

# **COSMOPOWER:** emulating cosmological power spectra for accelerated Bayesian inference from next-generation surveys

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MULLARD SPACE  
SCIENCE LABORATORY

Based on ASM+, [2106.03846](#)

# COSMOPOWER

ASM+, [2106.03846](#)

We introduce a suite of  
neural cosmological power spectrum emulators  
covering both CMB (temperature, polarization and lensing),  
and large-scale structure power spectra

# EMULATION

- Boltzmann solvers: computational **bottleneck** for 2pt stats analysis

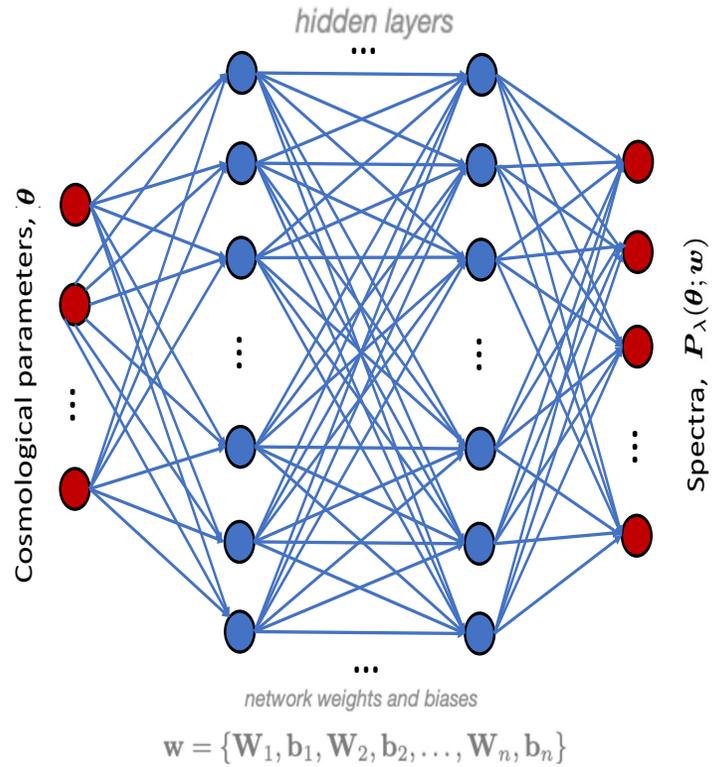
- **emulation** of power spectra speeds up theory predictions  
(Fendt & Wandelt 07, Auld+08, Agarwal+12..., Aricò+21, Mootoovaloo+21)

- a “simple” Machine Learning problem ...
- ... with exceptionally high levels of **accuracy** required!

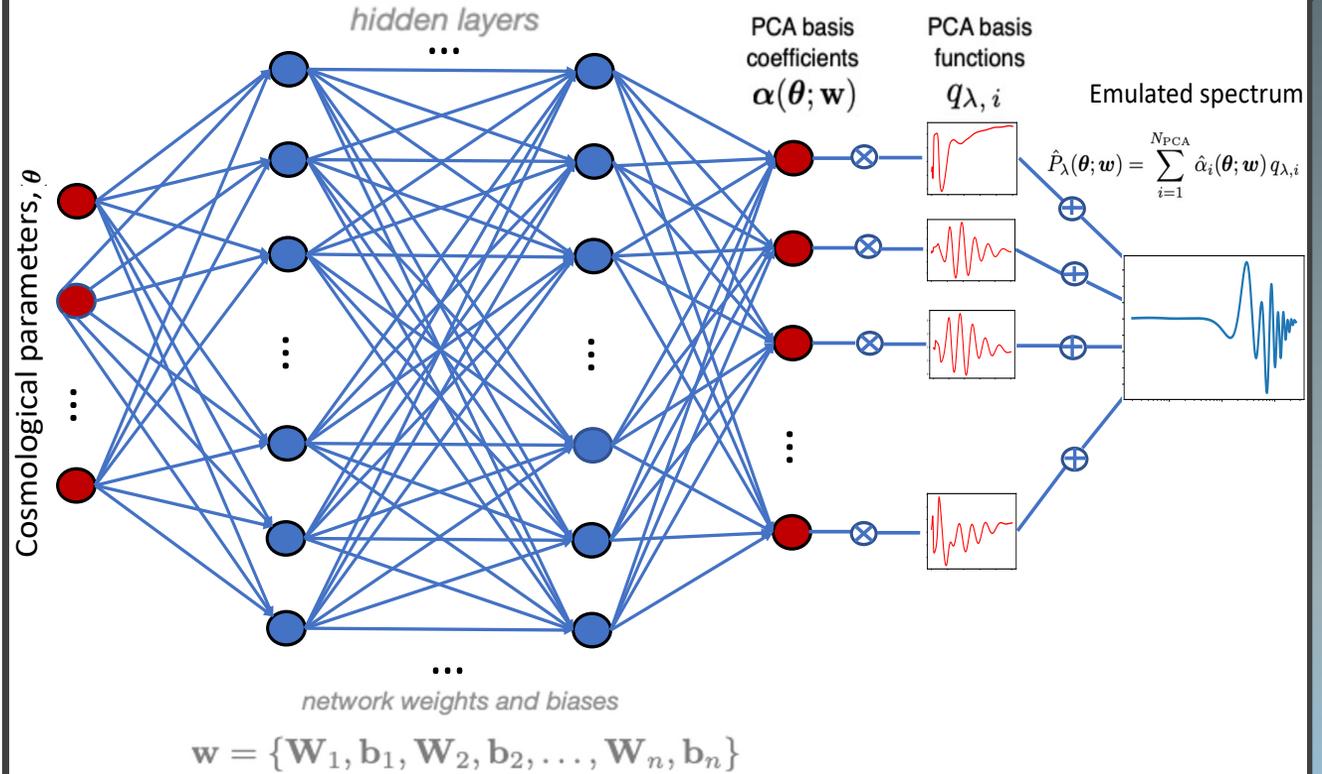
→ need **flexible** and **well tested** tool. CosmoPower emulates

- $P(k, z)$  (LIN+NL BOOST)
- CMB TT, TE, EE,  $\phi\phi$

# METHODS

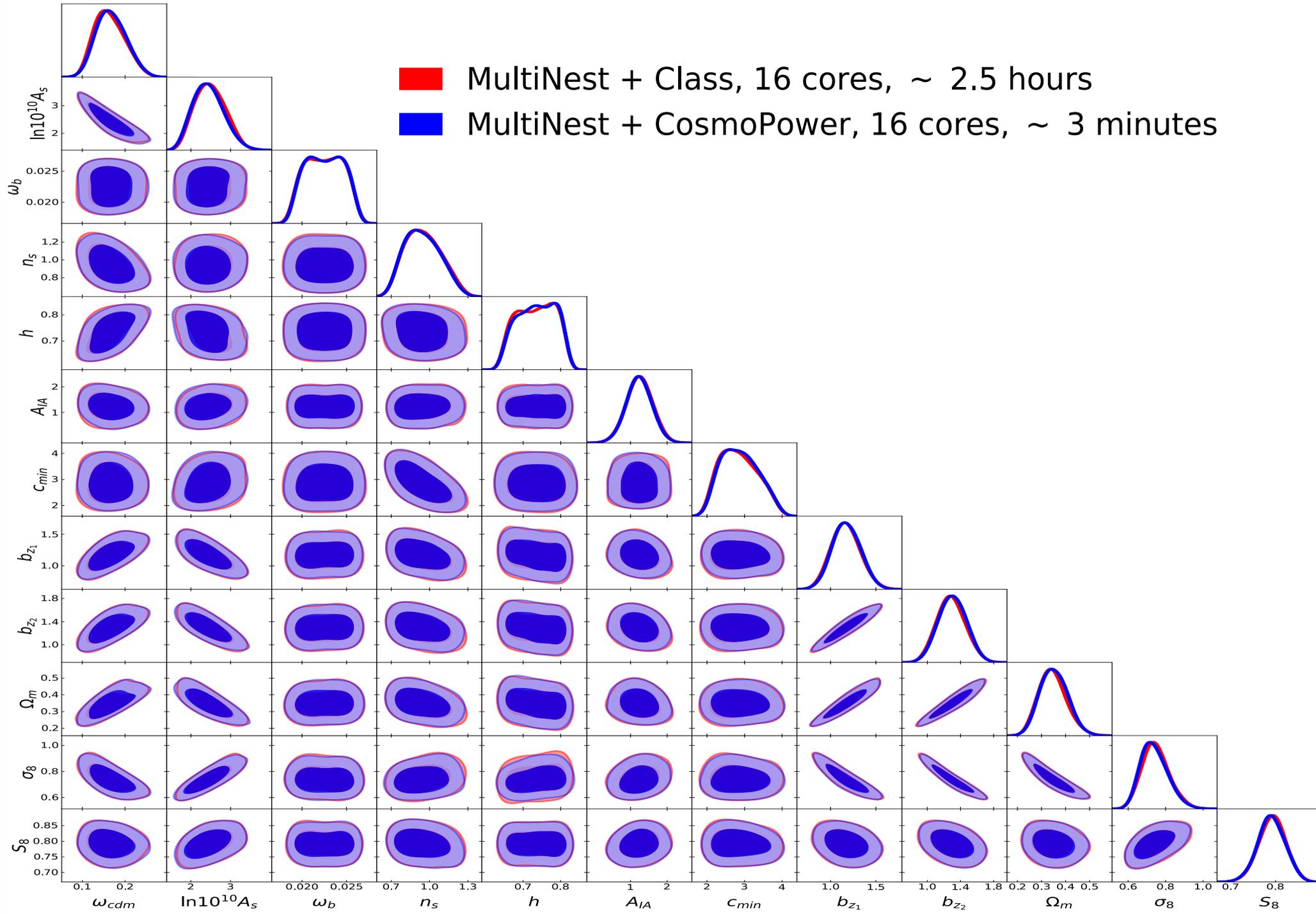


NEURAL NETWORK



NEURAL NETWORK + PCA

KIDS-450+GAMA 3X2PT



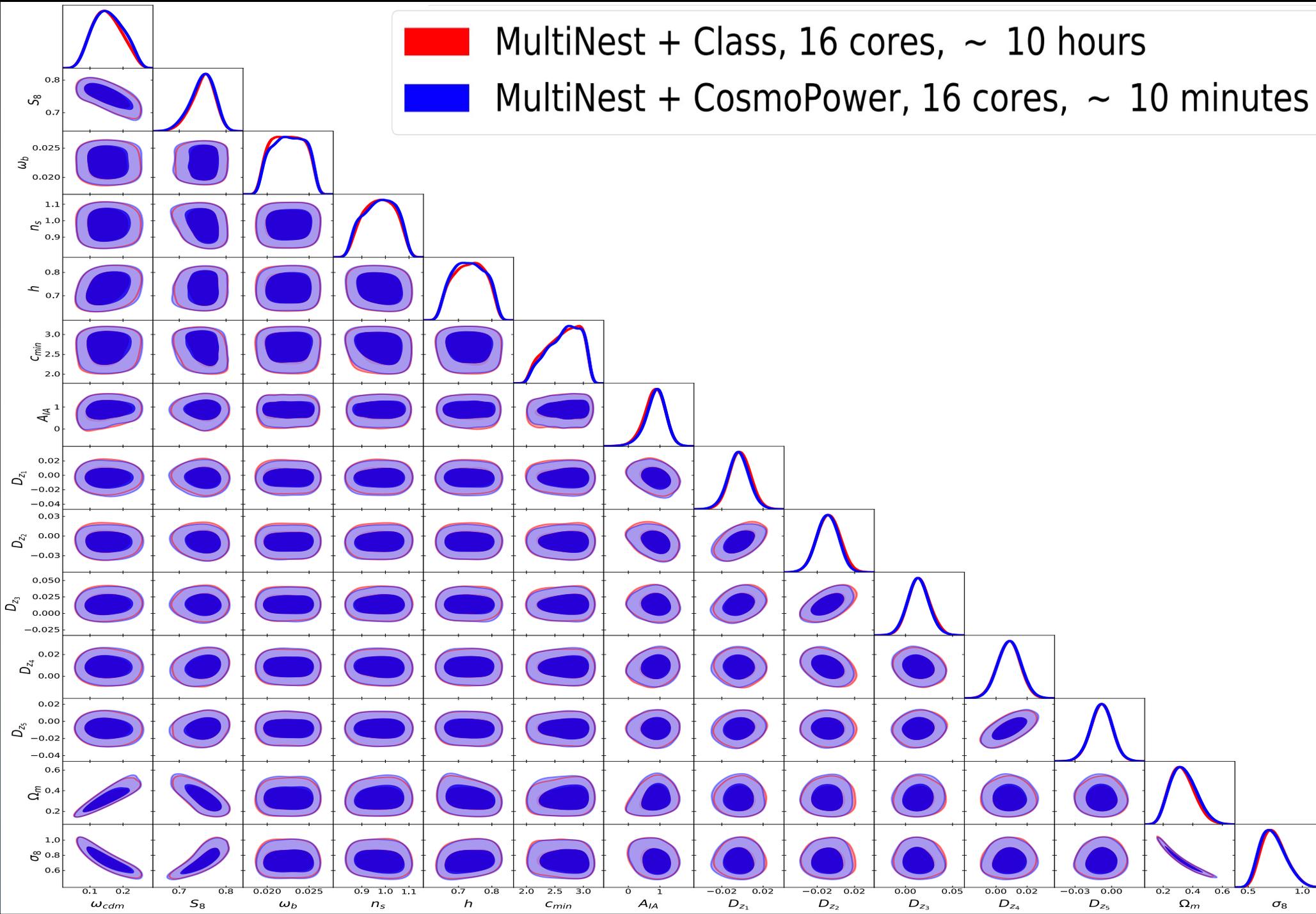
# KIDS-1000 COSMIC SHEAR



MultiNest + Class, 16 cores, ~ 10 hours



MultiNest + CosmoPower, 16 cores, ~ 10 minutes



# EUCLID-LIKE COSMIC SHEAR



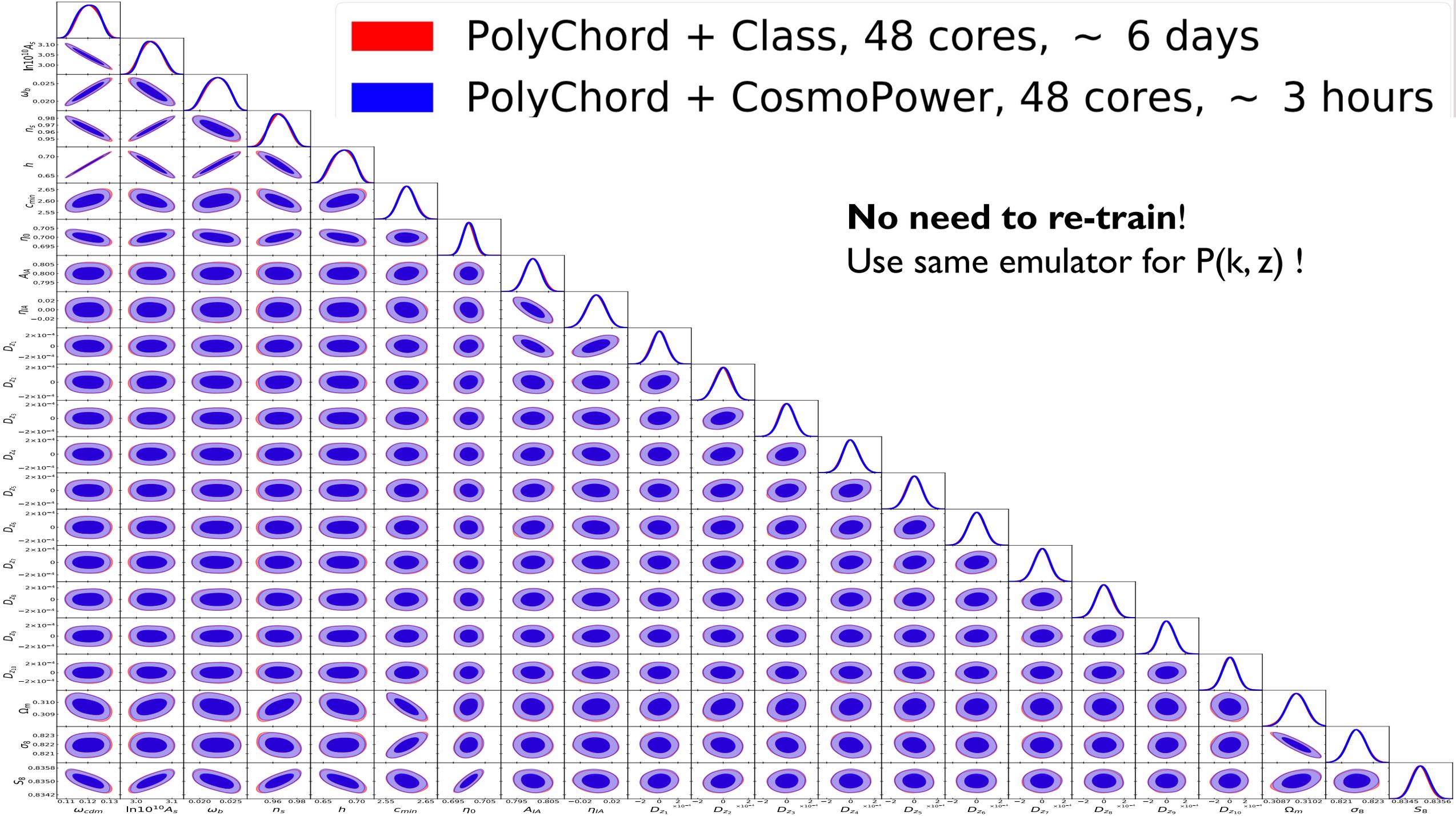
PolyChord + Class, 48 cores, ~ 6 days



PolyChord + CosmoPower, 48 cores, ~ 3 hours

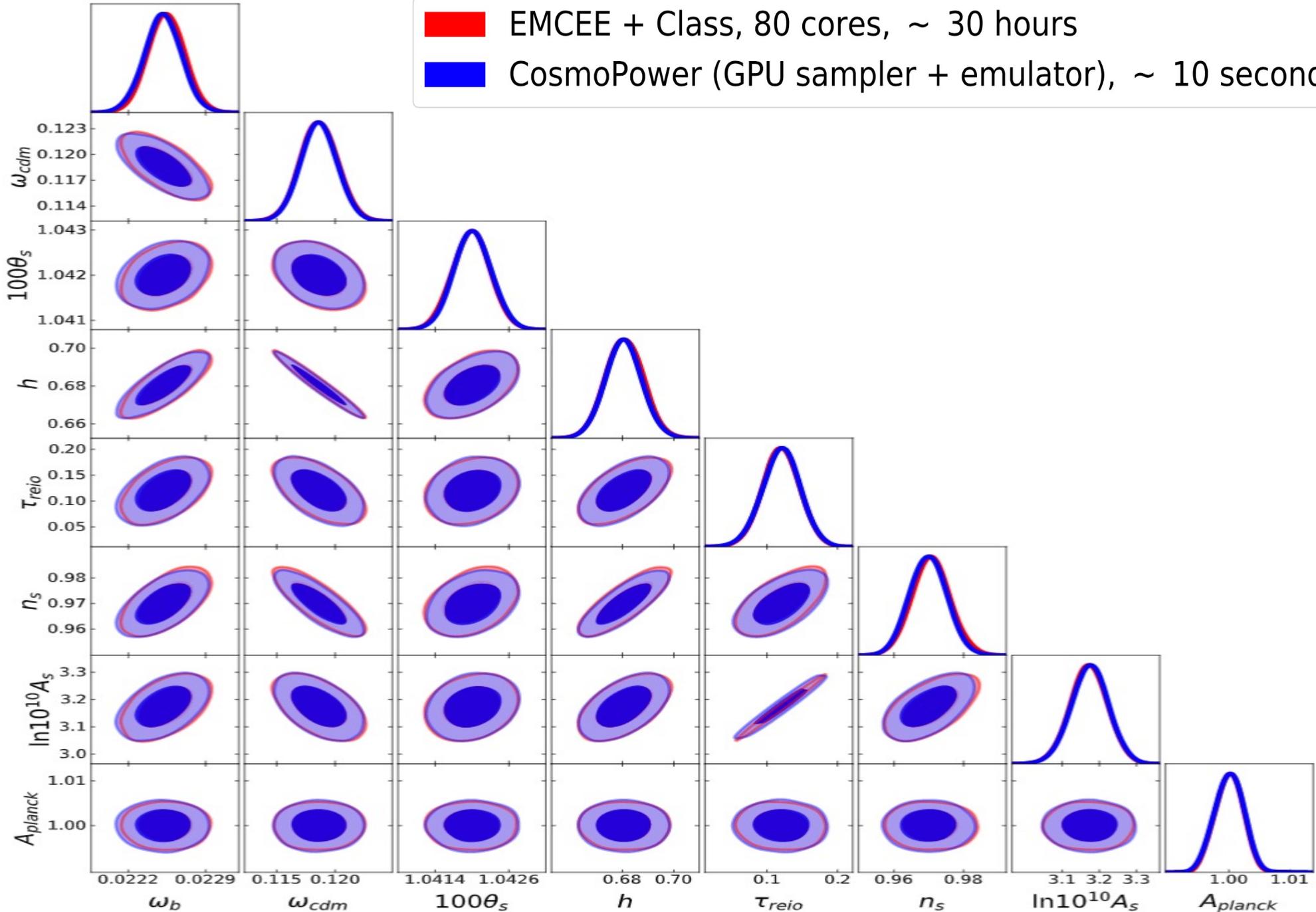
**No need to re-train!**

Use same emulator for  $P(k, z)$  !



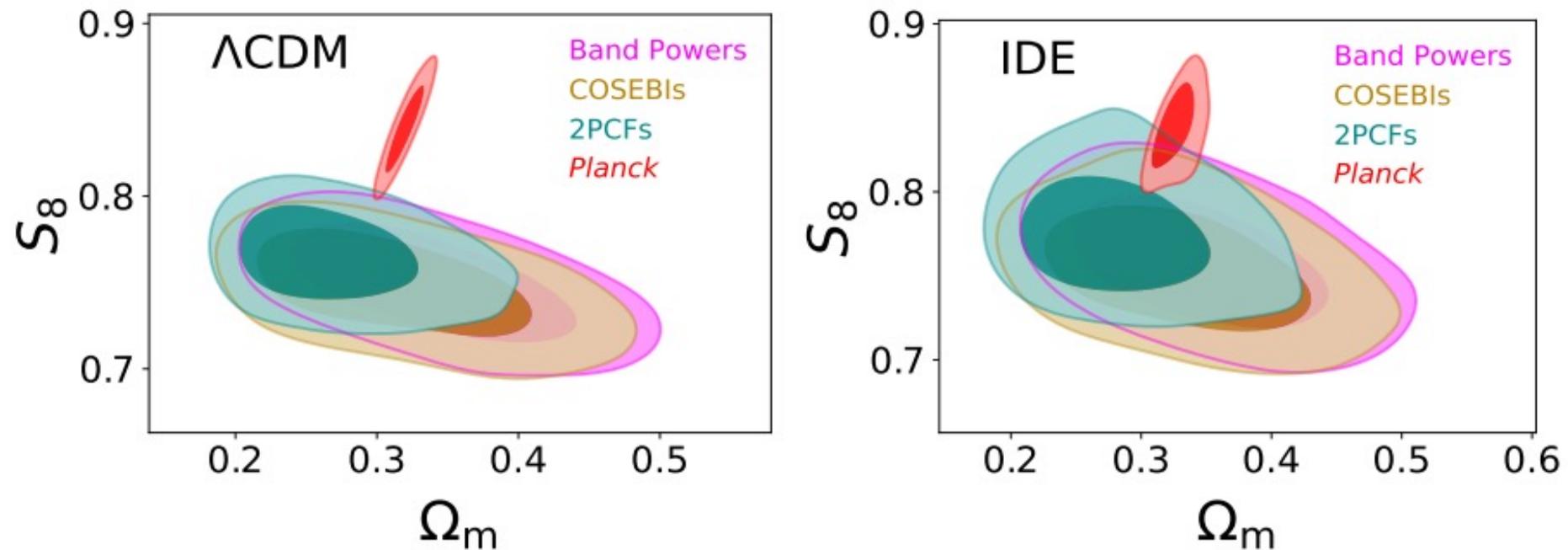
PLANCK 2018 TTTEEE

EMCEE + Class, 80 cores, ~ 30 hours  
CosmoPower (GPU sampler + emulator), ~ 10 seconds



# BEYOND $\Lambda$ CDM

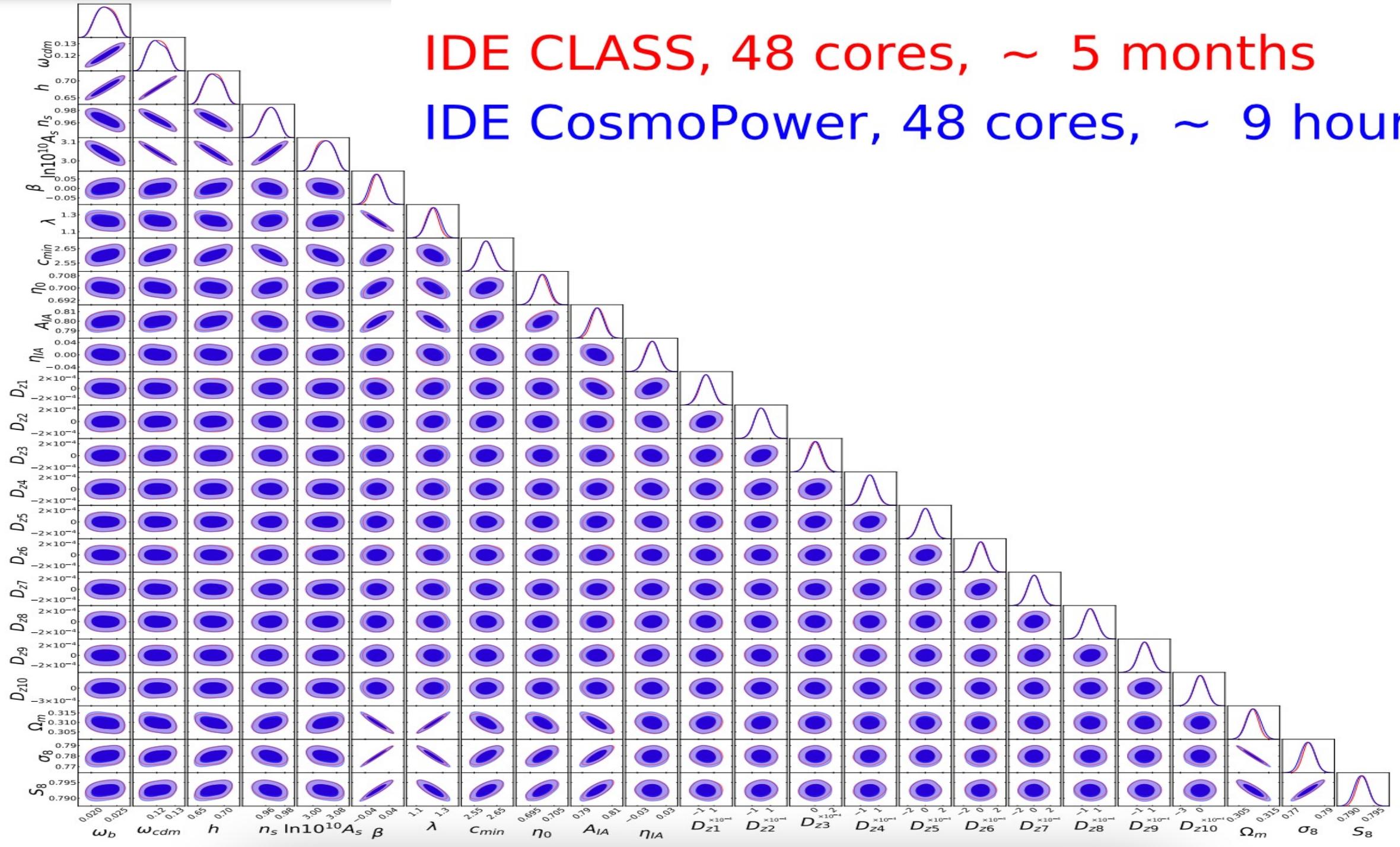
# KIDS-1000 COSMOLOGY: MACHINE LEARNING - ACCELERATED CONSTRAINTS ON INTERACTING DARK ENERGY WITH COSMOPOWER



ASM & Pourtsidou, [2110.07587](https://arxiv.org/abs/2110.07587)

IDE CLASS, 48 cores, ~ 5 months

IDE CosmoPower, 48 cores, ~ 9 hours



# COSMOPOWER: MAIN FEATURES

- **Tested** at inference level + evidence, on **large parameter ranges**
- Massive **speed-up**: up to  $O(10^4)$  on inference (even more beyond  $\Lambda$ CDM!)
- **Flexible**, no need to re-train e.g. for different  $n(z)$ 's
- Get derived parameters without re-training/re-running
- Training infrastructure provided
- Compatible with all cosmological samplers: COBAYA, MONTEPYTHON...
- **GPU/TPU**: additional speed-up
- Fully **differentiable**

# COSMOPOWER: FUTURE WORK

A fully differentiable library for cosmology:

- Beyond  $\Lambda$ CDM
- Beyond-Limber
- Higher-order statistics
- Systematics
- ... and more!



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

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ASM+ 2106.03846

THANK YOU!

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