Credit: ESA/Euclid/

Field-level cosmological model selection

Alessio Spurio Mancini

ROYAL HOLLOWAY UNIVERSITY OF LONDON

Image: ESA/Euclid/Euclid Consortium/NASA

Challenges for cosmological inference

- Accelerating parameter estimation
- Beyond LCDM modelling
- Systematics modelling
- Beyond 2pt statistics

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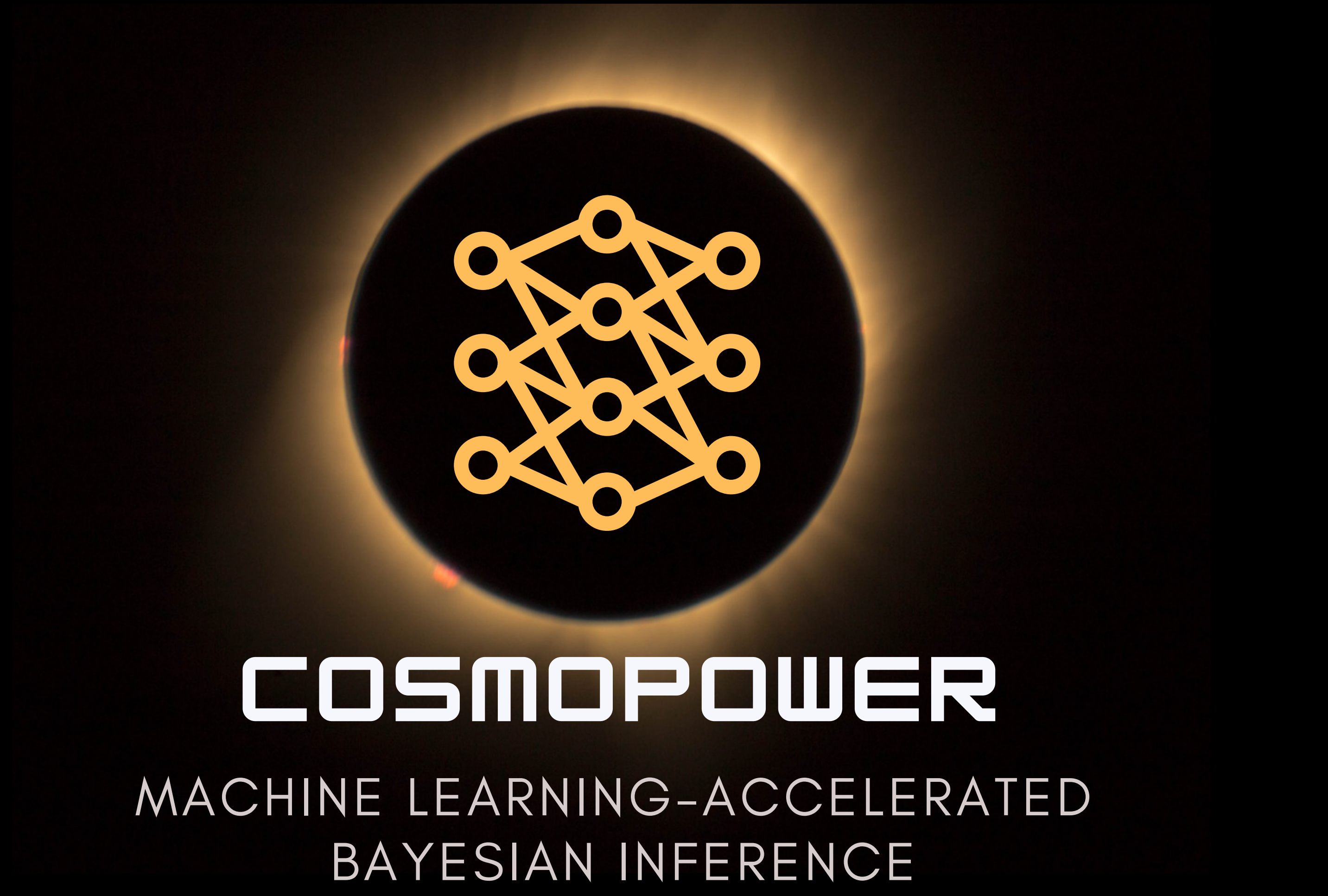

The future of cosmological inference

- Emulation
- Differentiable and probabilistic programming
- Gradient-based sampling
- Model selection decoupled from sampling

The future of cosmological inference

Piras, Polanska, Price, Spurio Mancini, McEwen 24

- Emulation

COSMOPOWER-JAX
(Piras & Spurio Mancini 23)

- Differentiable and probabilistic programming

JAX (Bradbury+18)

NUMPYRO (Phan+19)

- Gradient-based sampling

NUTS (Hoffman+ 14)

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HARMONIC
(Polanska, Price, Piras,
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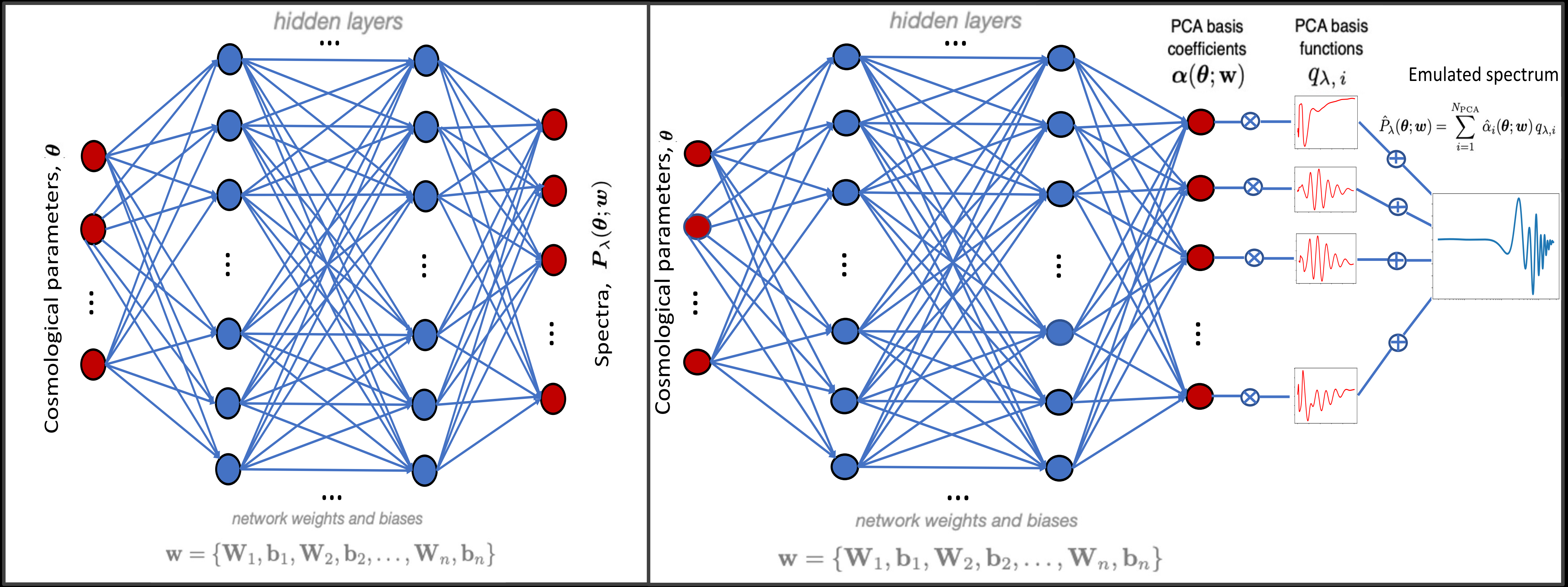
COSMOPOWER

Spurio Mancini, Piras, Alsing, Joachimi, Hobson 2022

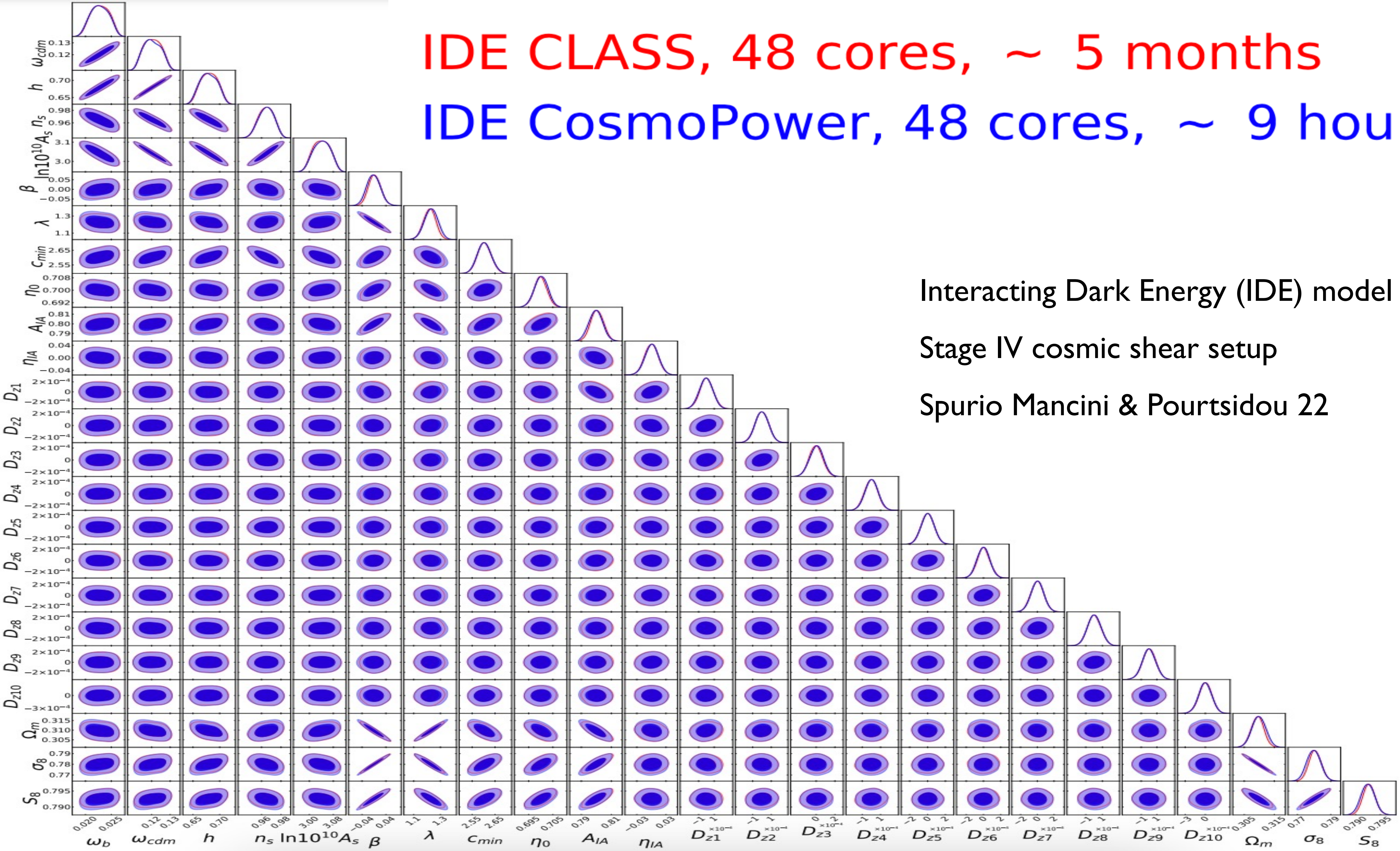


python GitHub

alessiospuriomancini/cosmopower

IDE CLASS, 48 cores, ~ 5 months

IDE CosmoPower, 48 cores, ~ 9 hours

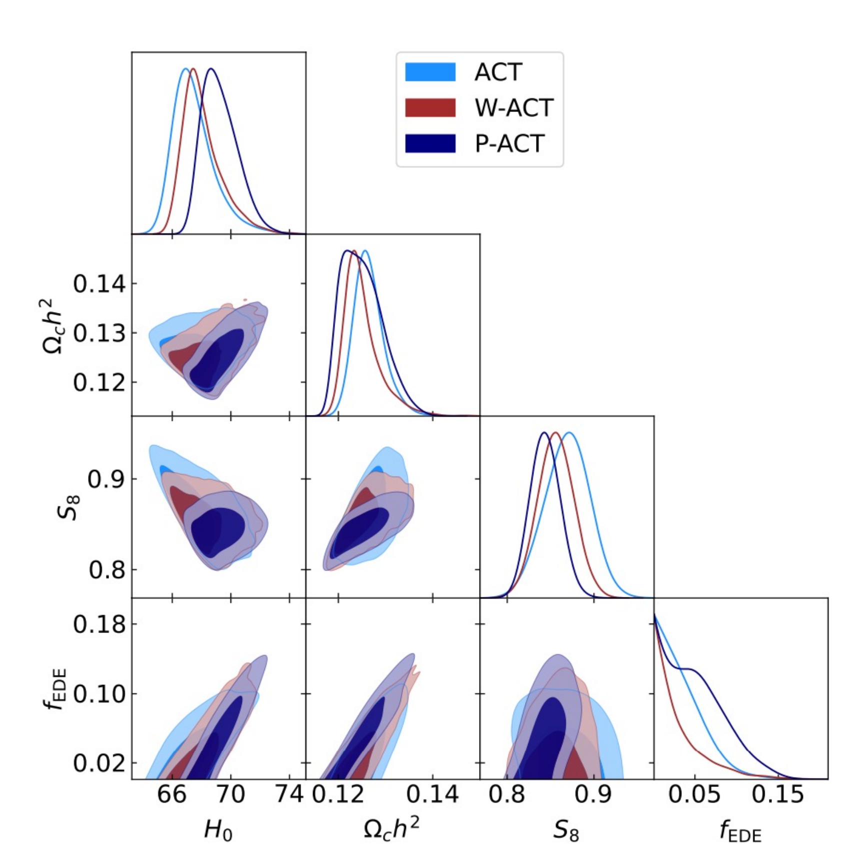


Interacting Dark Energy (IDE) model

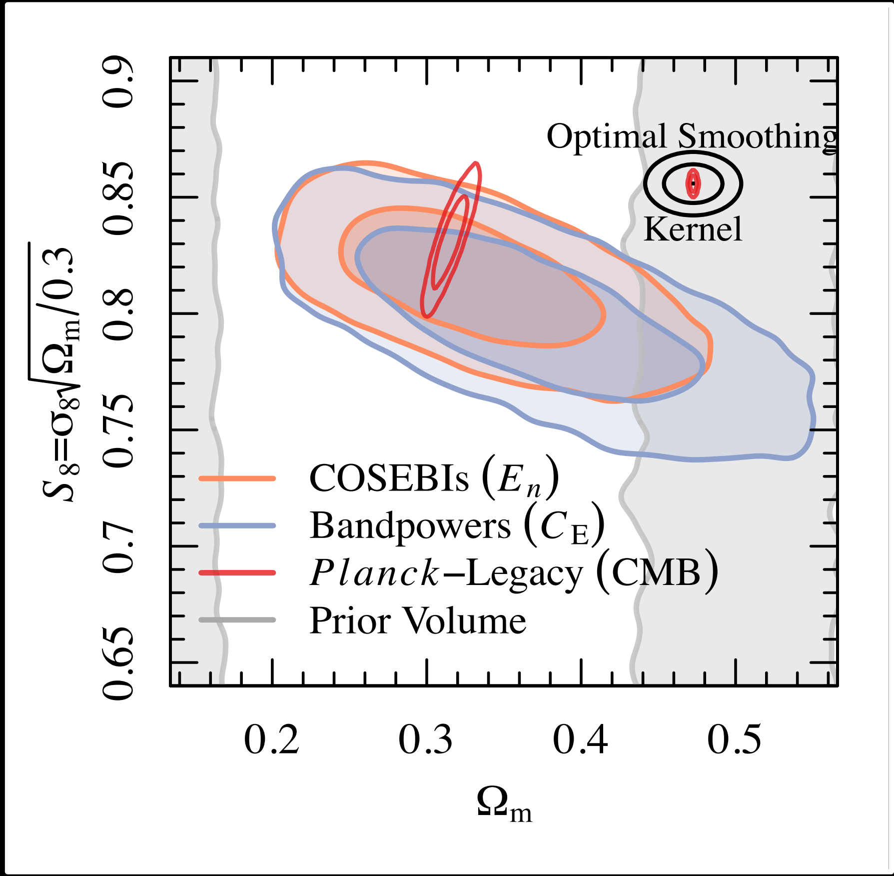
Stage IV cosmic shear setup

Spurio Mancini & Pourtsidou 22

Hot off the press: COSMOPOWER in action

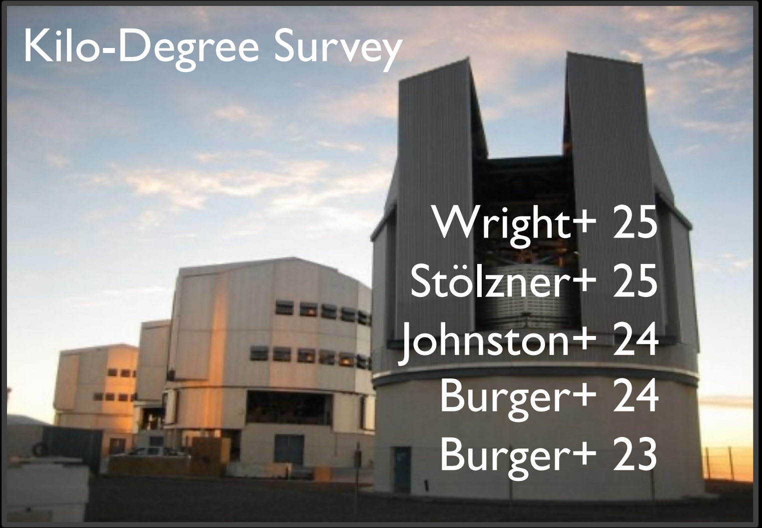


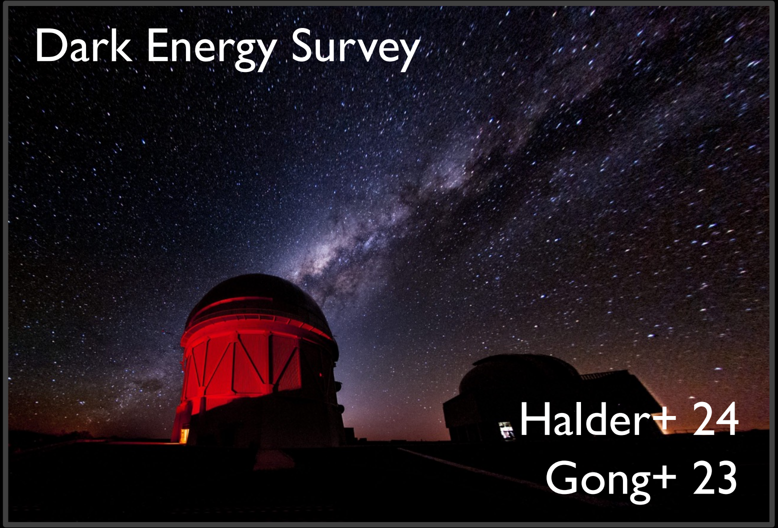
ACT DR6, Calabrese+ 25

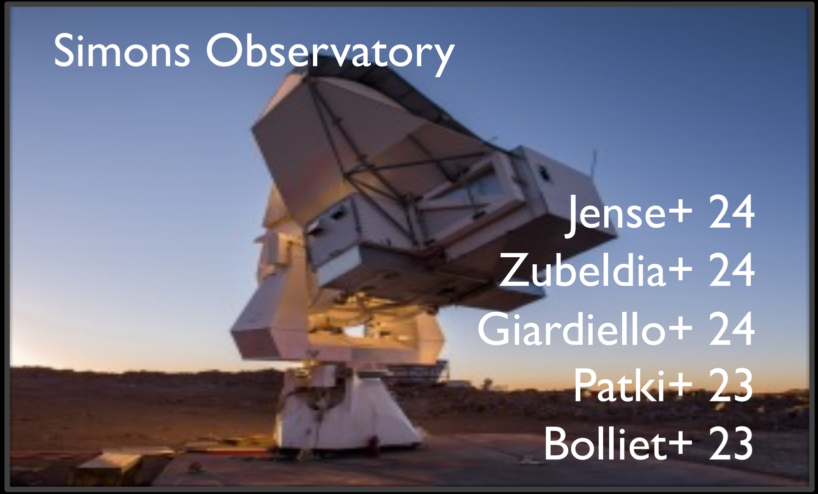


KiDS Legacy, Wright+ 25

Collaborations using COSMOPOWER







https://github.com/alessiospuriomancini/cosmopower

README.md

COSMOPOWER

MACHINE LEARNING-ACCELERATED BAYESIAN INFERENCE

Python | Tensorflow | License GPLv3 | Author Alessio Spurio Mancini | Installation pip install cosmopower

Overview • Documentation • Installation • Getting Started • Training • Trained Models • Likelihoods • Support • Citation

```
pip install cosmopower
```

```python
import cosmopower as cp

# load pre-trained NN model: maps cosmological parameters to CMB TT log-C_ell
cp_nn = cp.cosmopower_NN(restore=True,
                         restore_filename='/path/to/cosmopower'\
                         +'/cosmopower/trained_models/CP_paper/CMB/cmb_TT_NN')

# create a dict of cosmological parameters
params = {'omega_b': [0.0225],
          'omega_cdm': [0.113],
          'h': [0.7],
          'tau_reio': [0.055],
          'n_s': [0.96],
          'ln10^{10}A_s': [3.07],
          }

# predictions (= forward pass through the network) -> 10^predictions
spectra = cp_nn.ten_to_predictions_np(params)
```

getting_started_with_cosmopower_NN.ipynb

File Edit View Insert Runtime Tools Help Changes will not be saved

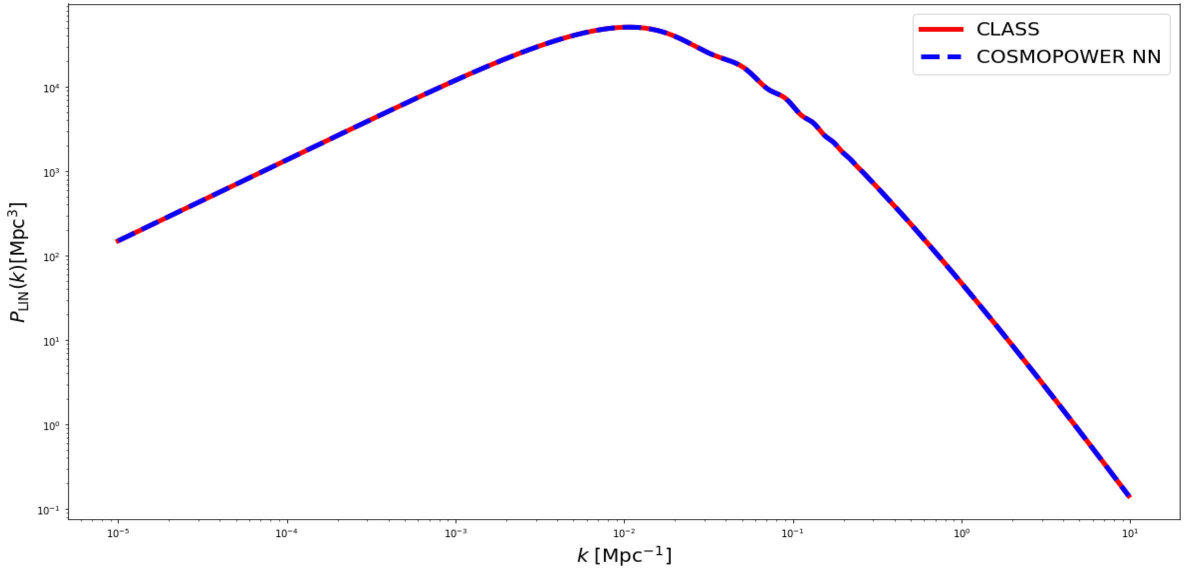
+ Code + Text Copy to Drive

COMPARING with CLASS

```python
k_modes = cp_nn.modes

cosmo = Class()

# Define your cosmology (what is not specified will be set to CLASS default parameters)
params = {'output': 'tCl mPk',
          'z_max_pk': 5,
          'P_k_max_1/Mpc': 10.,
          'nonlinear_min_k_max': 100.,
          'N_ncdm' : 0,
          'N_eff' : 3.046,
          'omega_b': 0.0225,
          'omega_cdm': 0.113,
          'h': 0.7,
          'n_s': 0.96,
          'ln10^{10}A_s': 3.07,
          }

# Set the parameters to the cosmological code
cosmo.set(params)
cosmo.compute()

z = 0.5

spectrum_class = np.array([cosmo.pk(ki, z) for ki in k_modes])
```

```python
pred = spectrum_cosmopower_NN
true = spectrum_class
fig = plt.figure(figsize=(20,10))
plt.loglog(k_modes, true, 'red', linewidth=5, label = 'CLASS')
plt.loglog(k_modes, pred, 'blue', label = 'COSMOPOWER NN', linewidth=5, linestyle='--')
plt.xlabel('$k$ [Mpc$^{-1}]$', fontsize=20)
plt.ylabel('$P_{\mathrm{LIN}}(k) [\mathrm{Mpc}^3]$', fontsize=20)
plt.legend(fontsize=20)
```

```
<matplotlib.legend.Legend at 0x7f25dd360fd0>
```



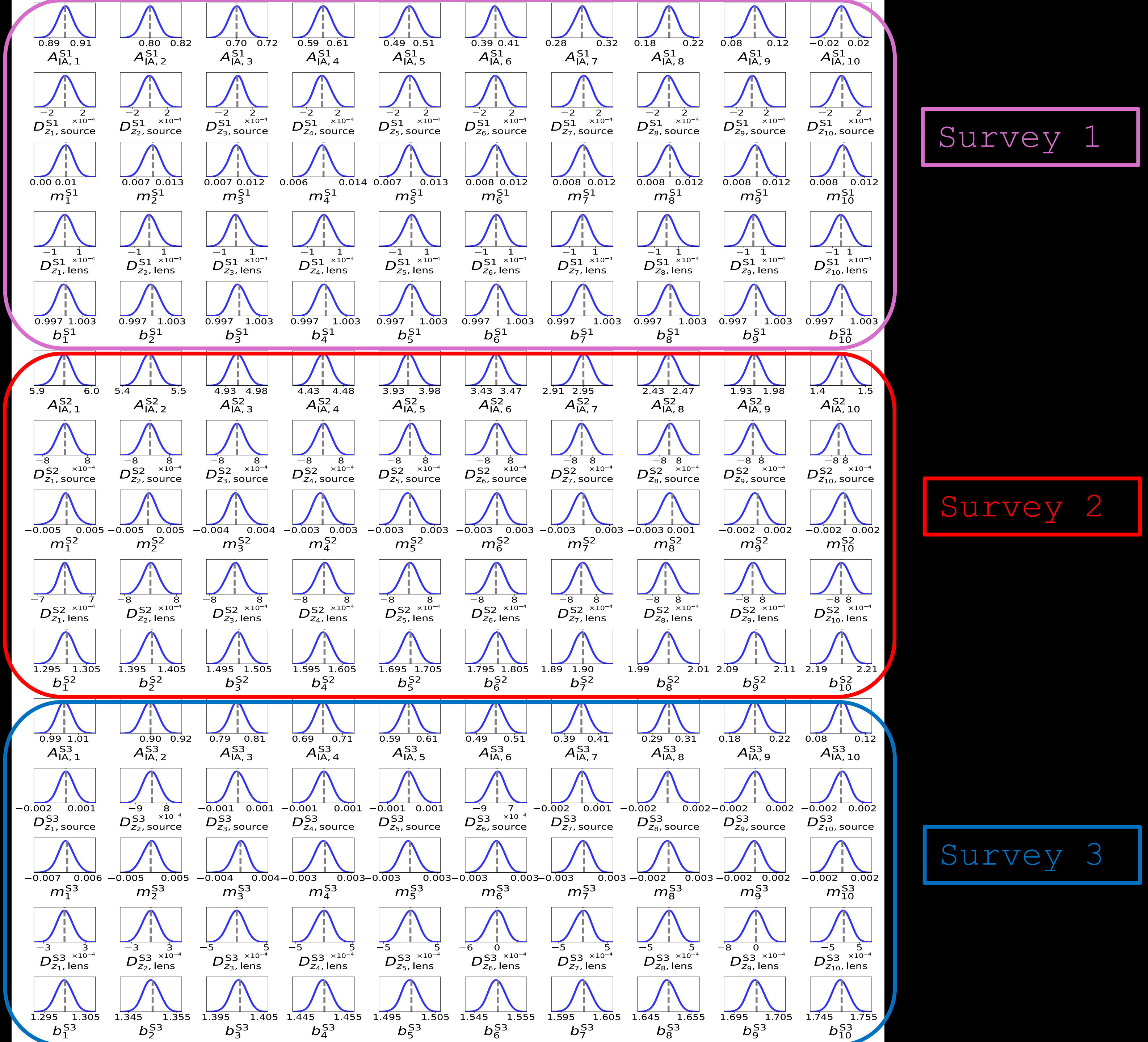
COSMOPOWER-JAX

Piras & Spurio Mancini 23

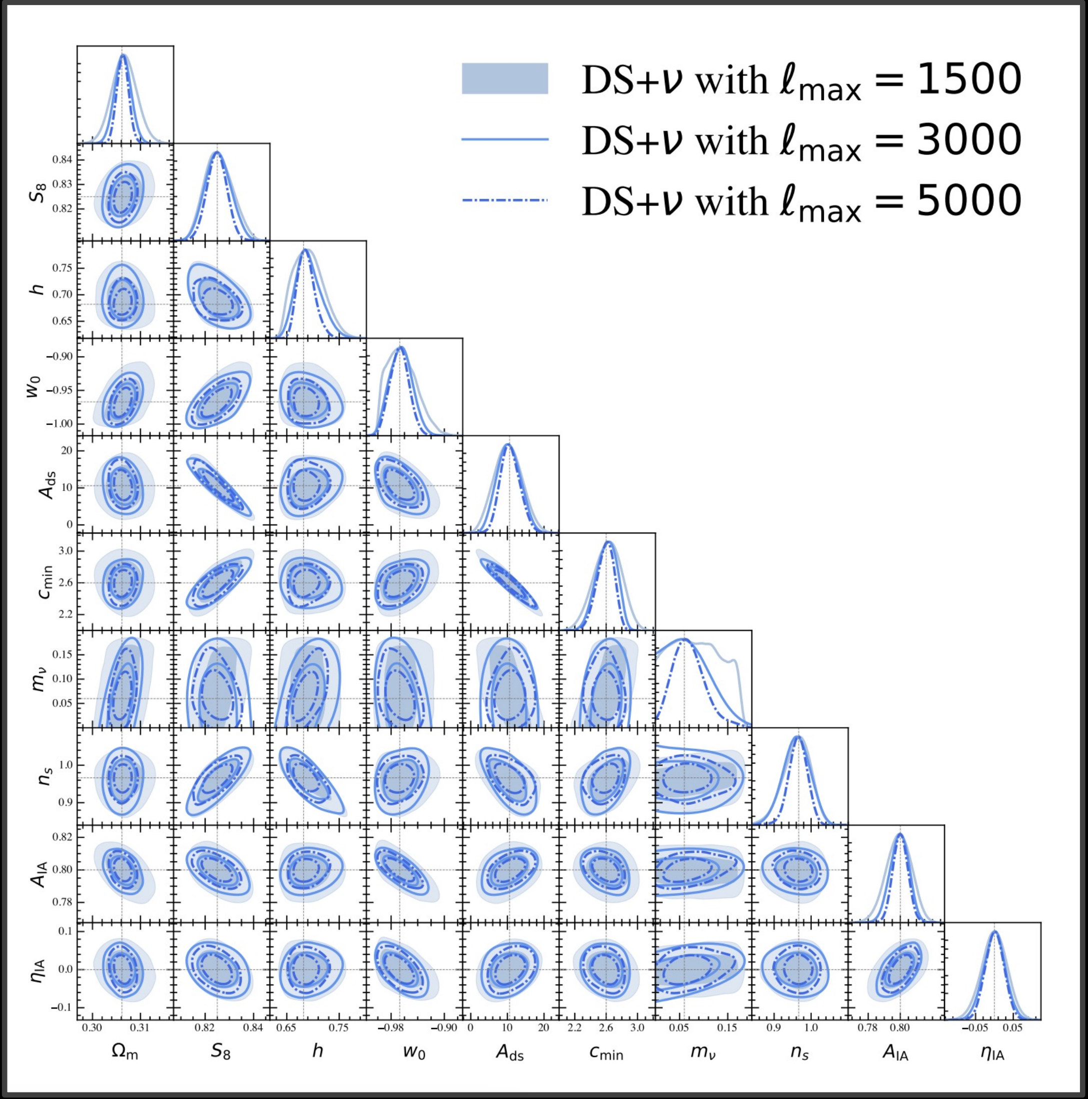
dpiras/cosmopower-jax

Differentiable inference

- COSMOPOWER-JAX + JAX-COSMO (Campagne+ 23)
- 3 Stage IV surveys → 157 (!) parameters
- 3 days on 3 GPUs with NUTS
- (Optimistic) estimate: 6 years (!!) on 48 CPUs with PolyChord



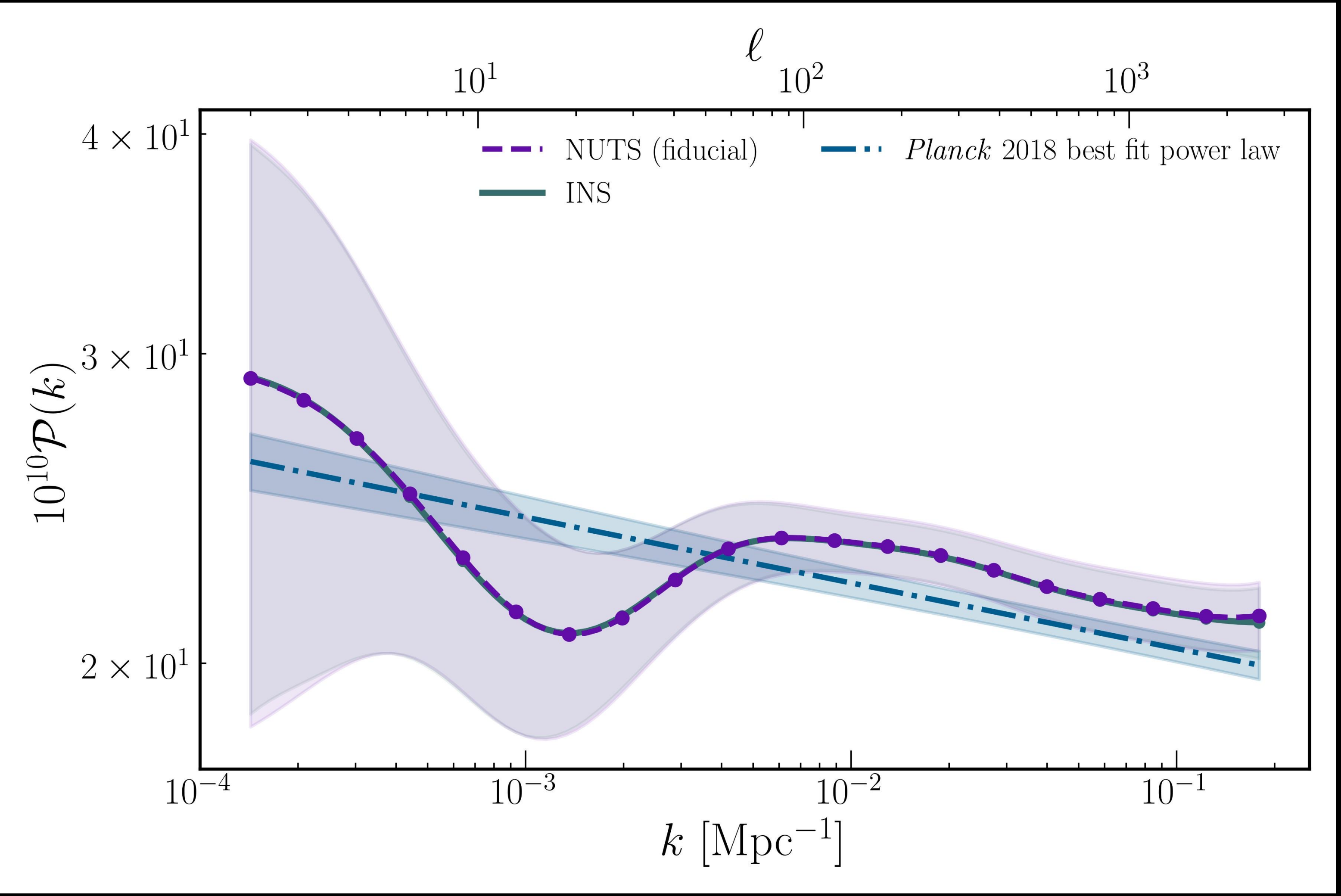
Stage IV Dark Scattering forecasts with differentiable inference



Carrion, Spurio Mancini, Piras, Hidalgo 24

- Stage IV cosmic shear forecast with differentiable framework
- Dark Scattering: interacting dark energy with pure momentum exchange (Simpson 10, Pourtsidou+ 13)
- Non-linear modelling based on halo model reaction, (ReACT, Cataneo et al. 19, Bose et al. 21) emulated with COSMOPOWER
- Example speed-up: 1000 spectra in 0.19s with differentiable framework, 8.3h with standard approach
- Baryonic parameters absorb a lot of the constraining power → need tight priors on them! (see Aurel's talk)

Differentiable reconstructions



Chaki, Nicola, Spurio Mancini, Piras, Reischke 25

Bayesian evidence and model comparison

$$\frac{p(M_1|\mathbf{d})}{p(M_2|\mathbf{d})} = \boxed{\frac{p(\mathbf{d}|M_1)}{p(\mathbf{d}|M_2)}}\,\frac{p(M_1)}{p(M_2)}$$

BAYES FACTOR

EVIDENCE

$$\mathcal{Z} = p(\mathbf{d}|M) = \int \mathrm{d}\boldsymbol{\theta}\,\mathcal{L}(\boldsymbol{\theta})\,\pi(\boldsymbol{\theta})$$

Learnt harmonic mean estimator

Learn an approximation of the optimal target distribution: (McEwen, Wallis, Price, Spurio Mancini 21)

$$\boxed{\varphi(\theta) \overset{\mathrm{ML}}{\simeq} \varphi^{\mathrm{optimal}}(\theta) = \frac{\mathcal{L}(\theta)\pi(\theta)}{z}}$$

→ ***agnostic* to sampling strategy !**

python GitHub

astro-informatics/harmonic

Differentiable inference
+
decoupled model comparison

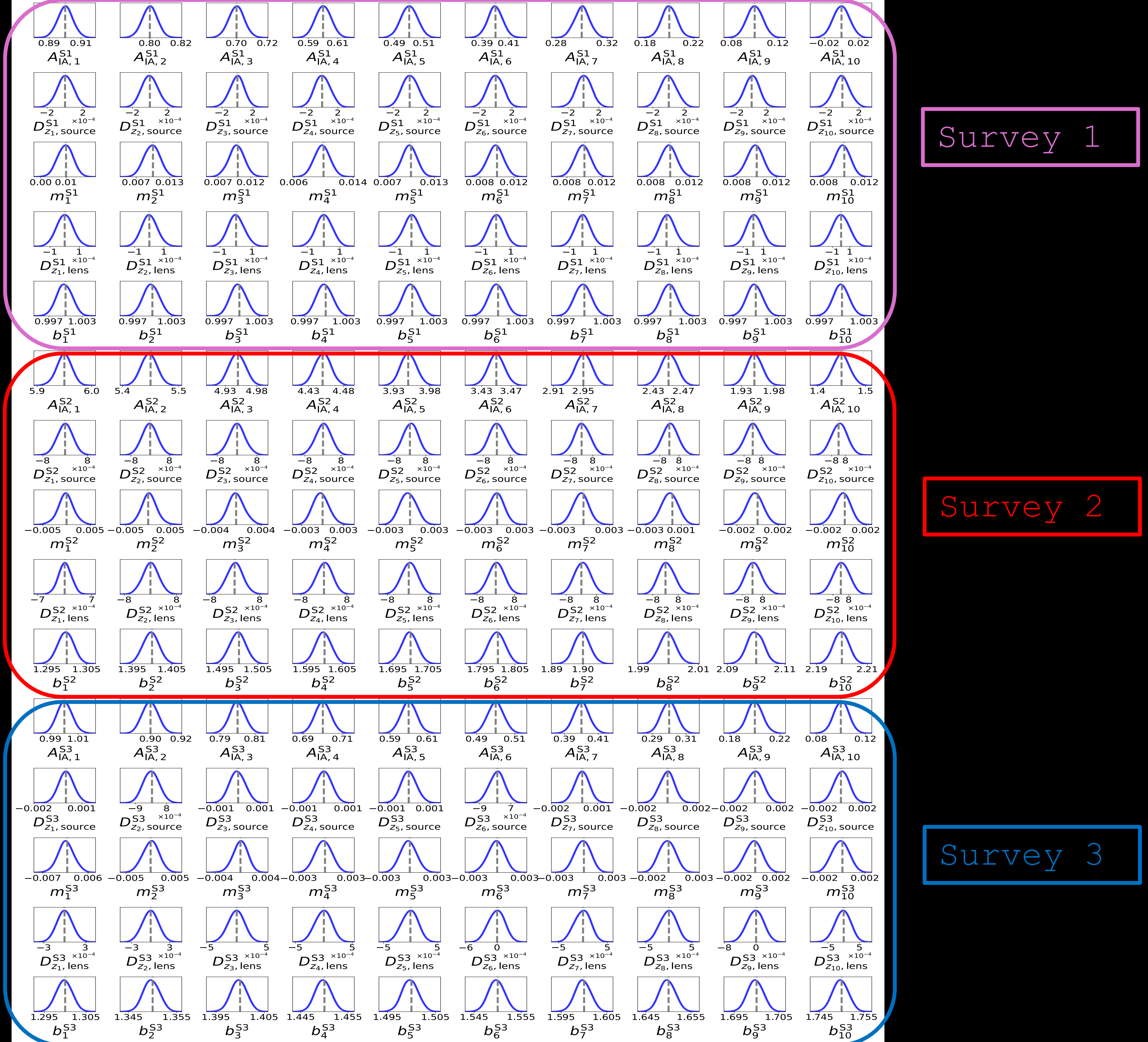
Same setup as Piras & Spurio Mancini (23):
3x2pt for 3 Stage IV surveys
LCDM vs w0waCDM (157 / 159 parameters)

Our estimate:

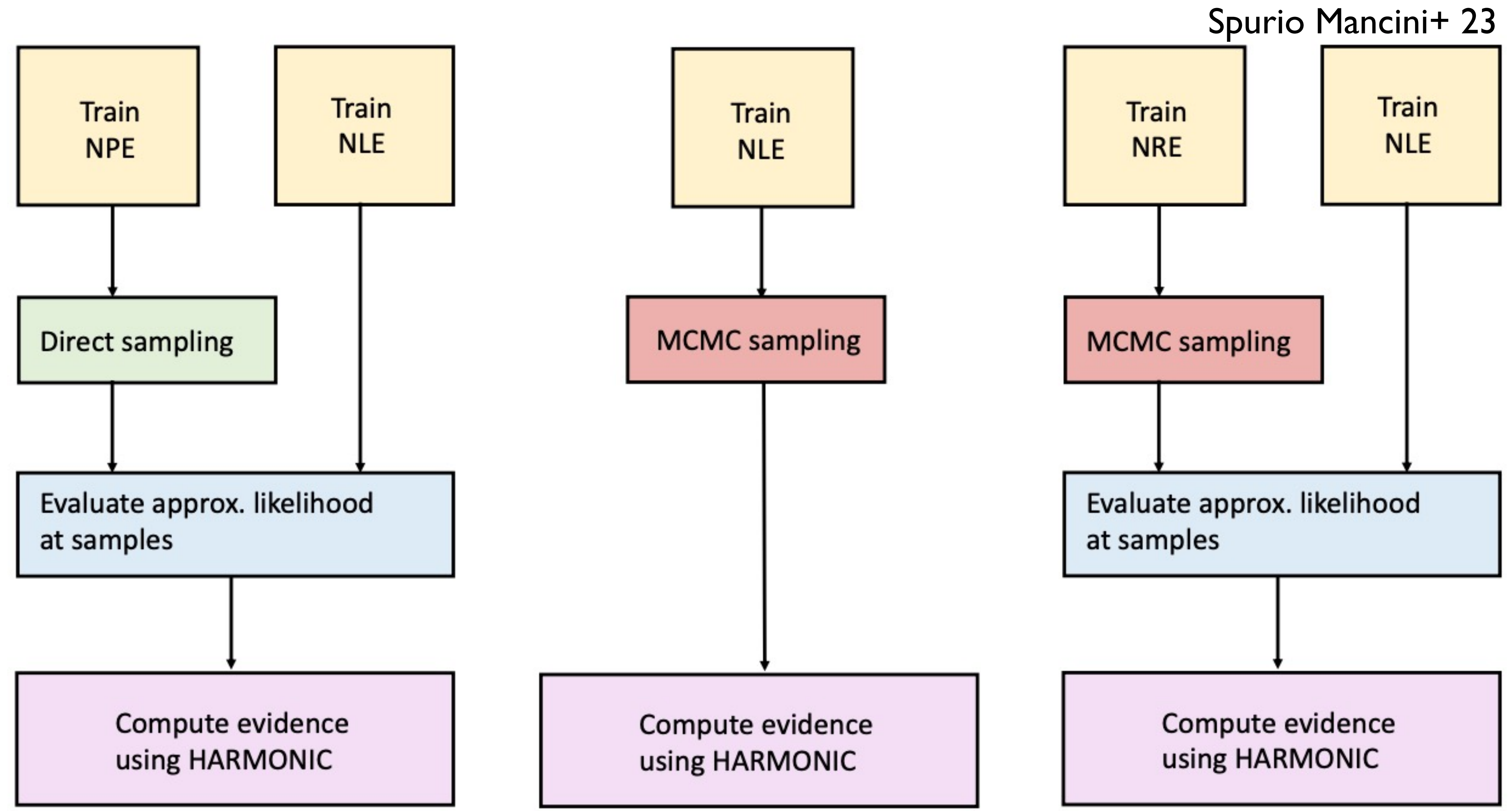
$\log \mathrm{BF} = 1.9^{+0.7}_{-0.5}$ (8 days on 24 GPUs)

Nested sampling:
Estimated computation time ~ 12 years

Piras, Polanska, Price, Spurio Mancini, McEwen 24

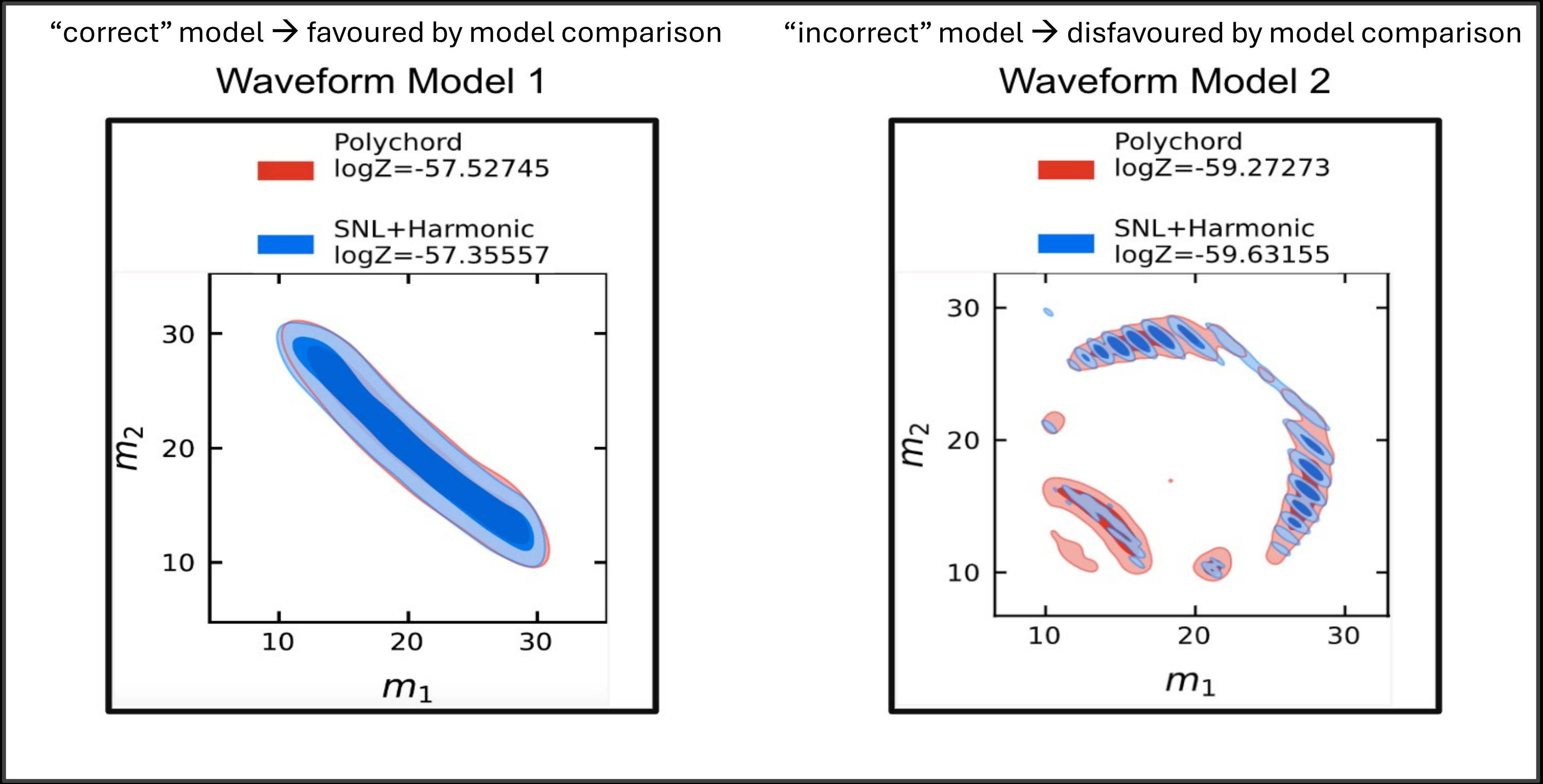


HARMONIC for Simulation-Based Inference



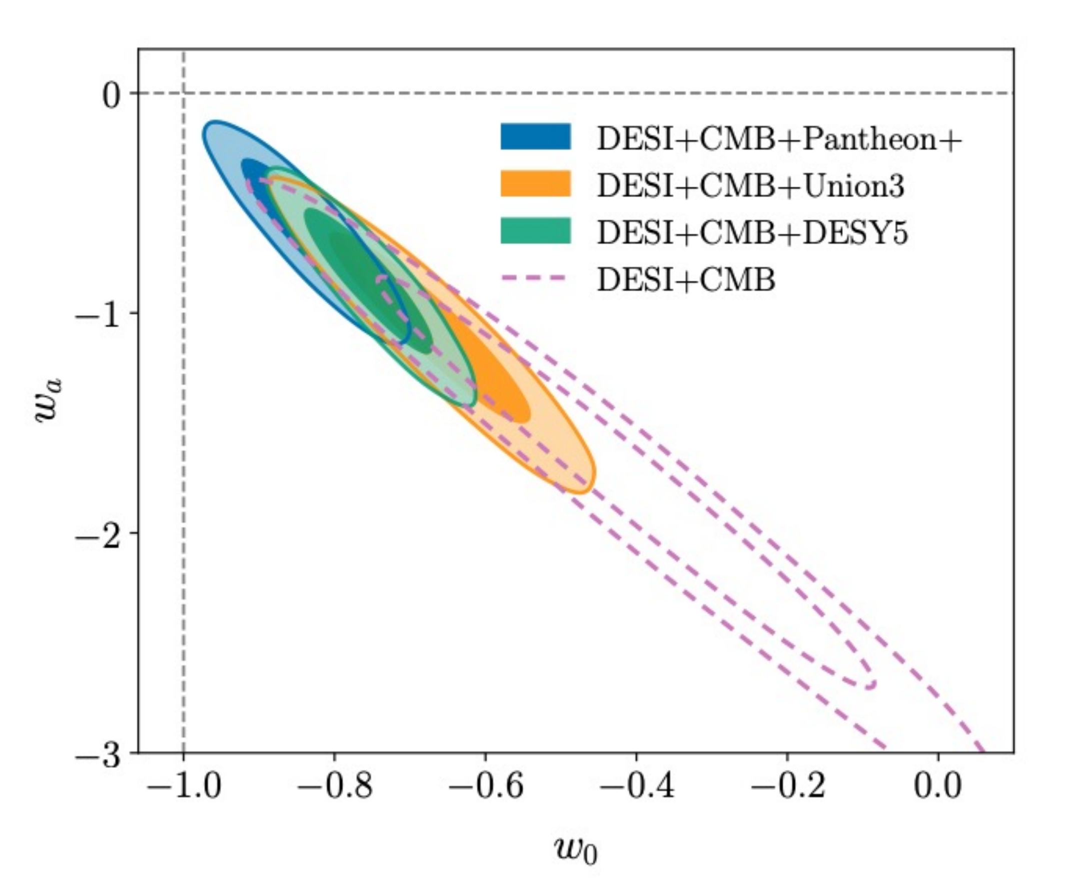
(a) Neural posterior estimation (NPE) (b) Neural likelihood estimation (NLE) (c) Neural ratio estimation (NRE)

Application to Gravitational Waves



Can field-level SBI distinguish dynamical dark energy?

If dark energy really was not a cosmological constant, could a field-level, simulation-based inference (SBI) analysis of Stage IV cosmic shear distinguish dynamical dark energy definitively?



DESI Collaboration 25

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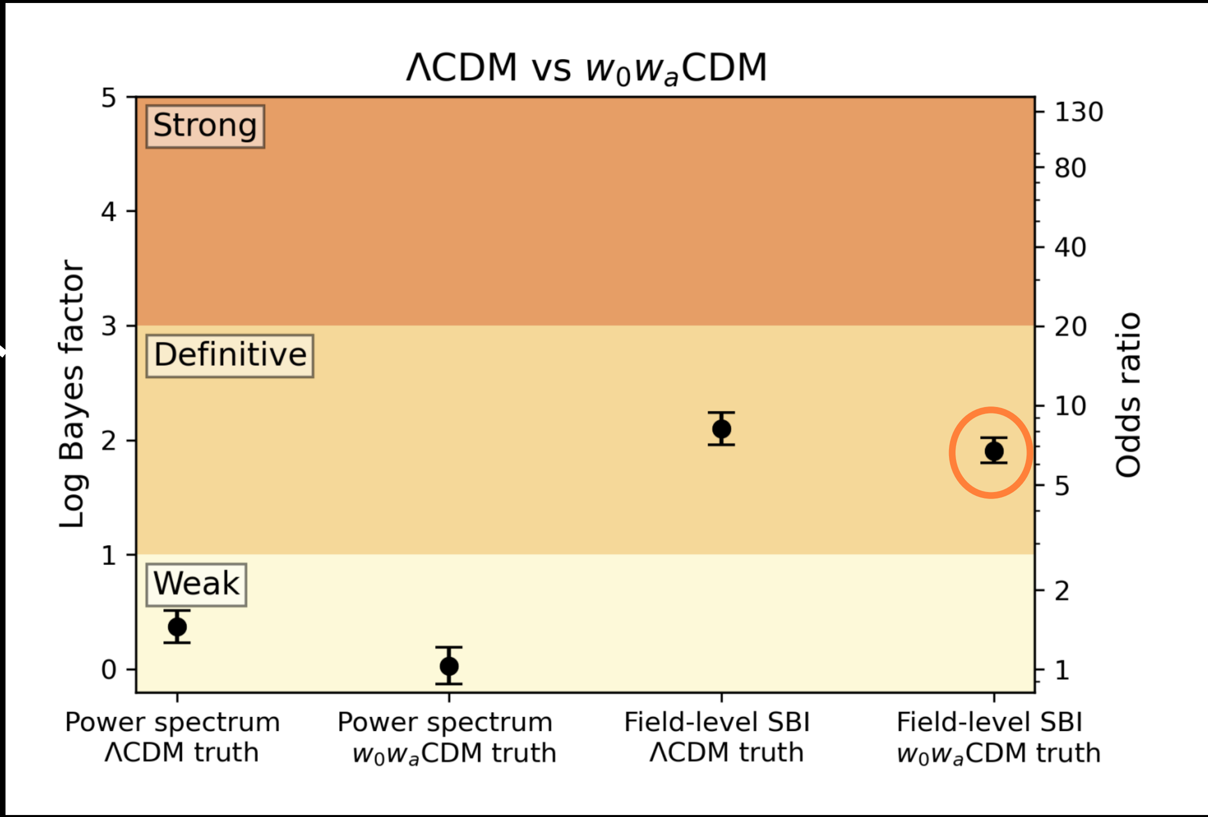

Differentiable lognormal field with COSMOPOWER-JAX + SBI_LENS (Zeghal et al. 24)

Spurio Mancini, Lin & McEwen 24

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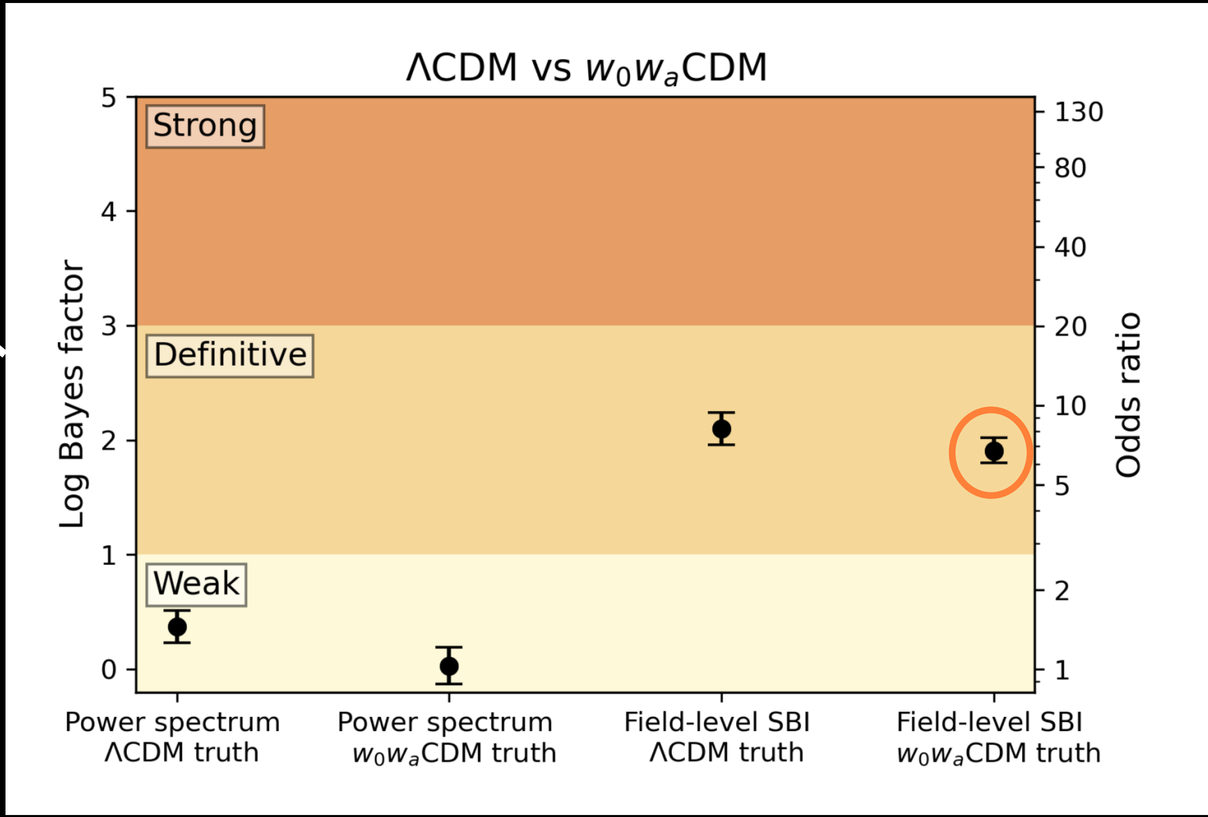

- Can now obtain same answer from field-level likelihood-based inference
- HARMONIC with Savage-Dickey density ratio (Lin, Polanska, Piras, Spurio Mancini, McEwen 25)

A differentiable future for cosmology

- COSMOPOWER: orders-of-magnitude speed up to parameter estimation pipeline
- HARMONIC: sampling-agnostic method for likelihood-based and –free evidence estimation
- COSMOPOWER + HARMONIC: high-dimensional, differentiable parameter estimation + model comparison

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alessiospuriomancini/cosmopower
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Thank you!

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