

The future of cosmological inference

Alessio
Spurio Mancini

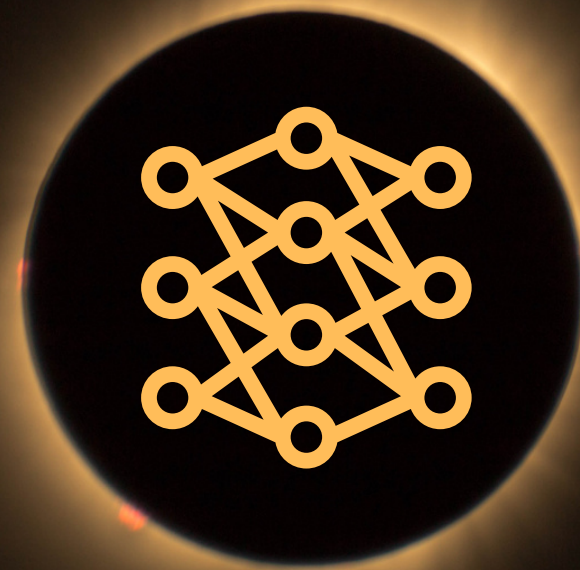


Challenges for cosmological inference

- Accelerating parameter estimation
- Beyond Λ CDM modelling
- Systematics modelling
- Beyond 2pt statistics

Challenges for cosmological inference

- Accelerating parameter estimation
- Beyond Λ CDM modelling
- Systematics modelling
- Beyond 2pt statistics



COSMOPOWER

MACHINE LEARNING-ACCELERATED
BAYESIAN INFERENCE

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, **ASM**, McEwen 24

- Emulation



COSMOPOWER-JAX
(Piras & **ASM** 23)

- Differentiable and probabilistic programming



JAX (Bradbury+18)



NUMPYRO (Phan+19)

- Gradient-based sampling

NUTS (Hoffman+ 14)

- Model selection decoupled from sampling



HARMONIC
(Polanska, Price, Piras,
ASM, McEwen 24)

The future of cosmological inference

Piras, Polanska, Price, **ASM**, McEwen 24

- Emulation



COSMOPOWER-JAX
(Piras & **ASM** 23)

- Differentiable and probabilistic programming



JAX (Bradbury+18)



NUMPYRO (Phan+19)

- Gradient-based sampling

NUTS (Hoffman+ 14)

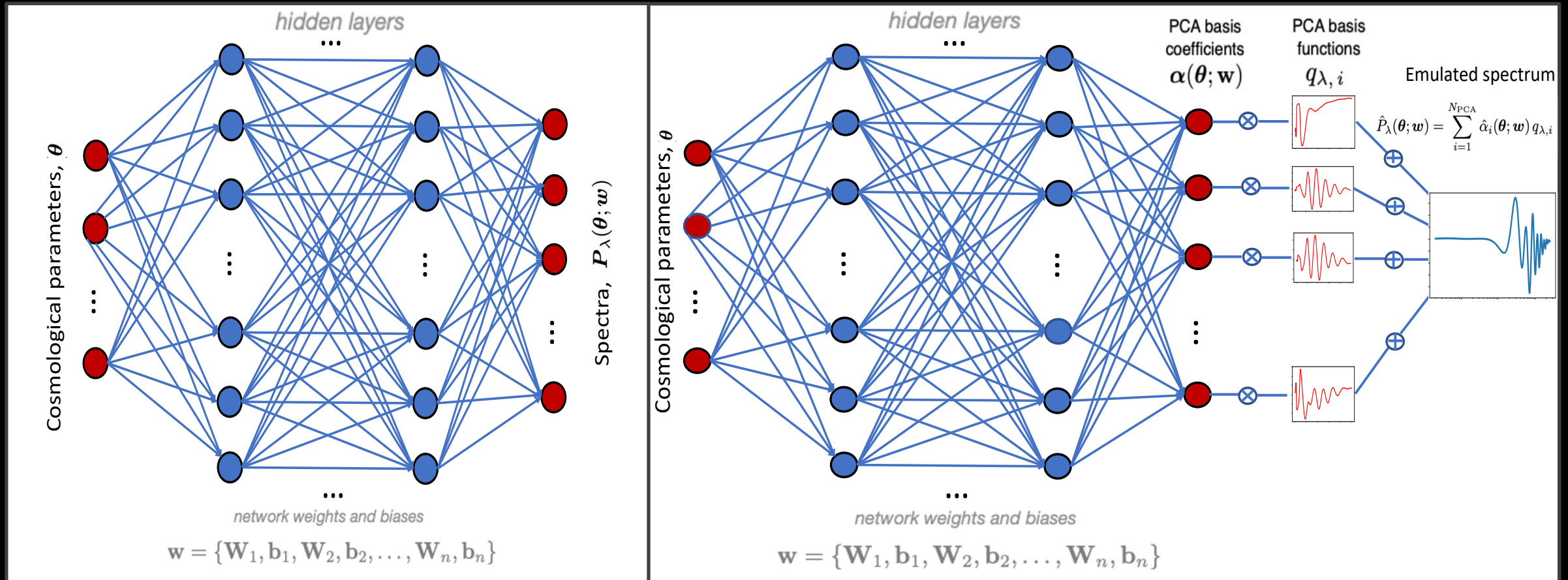
- Model selection decoupled from sampling



HARMONIC
(Polanska, Price, Piras,
ASM, McEwen 24)

COSMOPOWER

ASM+ 22

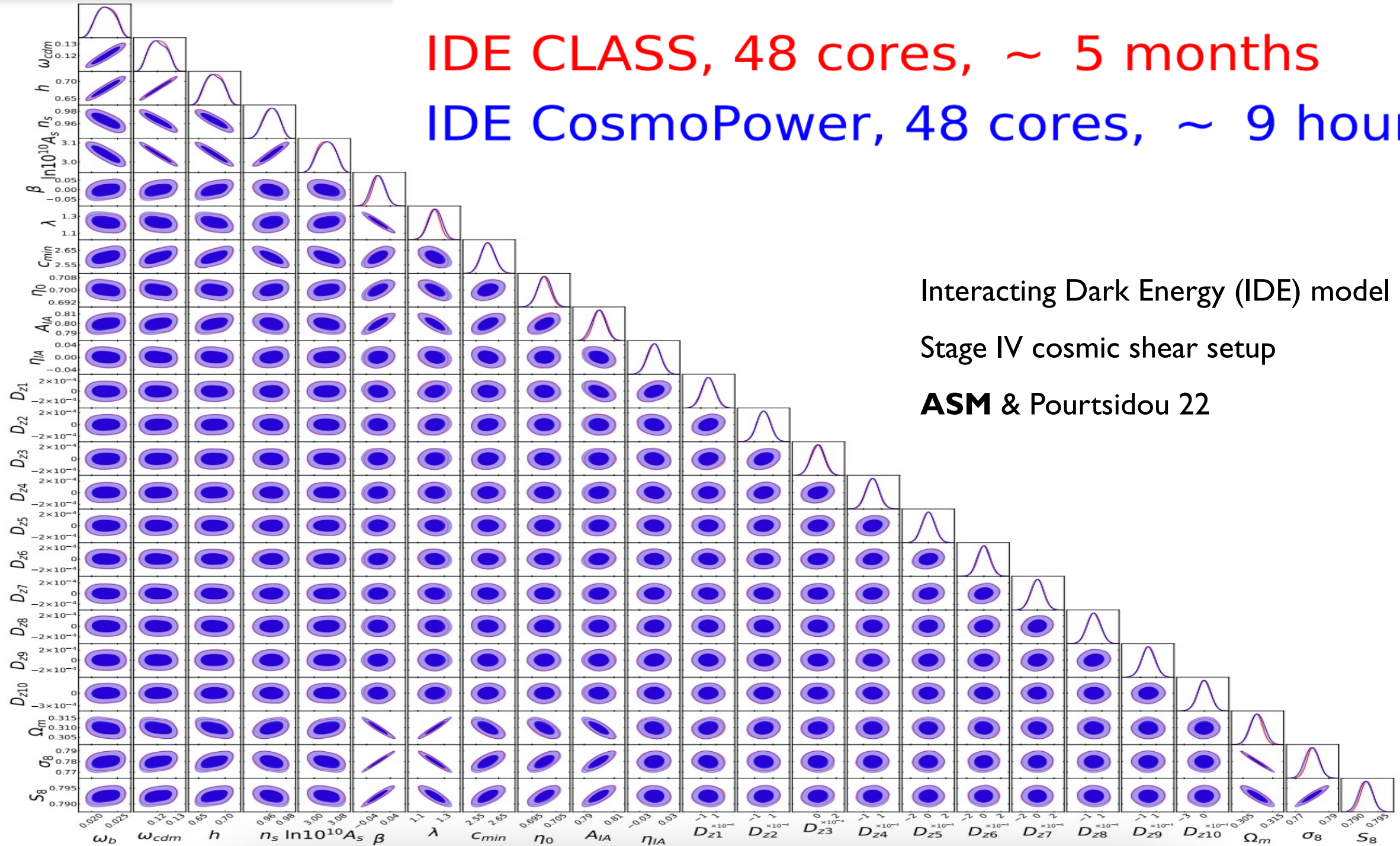


[alessiospurinomancini/cosmopower](https://github.com/alessiospurinomancini/cosmopower)

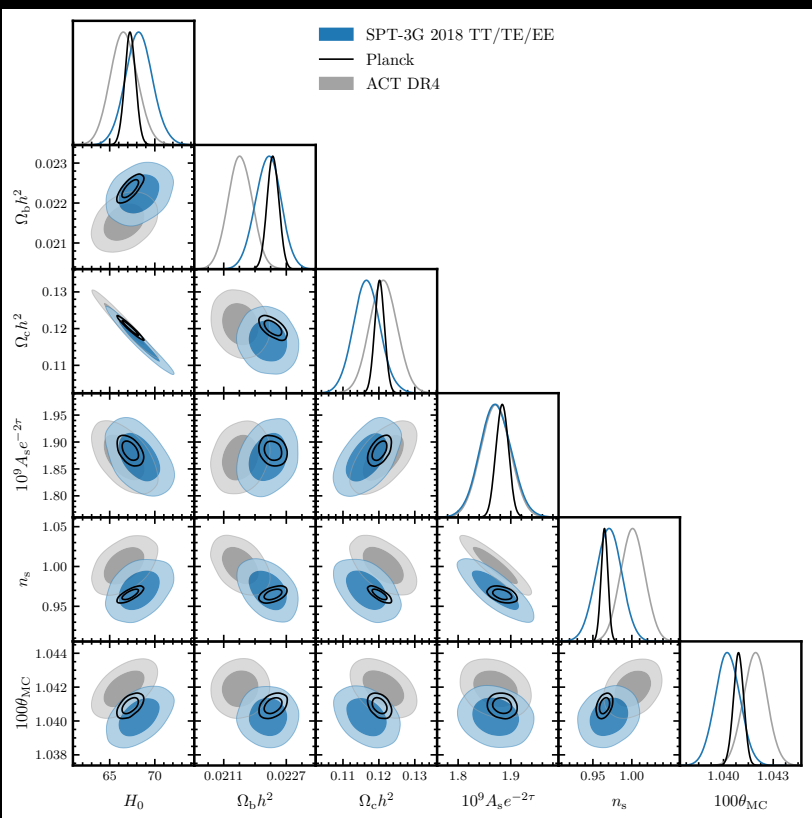
See Ivan's talk

IDE CLASS, 48 cores, ~ 5 months

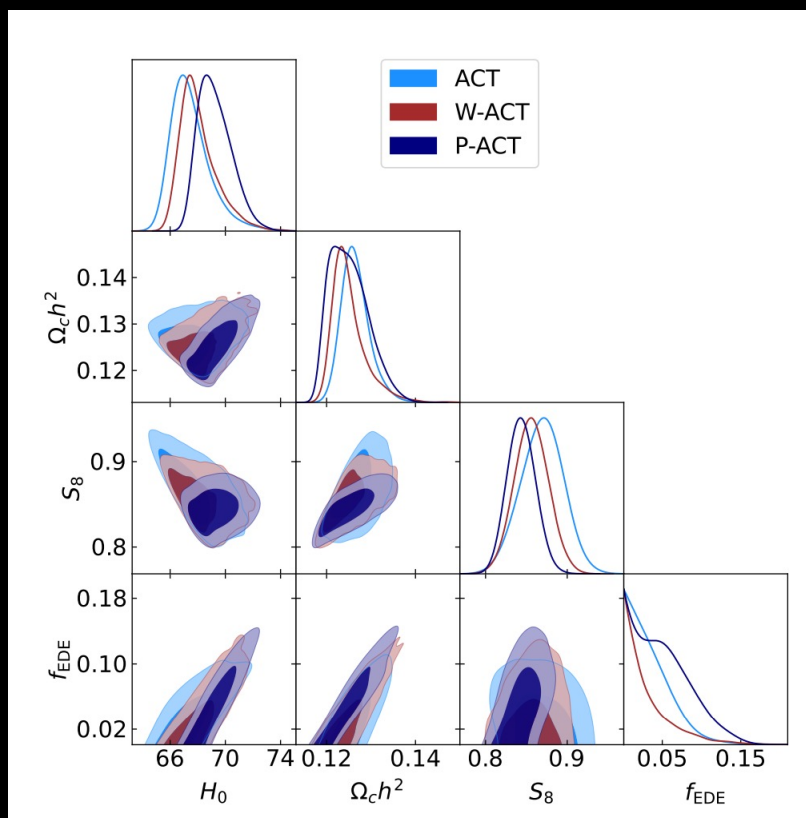
IDE CosmoPower, 48 cores, ~ 9 hours



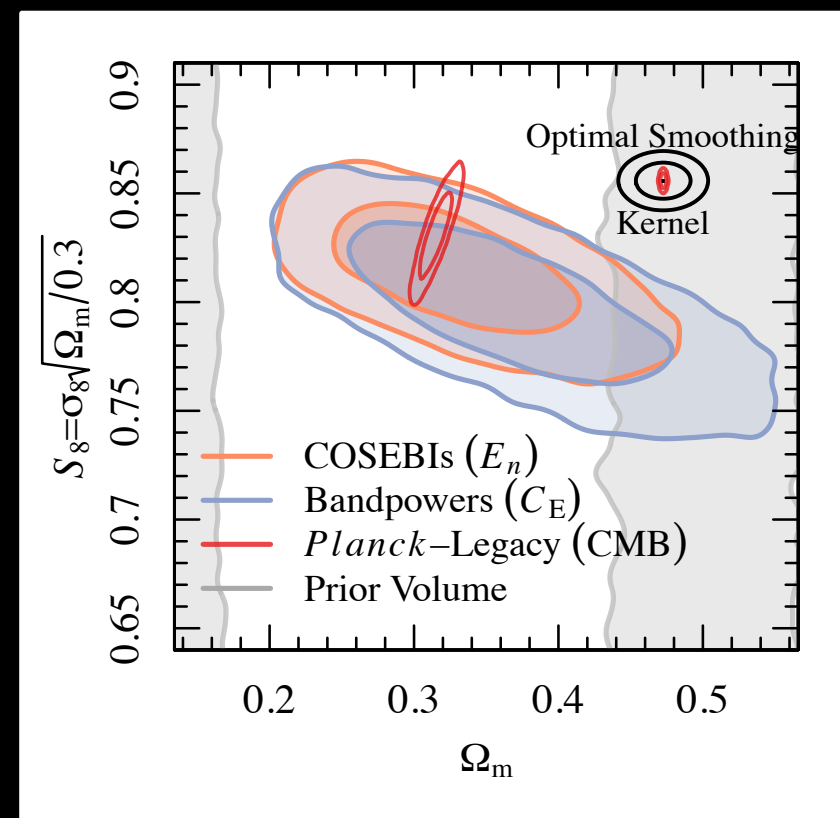
Hot off the press: COSMOPOWER in action



SPT-3G 2018, Balkenhol+ 23



ACT DR6, Calabrese+ 25



KiDS Legacy, Wright+ 25

Collaborations using COSMOPOWER

Kilo-Degree Survey

Wright+ 25
Stölzner+ 25
Johnston+ 24
Burger+ 24
Burger+ 23

Dark Energy Survey

Halder+ 24
Gong+ 23

Euclid

Koyama+ 24
Burger+ 23
Linke+ 23
Bose+ 23
Heydenreich+ 22

Atacama Cosmology Telescope

Calabrese+ 25
Louis+ 25
Qu+ 24
Farren+ 23
Bolliet+ 23

South Pole Telescope

Chou+25
Ge+ 24
Balkhenhol+ 24
Balkhenhol+ 23

Simons Observatory

Jense+ 24
Zubeldia+ 24
Giardiello+ 24
Patki+ 23
Bolliet+ 23

<https://github.com/alessiospuriomancini/cosmopower>

☰ README.md ✎



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`

```
import cosmopower as cp

# load pre-trained NN model: maps cosmological parameters to CMB TT log-Cℓℓ
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) -> 10^6 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

```
[ ] k_modes = cp_nn.modes

cosmo = Class()

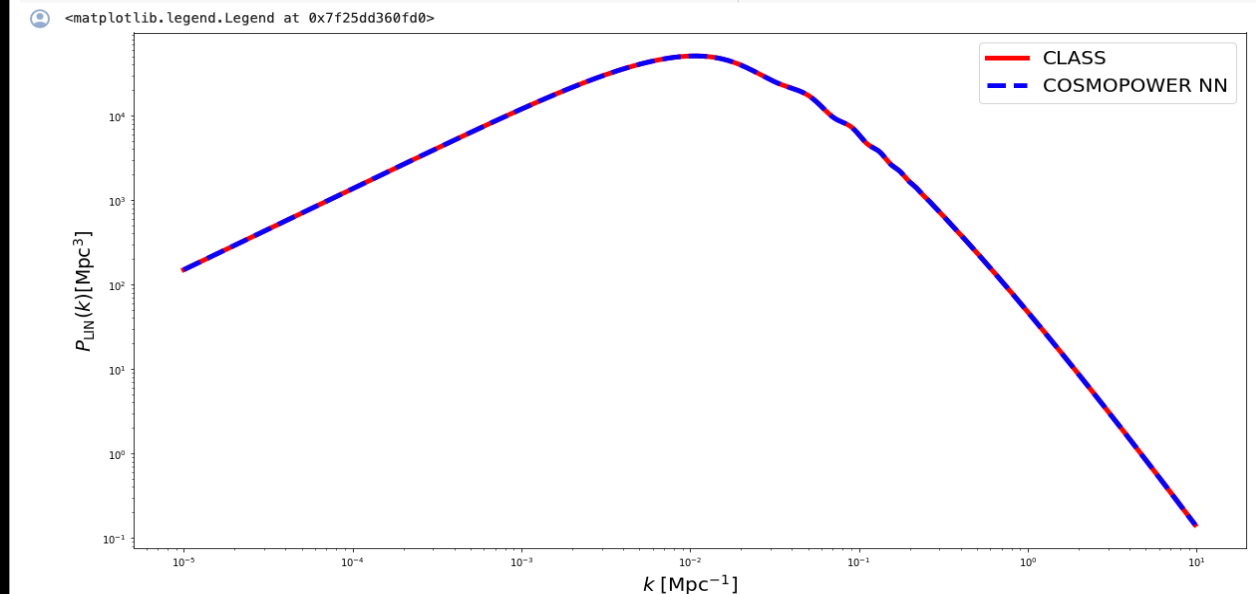
# Define your cosmology (what is not specified will be set to CLASS default parameters)
params = {'output': 'tCl mPk',
          'z_max_pk': 5,
          'P_k_max_1/Mpc': 10.,
          'nonlinear_min_k_max': 100.,
          'N_ncdm': 0,
          'N_eff': 3.046,
          'omega_b': 0.0225,
          '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()

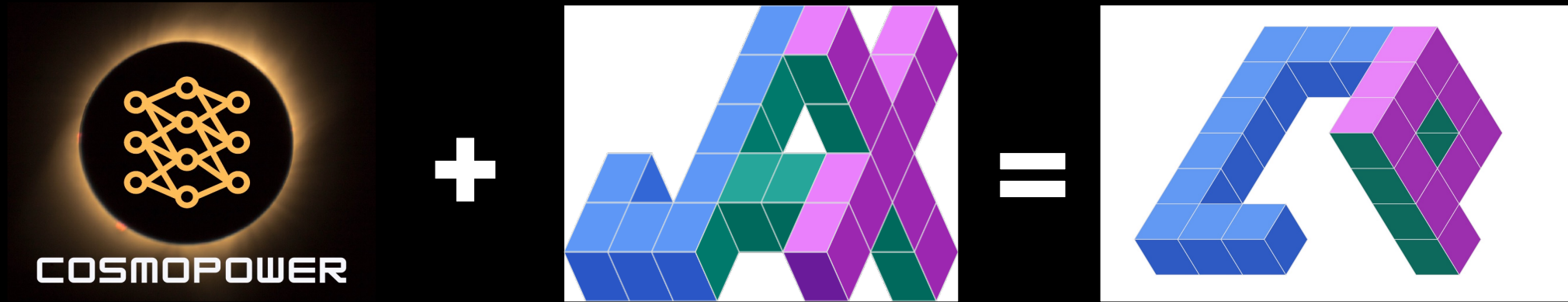
z = 0.5

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

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('$P_{\mathrm{LIN}}(k)$ [Mpc$^3$]', fontsize=20)
plt.legend(fontsize=20)
```



COSMOPOWER-JAX



Piras & **ASM** 23



`dpiras/cosmopower-jax`

Differentiable inference

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

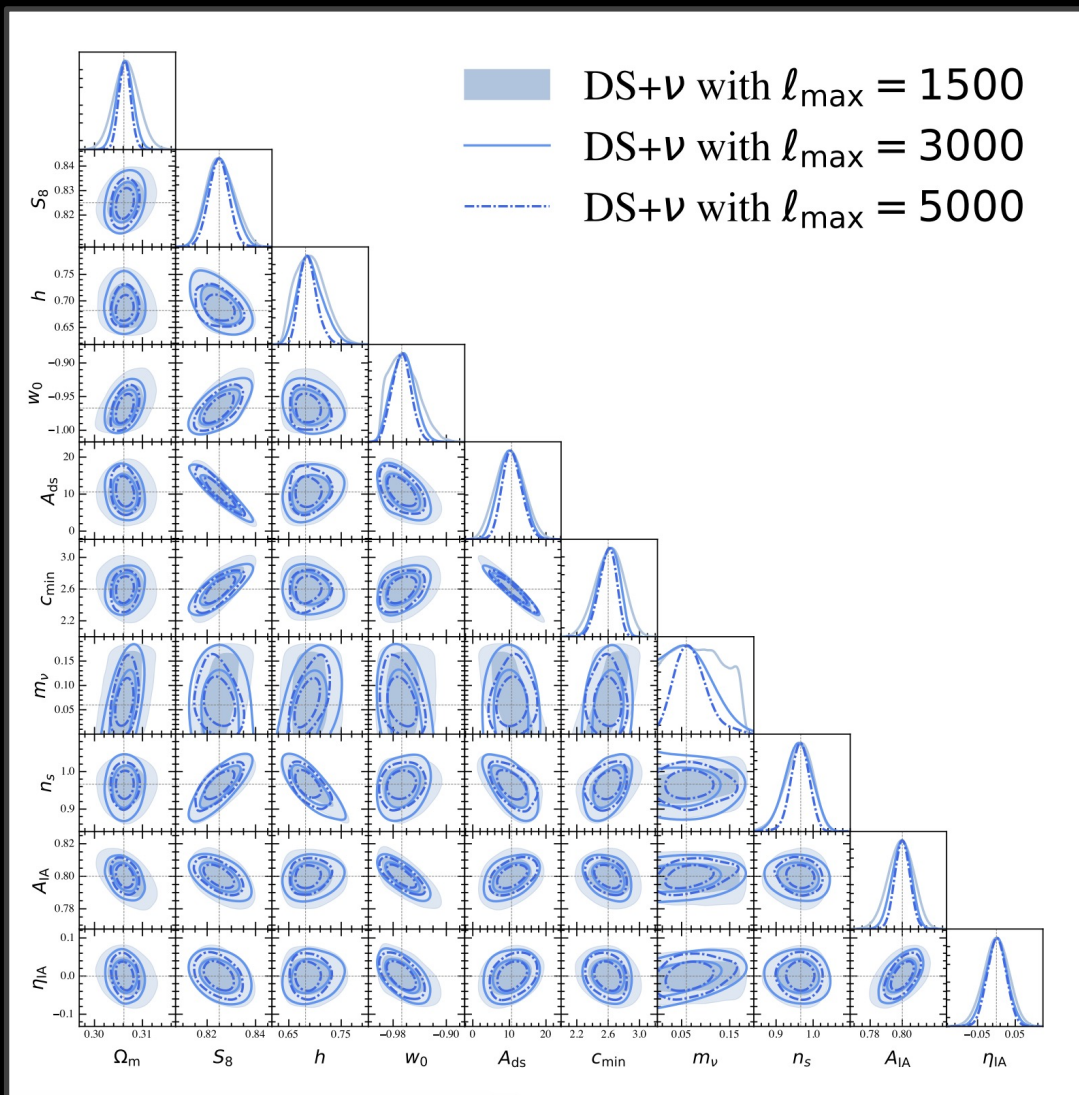


Survey 1

Survey 2

Survey 3

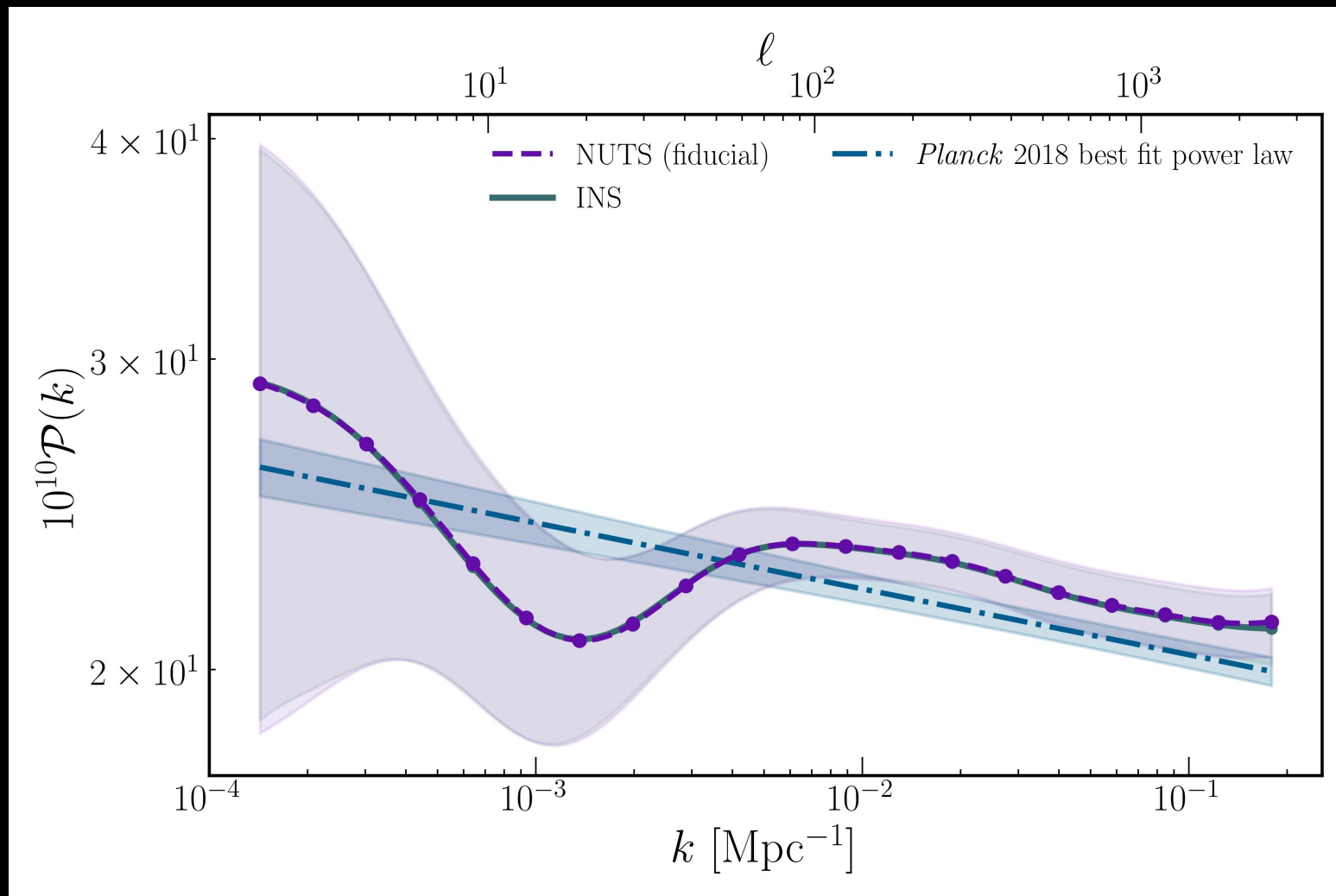
Stage IV Dark Scattering forecasts with differentiable inference



Carrión, **ASM**, 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!

Differentiable reconstructions



Bayesian evidence and model comparison

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


BAYES FACTOR

EVIDENCE

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

Learnt harmonic mean estimator

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

$$\varphi(\theta) \stackrel{\text{ML}}{\simeq} \varphi^{\text{optimal}}(\theta) = \frac{\mathcal{L}(\theta)\pi(\theta)}{Z}$$



agnostic to sampling strategy !



python



GitHub

astro-informatics/harmonic

Differentiable inference + decoupled model comparison

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

Our estimate:

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

Nested sampling:

Estimated computation time ~ 12 years

Piras, Polanska, Price, **ASM**, McEwen 24

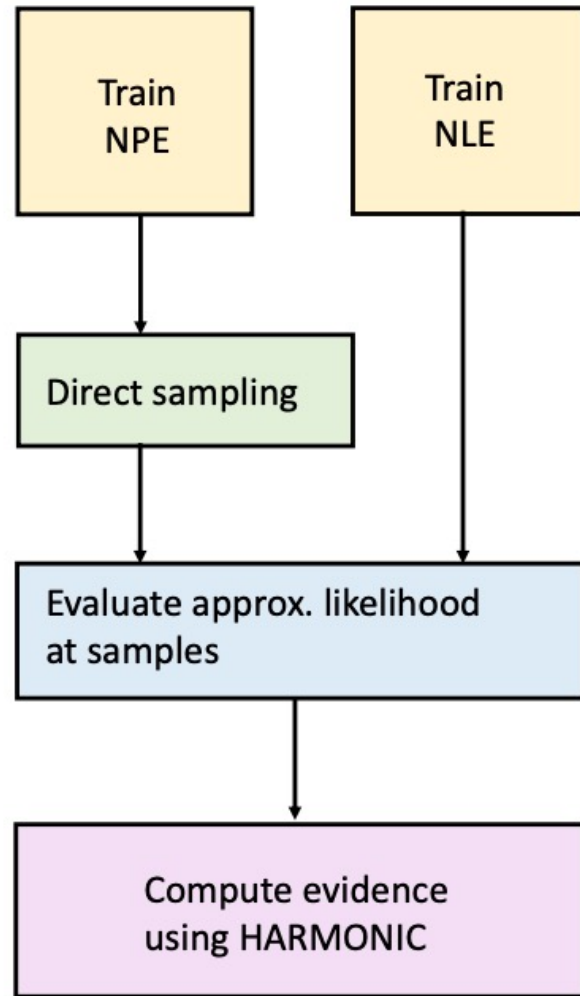


Survey 1

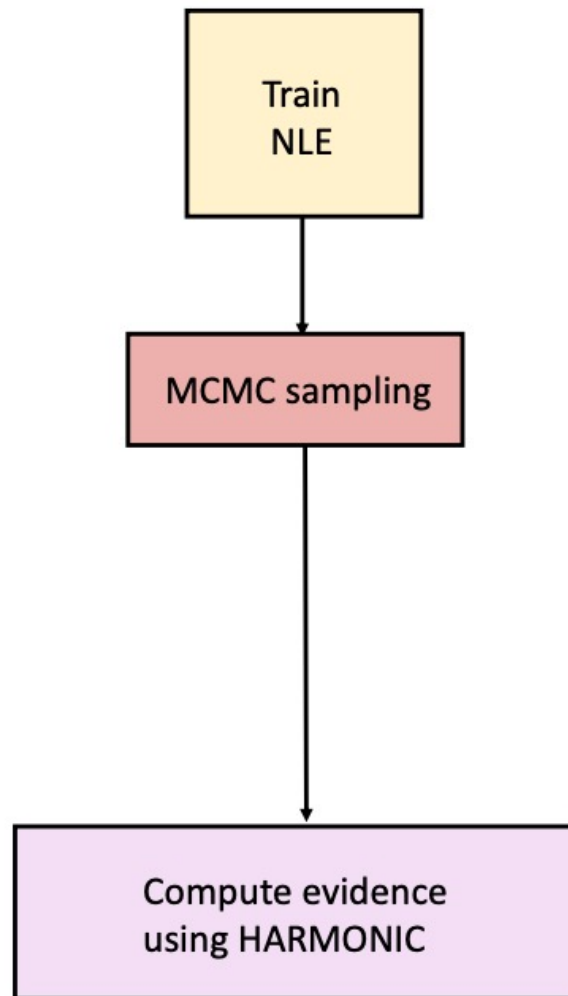
Survey 2

Survey 3

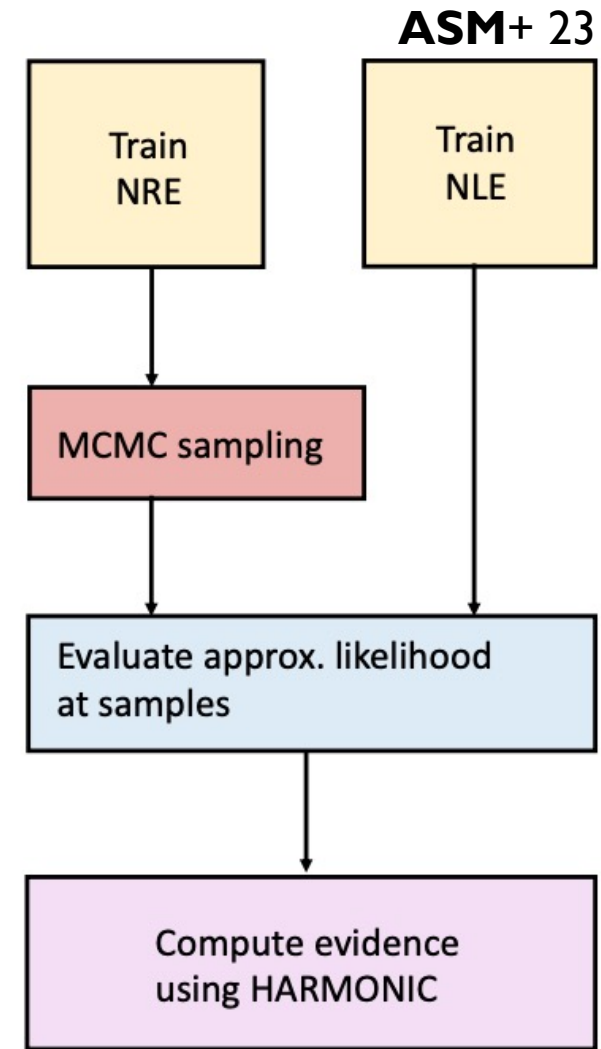
HARMONIC for Simulation-Based Inference



(a) Neural posterior estimation (NPE)



(b) Neural likelihood estimation (NLE)



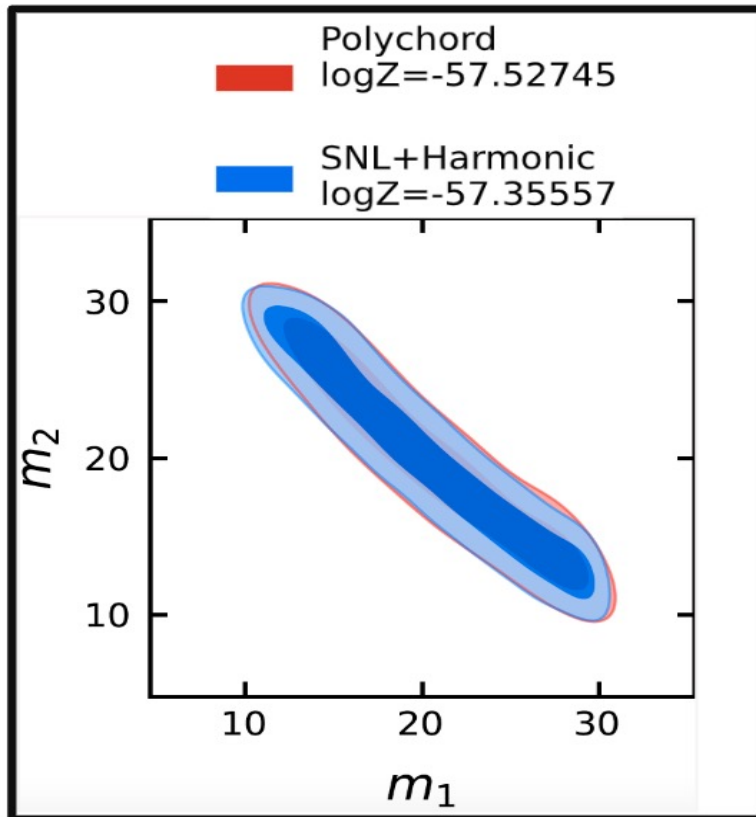
(c) Neural ratio estimation (NRE)

ASM+ 23

Application to Gravitational Waves

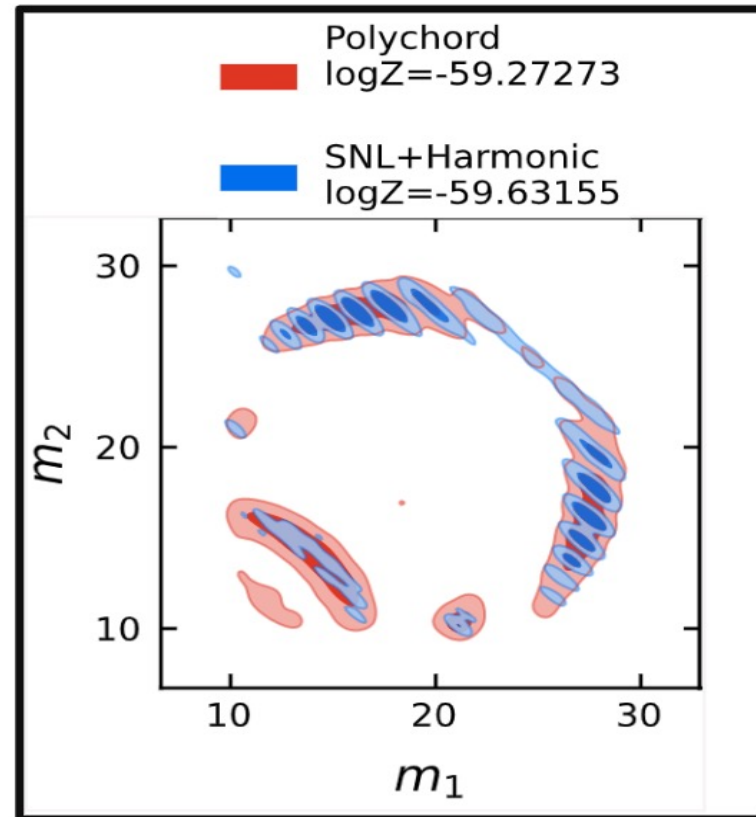
“correct” model → favoured by model comparison

Waveform Model 1



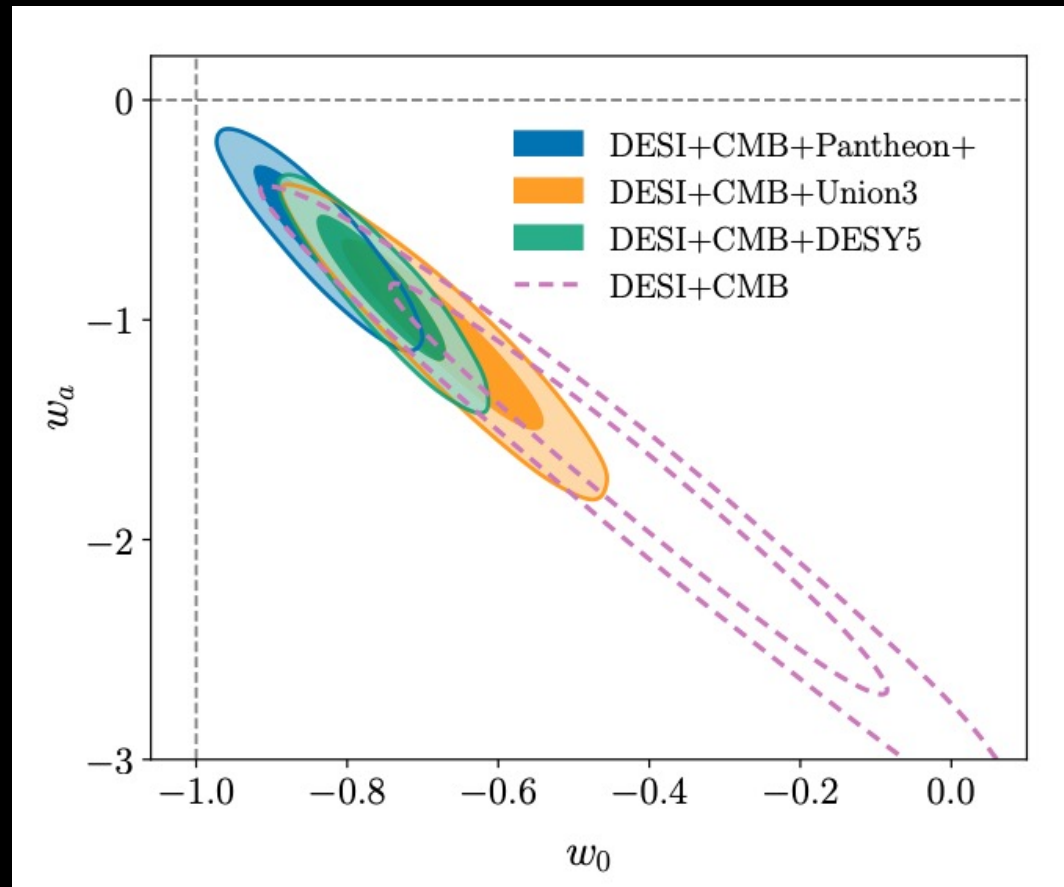
“incorrect” model → disfavoured by model comparison

Waveform Model 2



Can field-level SBI distinguish dynamical dark energy?

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



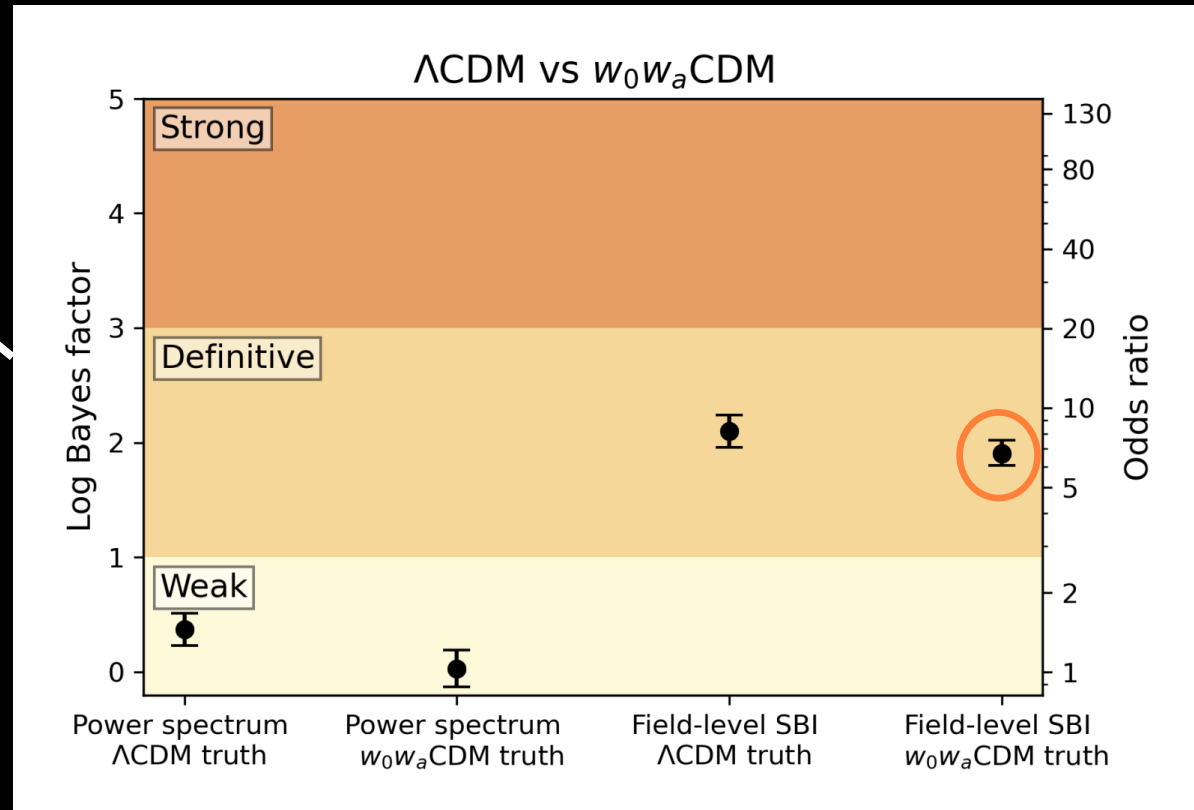
Can field-level SBI distinguish dynamical dark energy?

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

YES.

Obtained using HARMONIC

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



ASM, Lin & McEwen 24

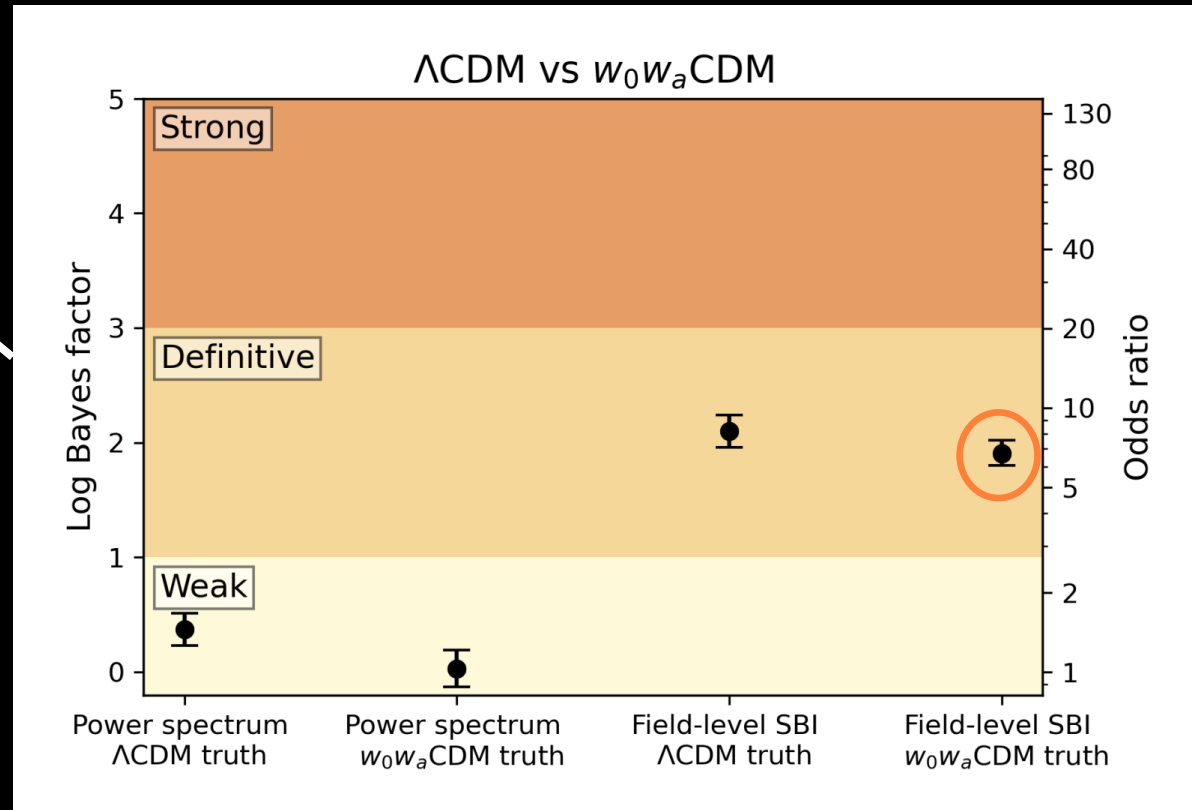
Can field-level SBI distinguish dynamical dark energy?

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

YES.

Obtained using HARMONIC

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



- Can now obtain same answer from field-level likelihood-based inference
- HARMONIC with Savage-Dickey density ratio (Lin, Polanska, Piras, **ASM**, 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



```
alessiospurinomancini/cosmopower  
dpiras/cosmopower-jax  
astro-informatics/harmonic
```

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



```
alessiospuriomancini/cosmopower  
dpiras/cosmopower-jax  
astro-informatics/harmonic
```



Thank you!



ROYAL
HOLLOWAY
UNIVERSITY
OF LONDON

alessio.spuriomancini@rhul.ac.uk