear vs. non-linear)

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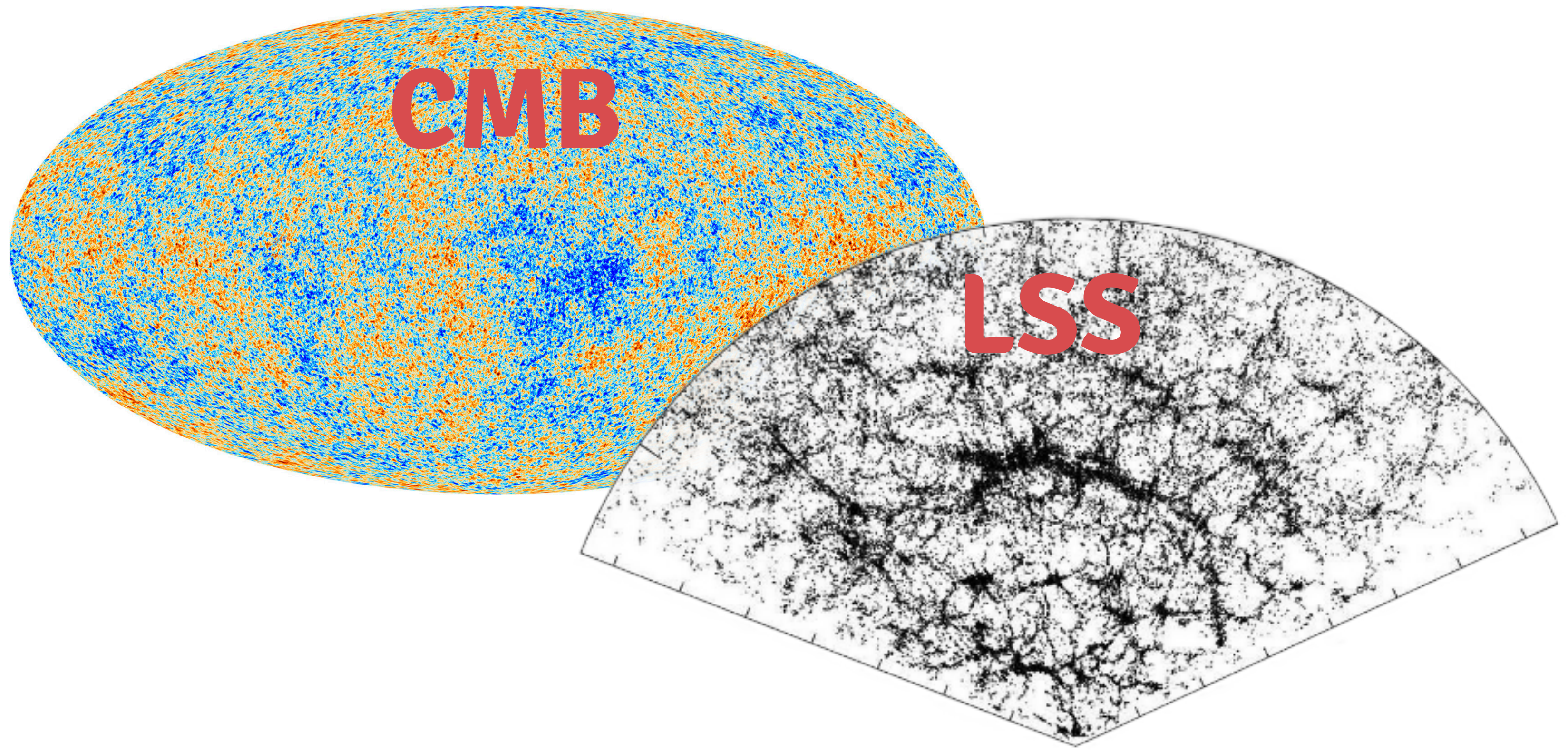

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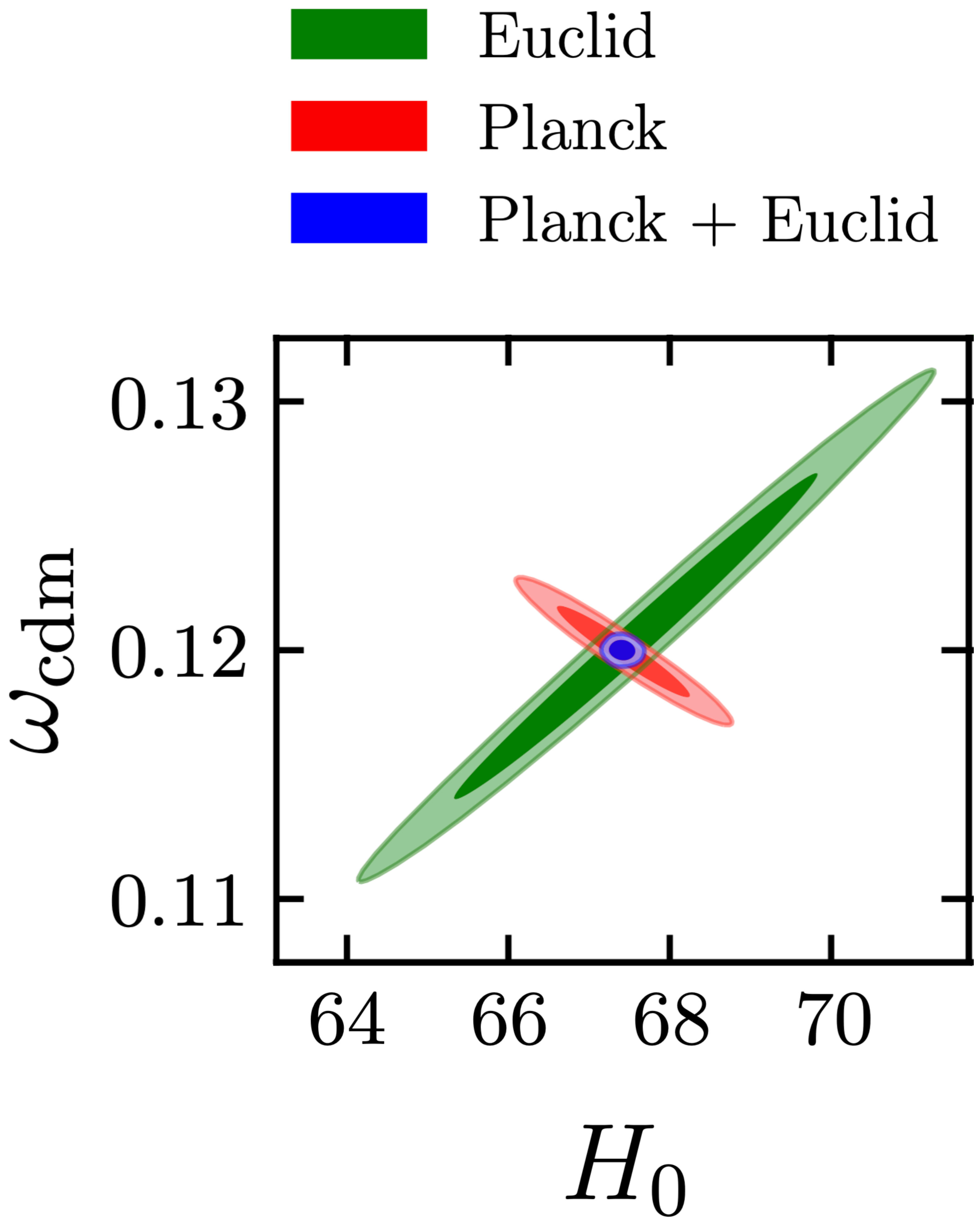
↓

Break parameter degeneracies



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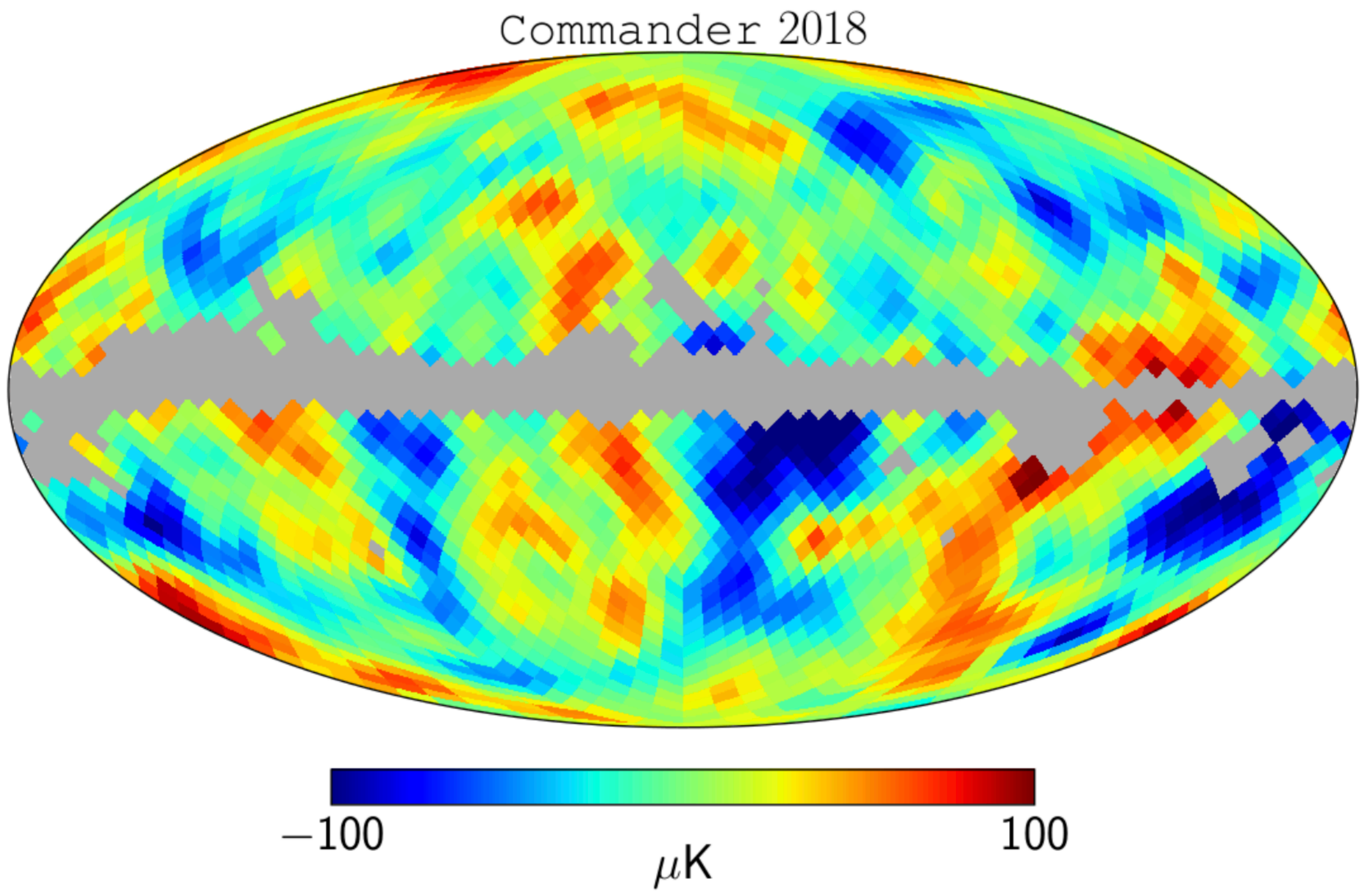

low-ℓ: non-gaussian, pixel-based

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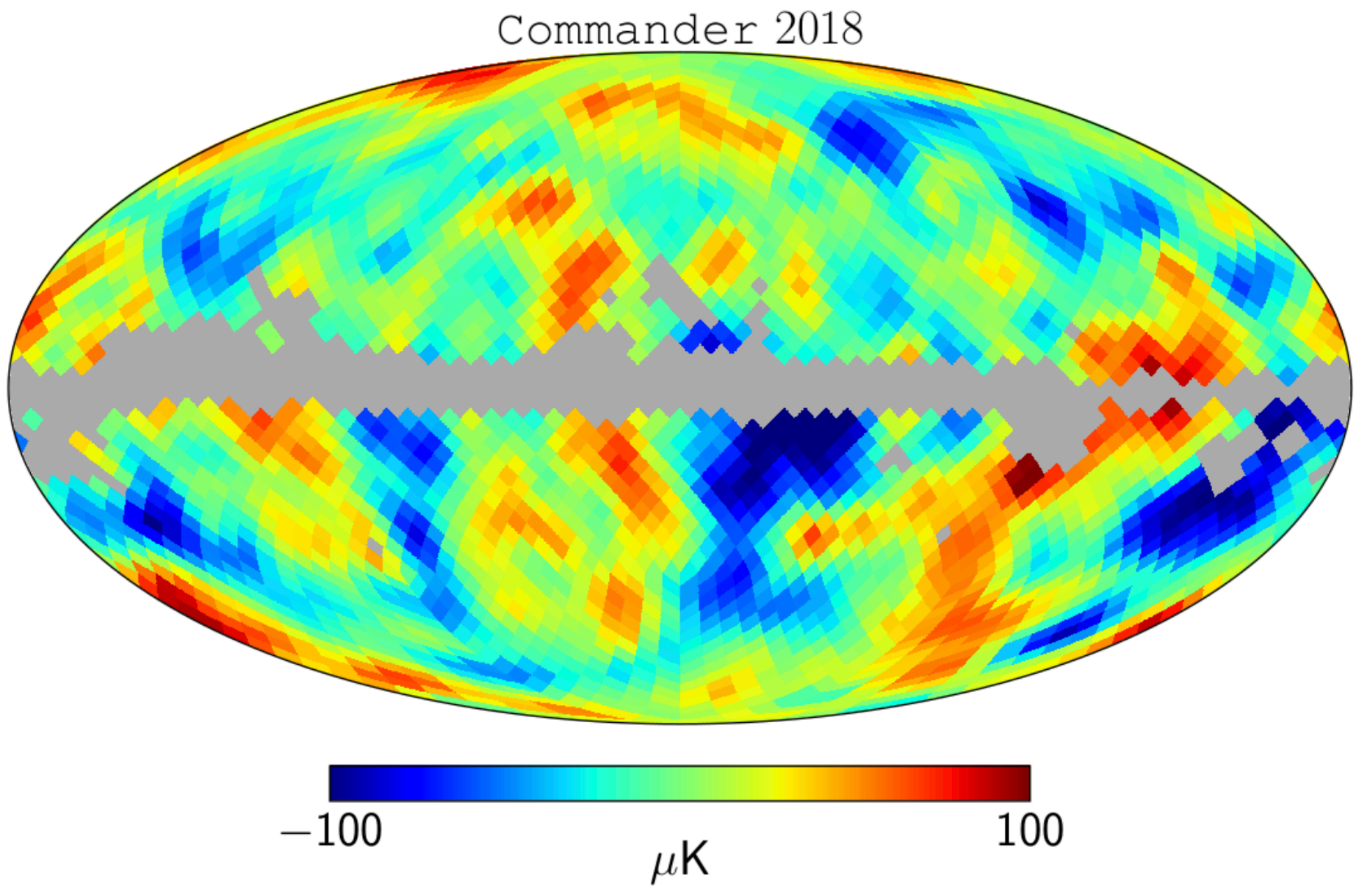

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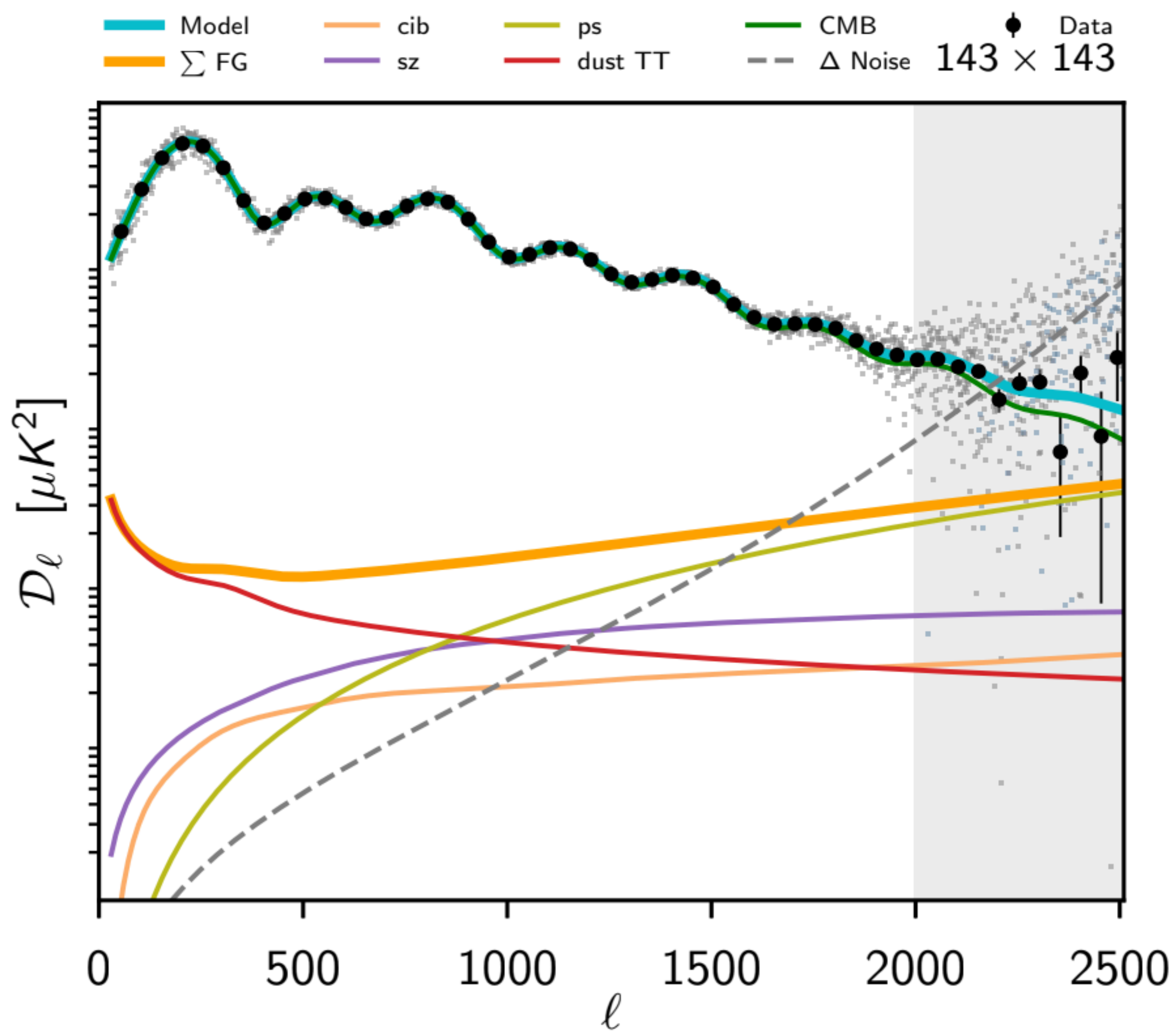

high-ℓ: 47 nuisance to model instrument & foregrounds

The auxiliary variable trick

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I. Train NN with $\boldsymbol{a} \sim p(\boldsymbol{a}\,|\,\boldsymbol{\theta}) \iff \boldsymbol{a} = \boldsymbol{\theta} - \boldsymbol{\theta}'$

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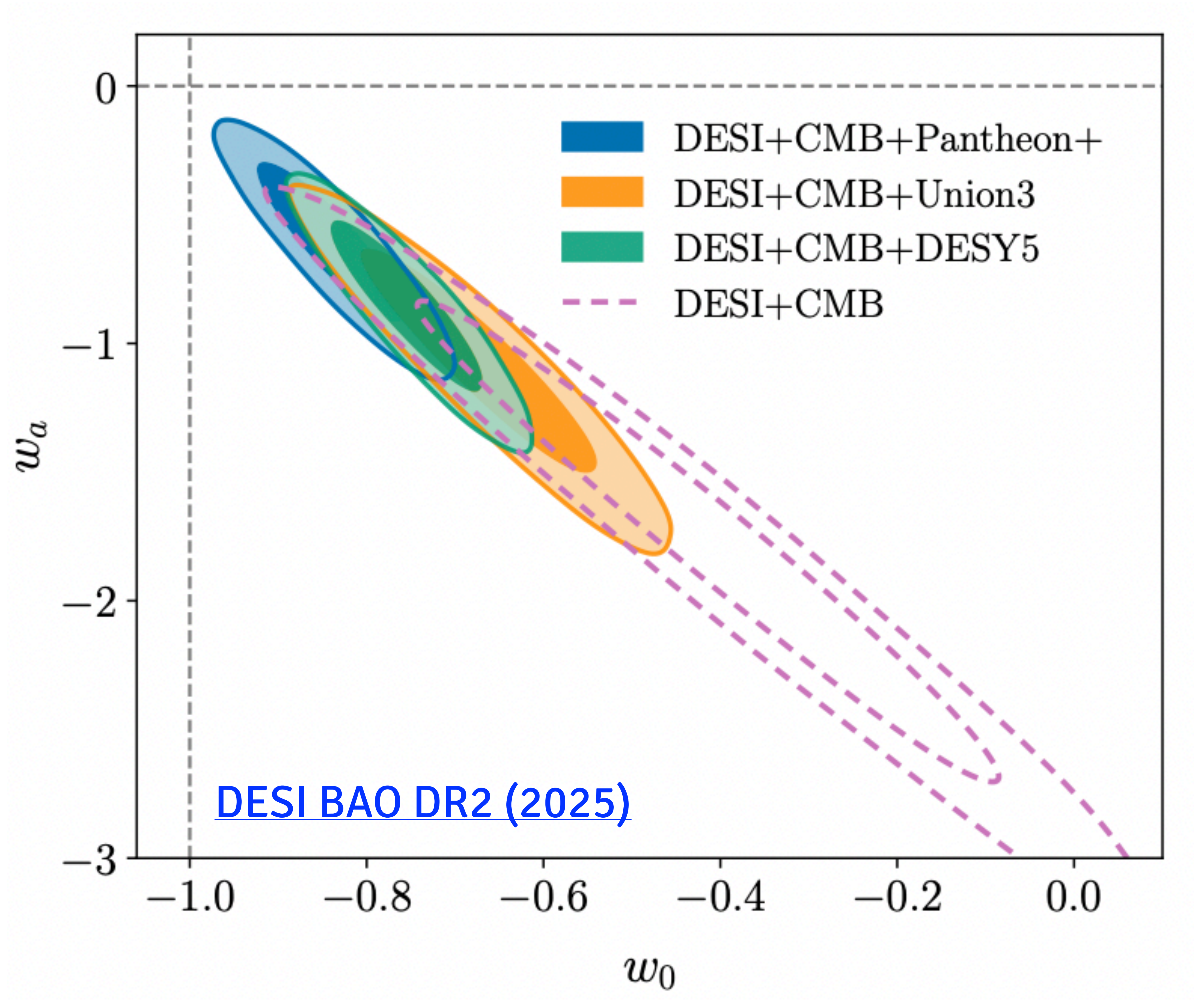
This can now be combined with an **arbitrary simulator**

$$\boldsymbol{a}, \mathrm{y}, \boldsymbol{\theta} \sim \underbrace{p(\boldsymbol{a}\,|\,\boldsymbol{\theta})}_{\text{Explicit likelihood}}\ \underbrace{p(\mathrm{y}\,|\,\boldsymbol{\theta})}_{\text{Simulator / implicit likelihood}}\ p(\boldsymbol{\theta})$$

Application to evolving dark energy

$$w(a) = w_0 + w_a(1 - a)$$



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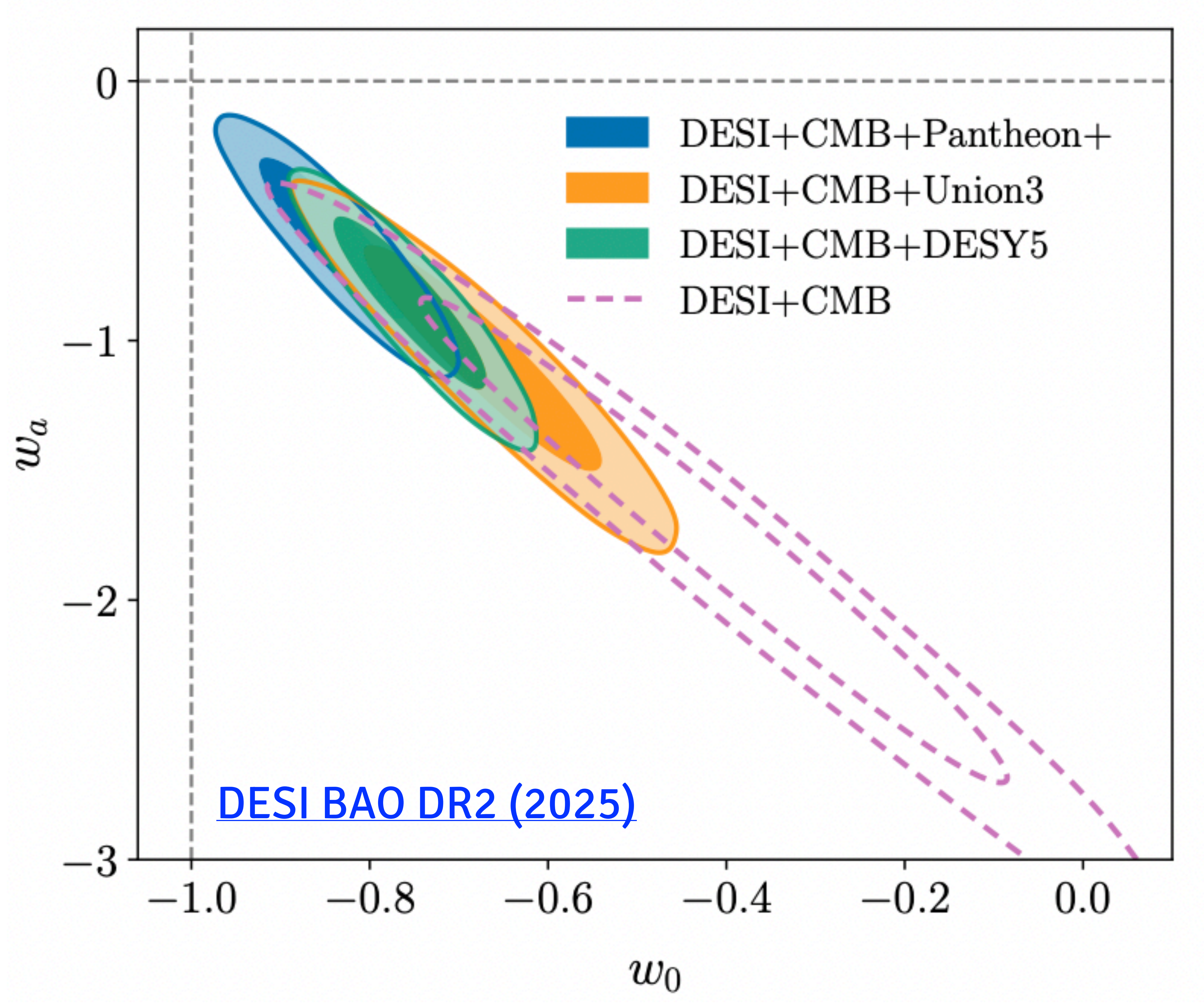

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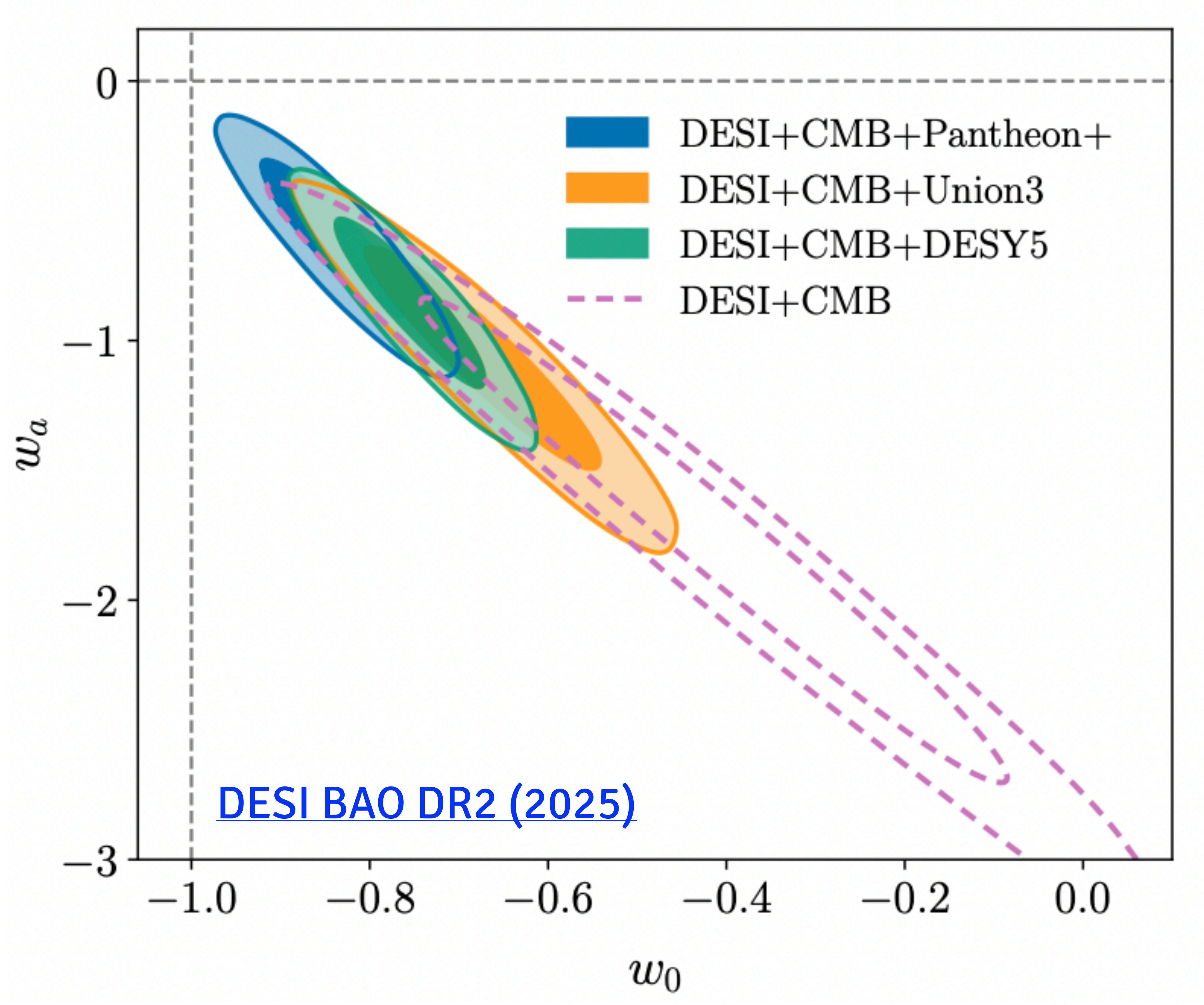

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GOAL

Perform forecast assuming the bestfit $w_0 w_a$CDM model hinted by DESI + CMB + SNIa with SBI

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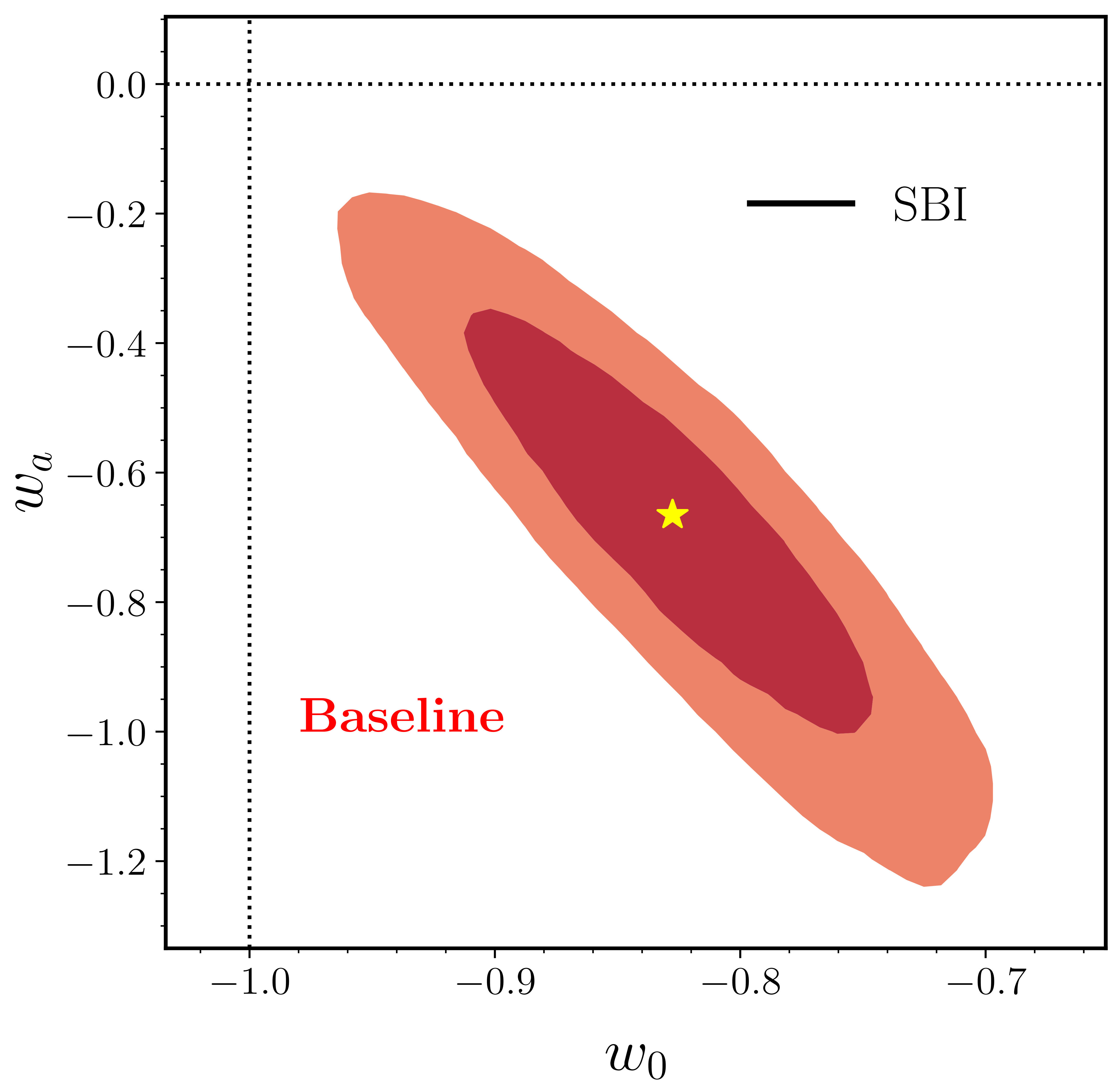
Forecast w_0w_aCDM posteriors

Baseline = Planck + DESI BAO + Pantheon+



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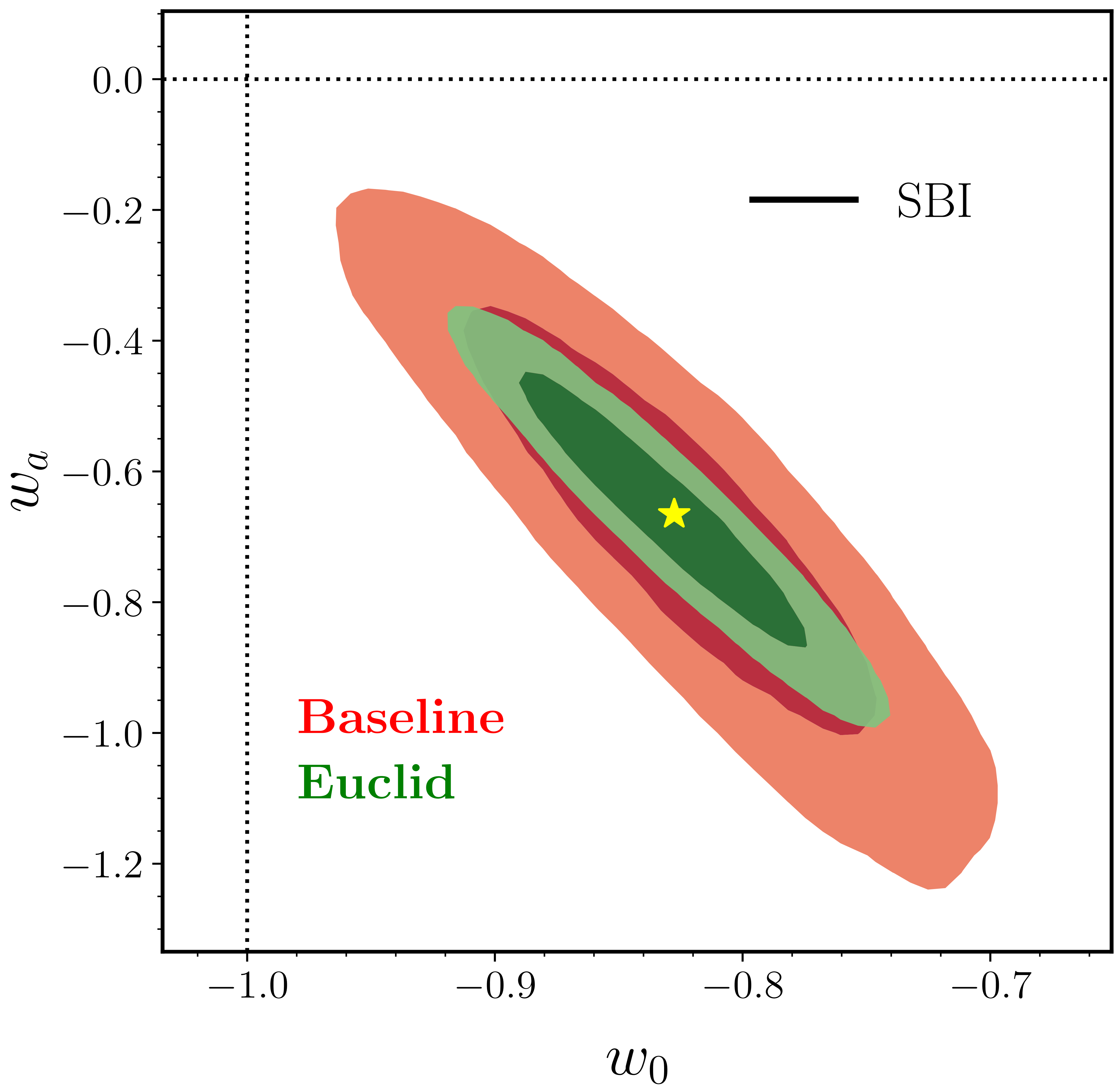

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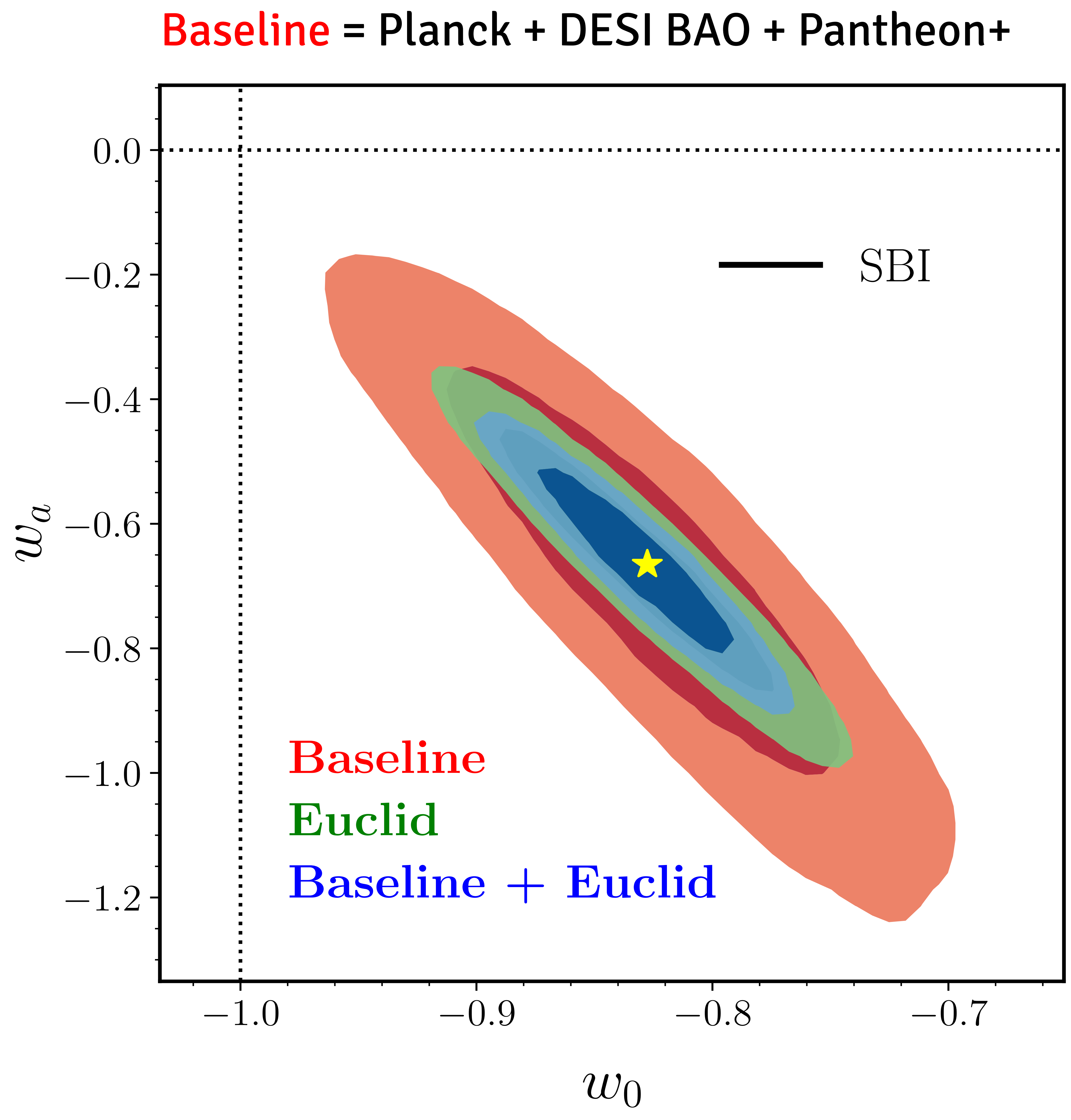

- **Euclid 3x2pt alone** could detect the fid. $w_0 w_a$CDM model at the $\sim 5\sigma$ **level**
- The **combination with Planck+DESI** data would rise the detection to $\sim 7\sigma$

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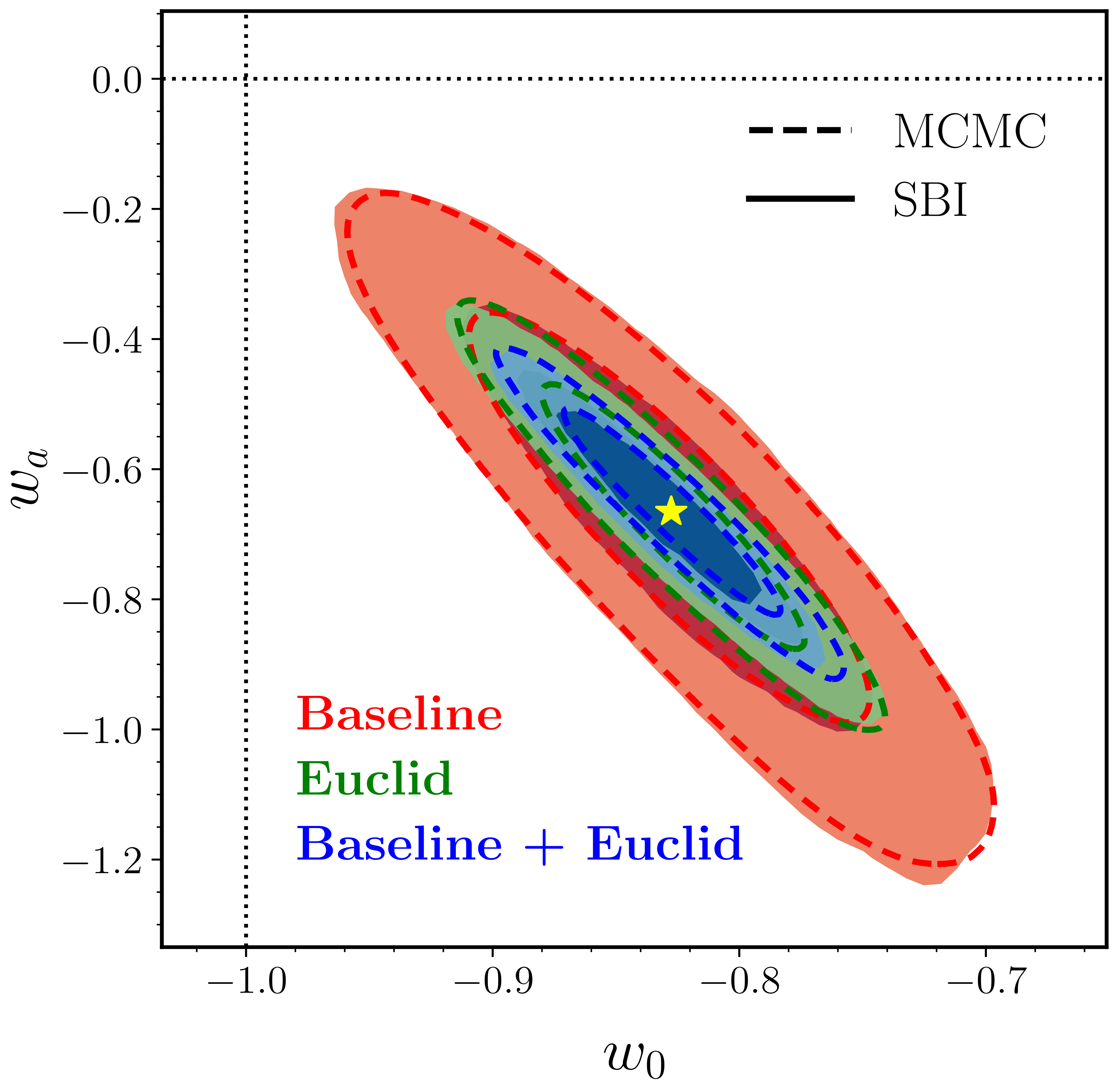
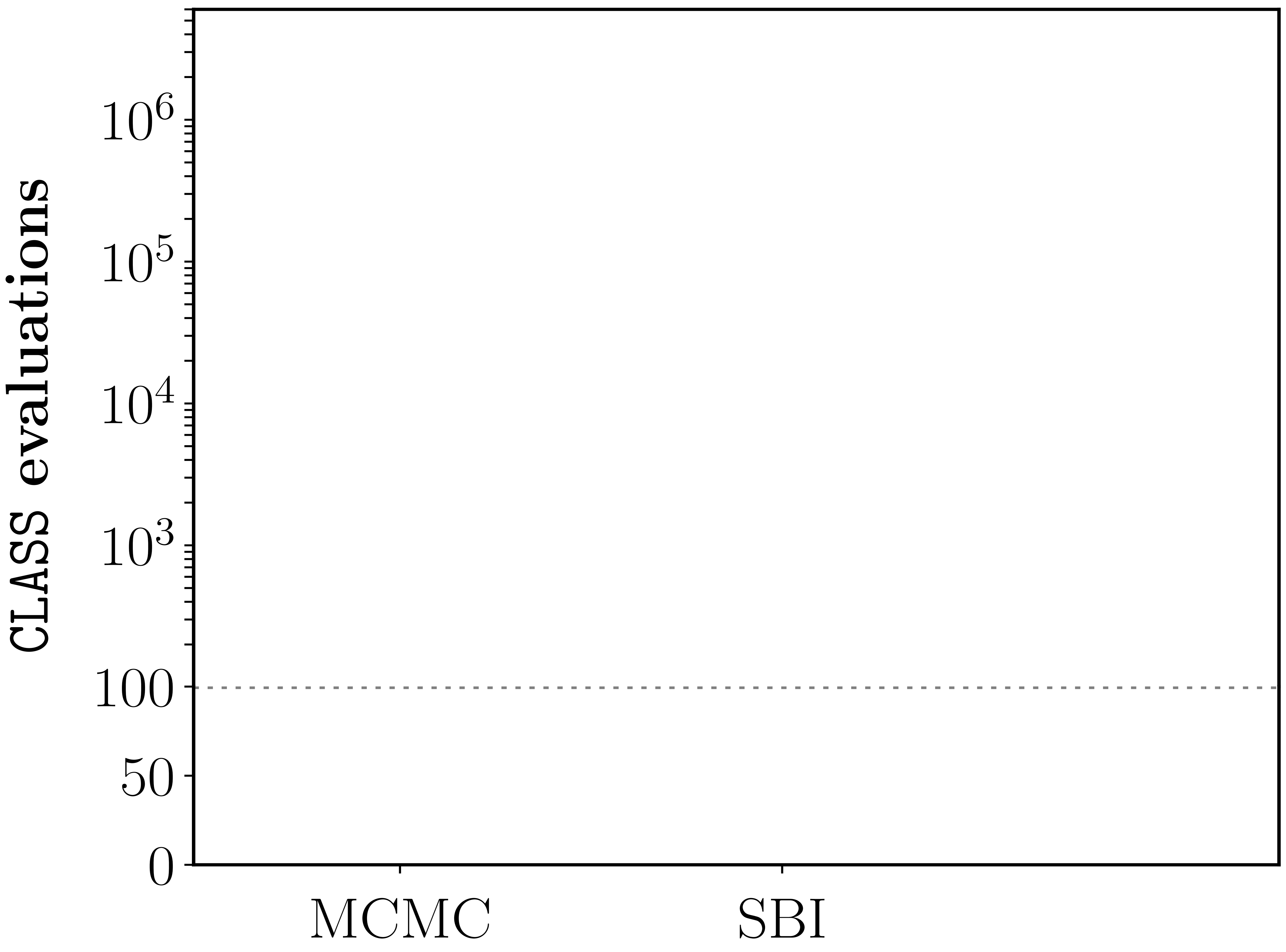


Excellent agreement with MCMC

Number of model evaluations



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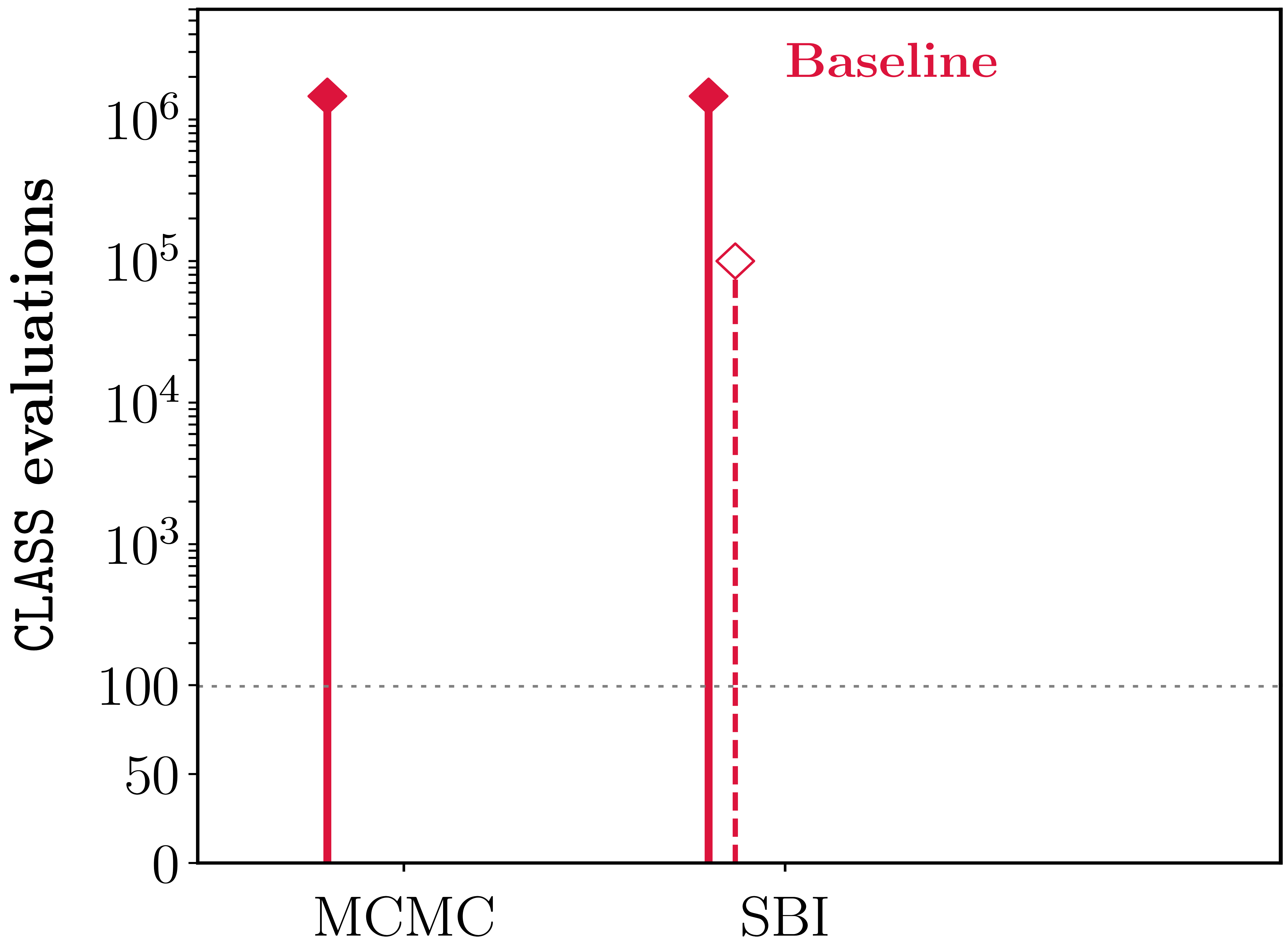

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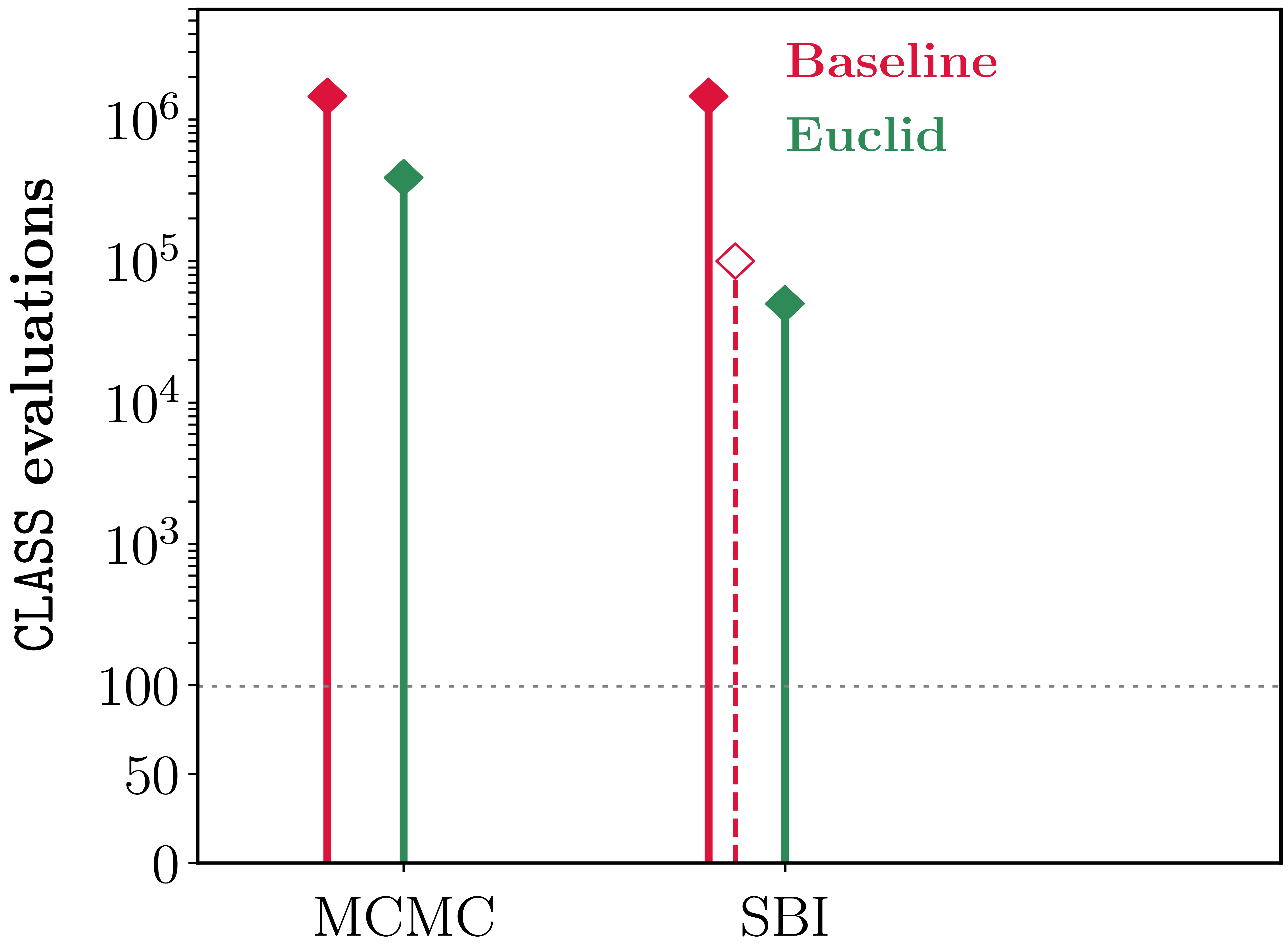

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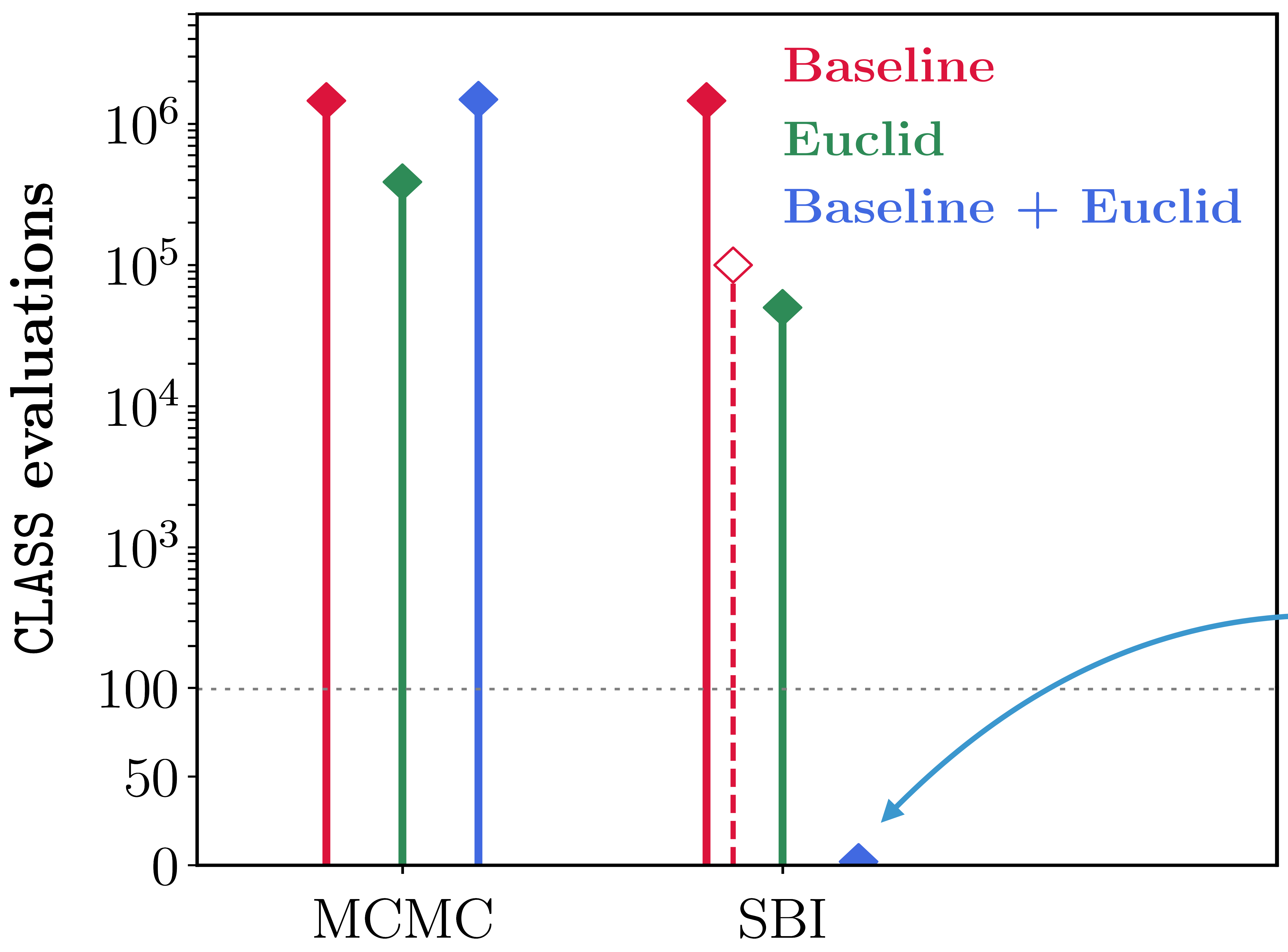

Zero additional model evaluations thanks to **reuse** of simulations!

Summary


Euclid's view of the Perseus cluster of galaxies

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THANK YOU!

g.francoabellan@uva.nl

BACK-UP

Strategy: train a neural network $d_\phi(\mathbf{x}, \boldsymbol{\theta}) \in [0,1]$ as a binary classifier, so that

$$d_\phi(\mathbf{x}, \boldsymbol{\theta}) \simeq 1 \quad \text{if} \quad (\mathbf{x}, \boldsymbol{\theta}) \sim p(\mathbf{x}, \boldsymbol{\theta}) = p(\mathbf{x} \,|\, \boldsymbol{\theta}) p(\boldsymbol{\theta})$$

$$d_\phi(\mathbf{x}, \boldsymbol{\theta}) \simeq 0 \quad \text{if} \quad (\mathbf{x}, \boldsymbol{\theta}) \sim p(\mathbf{x}) p(\boldsymbol{\theta})$$

Note: Φ denotes all the network parameters

We have to minimise a **loss function** w.r.t. the network params. Φ

$$L[d_\phi(\mathbf{x},\boldsymbol{\theta})] = -\int d\mathbf{x}d\boldsymbol{\theta}\left[p(\mathbf{x},\boldsymbol{\theta})\ln(d_\phi(\mathbf{x},\boldsymbol{\theta})) + p(\mathbf{x})p(\boldsymbol{\theta})\ln(1 - d_\phi(\mathbf{x},\boldsymbol{\theta}))\right]$$

which yields

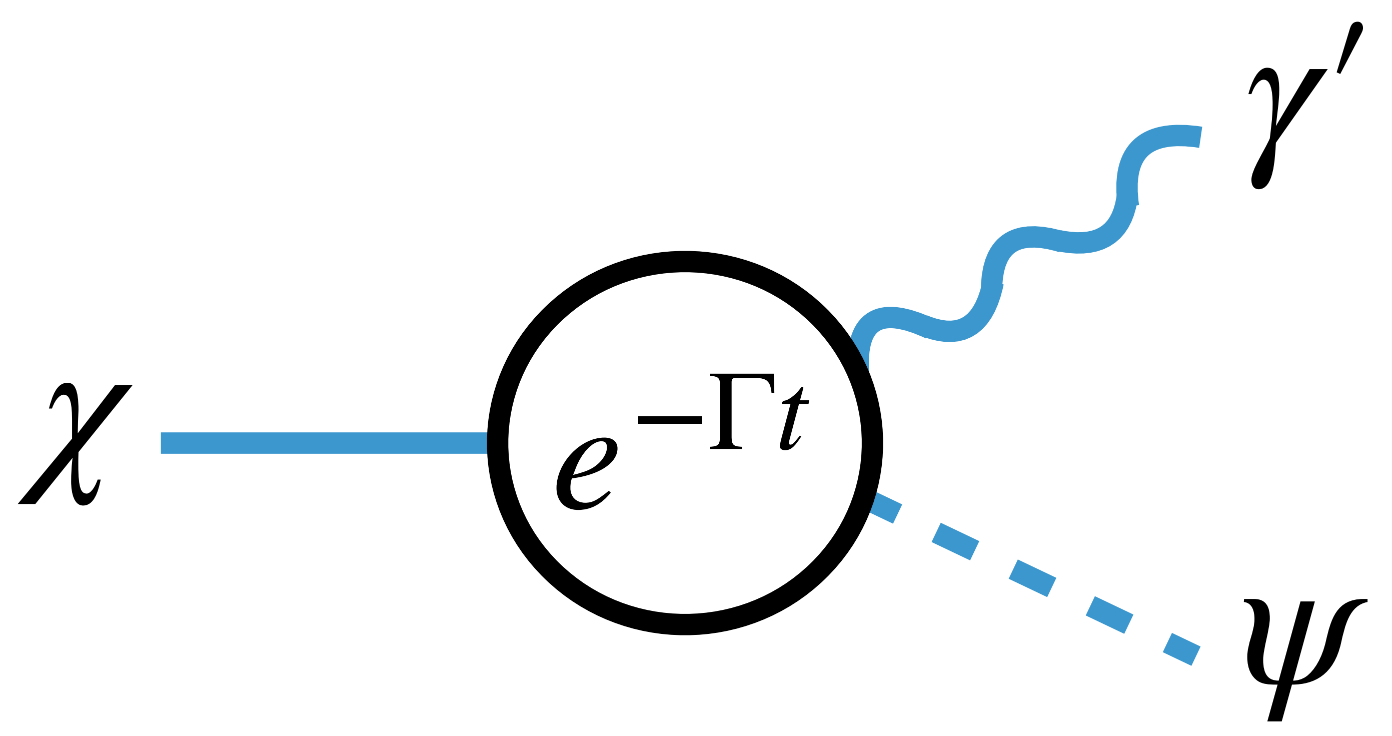
$$d_\phi(\mathbf{x},\boldsymbol{\theta}) \simeq \frac{p(\mathbf{x},\boldsymbol{\theta})}{p(\mathbf{x},\boldsymbol{\theta}) + p(\mathbf{x})p(\boldsymbol{\theta})} = \frac{r(\mathbf{x};\boldsymbol{\theta})}{r(\mathbf{x};\boldsymbol{\theta}) + 1}$$

Does MNRE perform well with **highly non-Gaussian** posteriors?

As an example, we test a model of **CDM decaying to DR + WDM** (proposed to explain the S_8 tension)

[Abellán et al. (2021)]

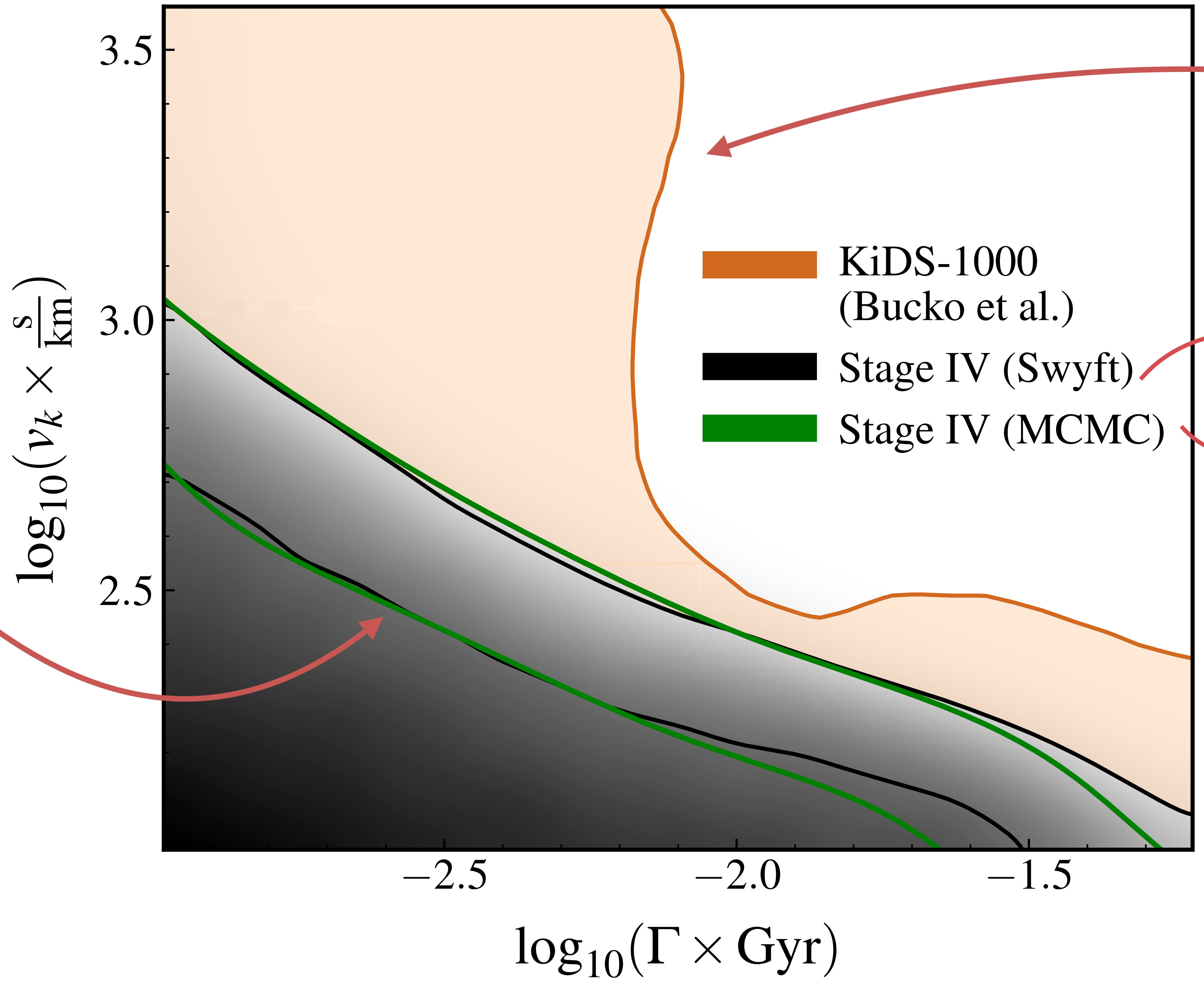
[Bucko et al. (2023)]



Decay rate Γ

WDM velocity kick v_k

Forecast constraints on decaying DM

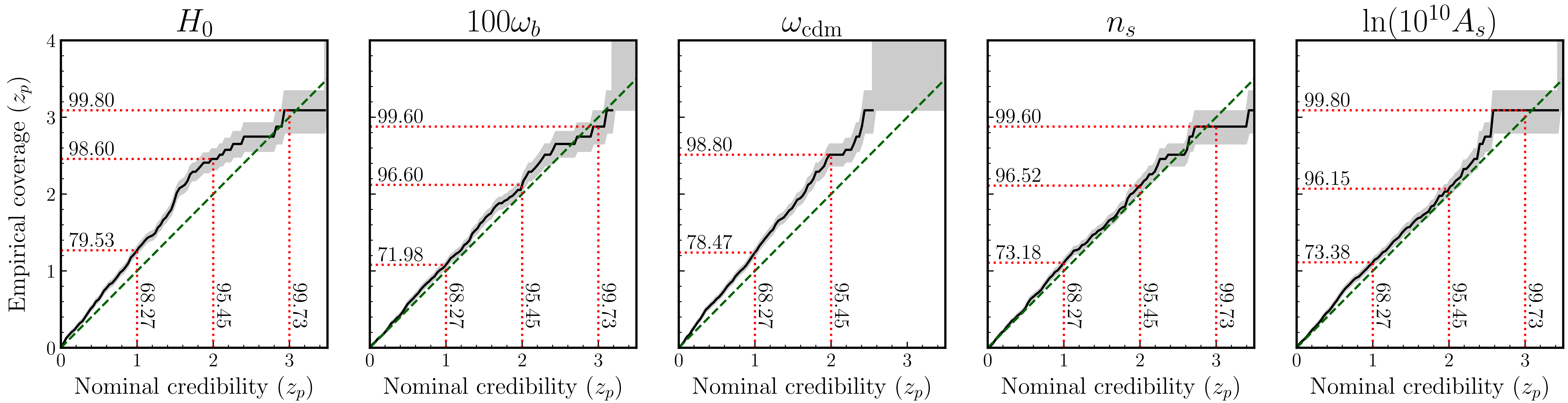


Improve current limits by ~1 order of magnitude!

3 hours vs. 8 days!

MNRE & MCMC in good agreement

Coverage test for Planck + 3x2pt (ΛCDM)



Empirical coverage and confidence level match to very good precision