Scanning for cosmological tensions across a DiRAC-enabled grid of models, datasets and samplers

Dily Duan Yi Ong Kavli Institute for Cosmology **University of Cambridge**









dlo26@cam.ac.uk CosmoVerse@Istanbul 2025



About me

- Dily Ong
- PhD Student at the University of Cambridge
- Dr. Will Handley's research group
- cosmological model selection and tension quantification
- Main author of the python package unimpeded





Research focuses on machine learning enhanced Bayesian inference in



Content

- **Background and Motivation**: The Rise of Cosmological Tensions \bullet
- Methodology: MCMC vs nested sampling
- The Solution: Introducing the unimpeded package
- **Results**: ullet
 - Tension statistics grid
 - Posterior samples from nested sampling runs
 - Machine learning emulators
- Summary and Future Work

CosmoVerse@Istanbul 2025

unimpeded



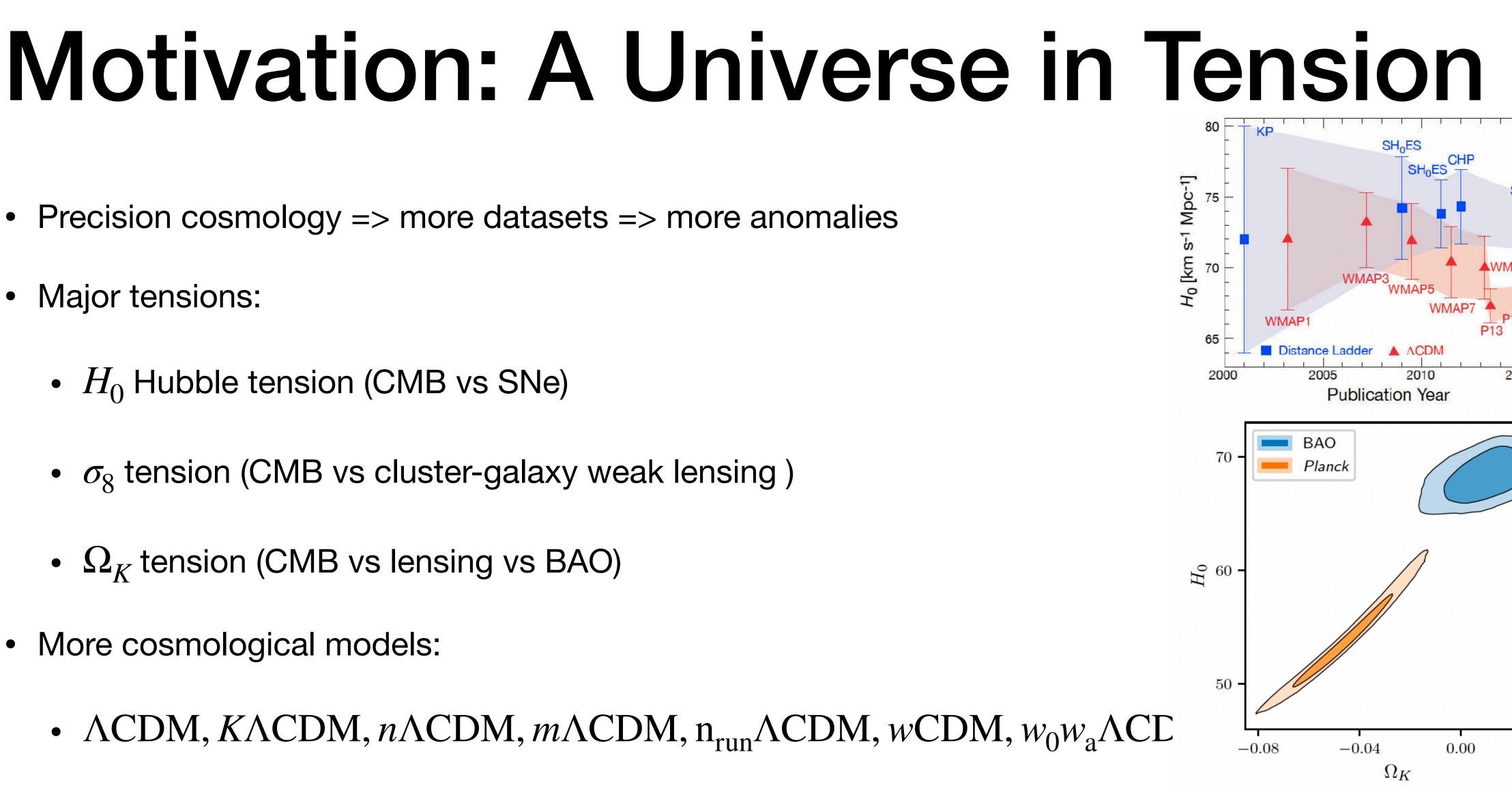
Bayesian Inference in Cosmology

Parameter Estimation	Model Comparison	Tension Quantification					
Using the observed data to estimate the values of cosmological parameters.	How much does the data support a particular model? Comparison between two models.	Do different datasets make consistent predictions from the same model? Study of discrepancies between different datasets.					
E.g. $H_0, n_s, \sigma_8, \tau, \omega_b h^2, \omega_{cdm} h^2$	$\mathbf{H} = \mathbf{A} + \mathbf{A} + \mathbf{H} + \mathbf{H} + \mathbf{H} + \mathbf{A} + $	e.g. CMB vs Type IA supernovae data -> Hubble tension					
Commonly uses the MCMC methods	Relies on the Bayesian evidence Z	Also needs evidence Z					



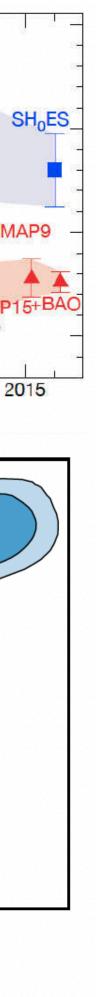


- Precision cosmology => more datasets => more anomalies
- Major tensions:
 - H_0 Hubble tension (CMB vs SNe)
 - σ_8 tension (CMB vs cluster-galaxy weak lensing)
 - Ω_K tension (CMB vs lensing vs BAO)
- More cosmological models:
 - $\Lambda CDM, K\Lambda CDM, n\Lambda CDM, m\Lambda CDM, n_{run}\Lambda CDM, wCDM, w_0w_a\Lambda CD$



• Need: robust ways to compare, combine, and check consistency across many datasets and models

unimpeded





Our challenge

- The problem of cost
 - methods)
- The problem of scale
 - Dozens of nuisance parameters per dataset
 - interest

 Model comparison and tension quantification are far more computationally expensive, than parameter estimation (traditionally performed by MCMC

• E.g. likelihood from the Year 1 DES analysis, 20 out of 26 parameters are nuisance parameters, only 6 corresponding to cosmological parameters of

unimpeded



The Need for a New Archive

- Planck legacy archive's MCMC chains grid
- Great for parameter estimation
- BUT: cannot compute evidences in high dimensions from MCMC chains
 - Only parameter estimation
 - No model comparison and tension quantification

ck Legacy A	rchive					
111111111111111111111111111111111111111	March	HIVE ss to all official data products ge	enerated by the Planck missi	on.		LATEST NEWS
PLANCK LEGACY ARCH	HIVE CONTENTS		TIMELINES AND RINGS	PLANCK SKY MODEL	SOFTWARE, BEAMS AND INSTRUMENT MODEL	-∿∿- OPERATIONAL DATA
USEFUL INFORMATIO	EXTERNAL DATA		USE OF PLANCK	UPDATE HISTORY	PLANCK SCIENCE	HELPDESK AND USER FORUM

Planck legacy archive

CosmoVerse@Istanbul 2025

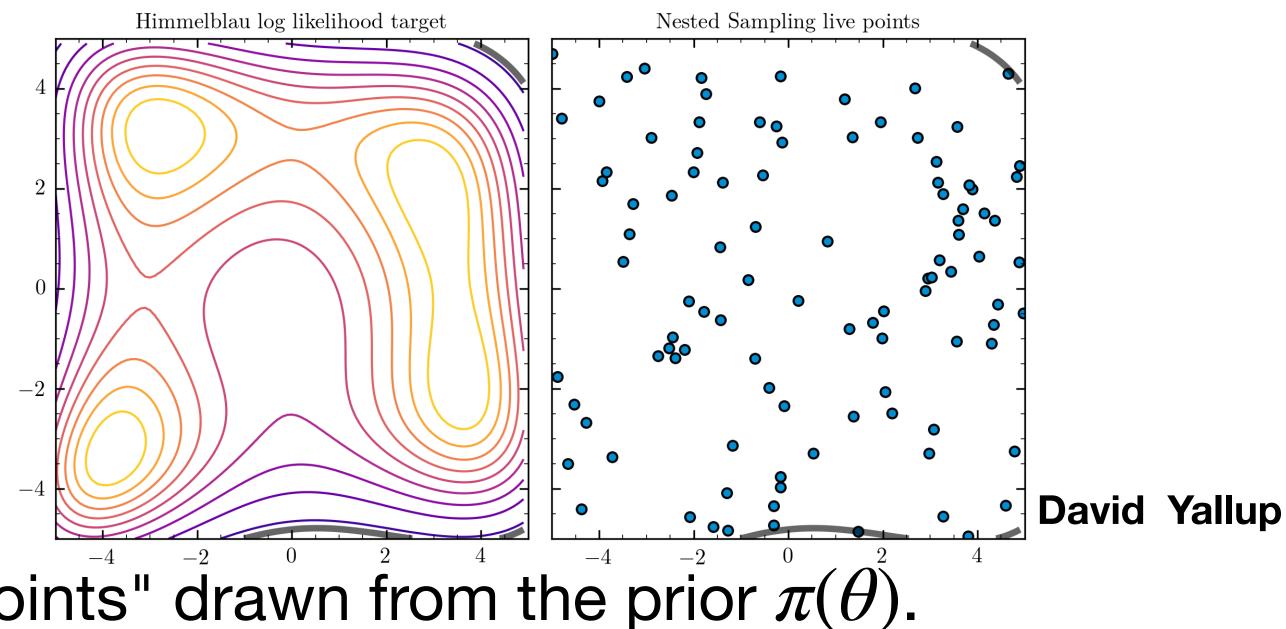
unimpeded





What is Nested Sampling?

- Proposed by [Skilling 2006]
- The Goal: Solve the evidence integral: $Z = \int L(\theta) \pi(\theta) d\theta$
- Algorithm:
 - 1. Initialise: Start with a set of N "live points" drawn from the prior $\pi(\theta)$.
 - 2. Iterate: At each step i:
 - Find the live point with the lowest likelihood, L_i .
 - higher likelihood.
 - 3. Terminate: Repeat until the entire prior volume has been traversed.



Remove (kill) this point and store it. The remaining live points define a "nested" remaining live points define a

Draw a new point from the prior, but constrained to have a likelihood

unimpeded





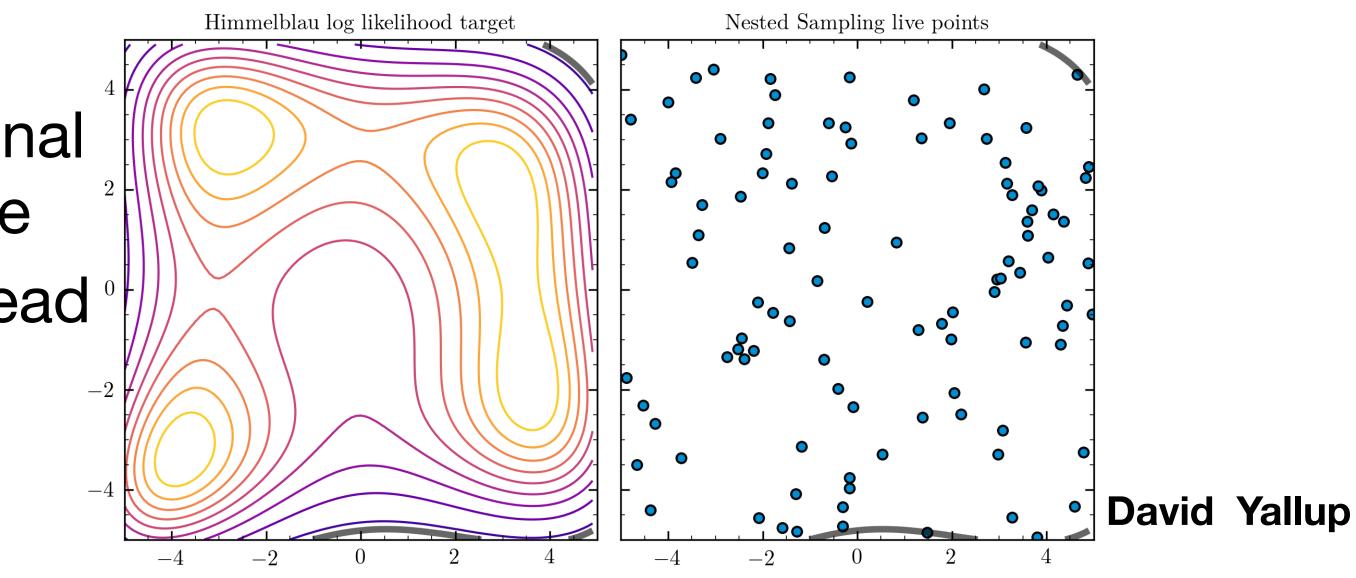
What is Nested Sampling?

Transform this complex multi-dimensional integral into a simple 1-dimensional one ² by integrating over prior volume *X* instead ⁰ of parameters *θ*.

$$Z = \int L(\theta) \pi(\theta) d\theta \quad rightarrow \quad Z = \int_0^1 L(X) d\theta$$

Multi-dimensional

1-dimensional



lX

What do we get?

- Numerically compute the evidence ${\boldsymbol Z}$ from the sequence of killed points
- Weighted set of posterior samples

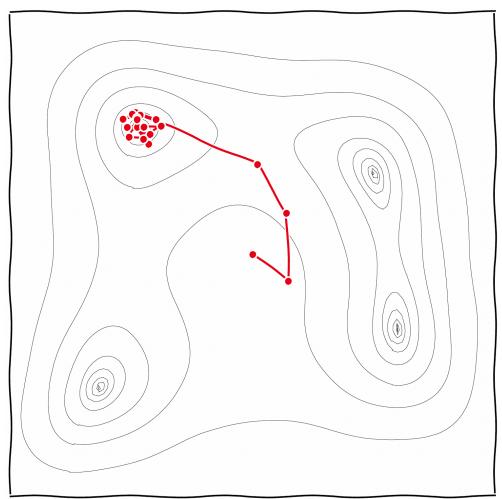




Generating Samples: MCMC vs Nested Sampling

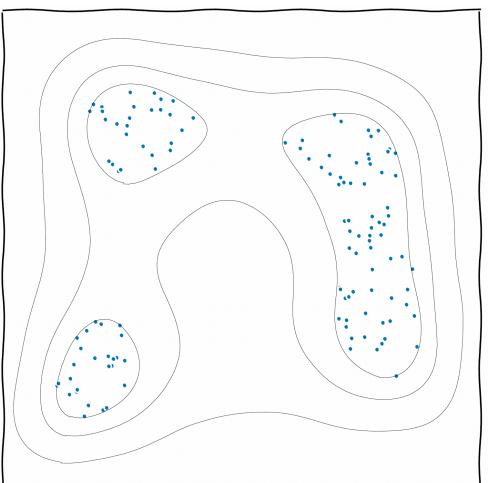
MCMC

- Single "walker"
- Explores posterior
- Cannot calculate the Bayesian Evidence Z
- Use Case: Parameter Estimation, suspiciousness calculation
- Fast, if proposal matrix is tuned



Nested Sampling

- Ensemble of "live points"
- Scans from prior to peak of likelihood
- Bayesian Evidence Z as its primary output
- Use Case: Parameter Estimation, Model **Comparison, and Tension Quantification**
- Slower, no tuning required



CosmoVerse@Istanbul 2025

unimpeded



Introducing unimpeded

- A re-usable library of posterior samples, Nested Sampling chains, and machine learning emulators
- Systematic coverage of cosmological models/datasets, for tension/model comparison
- Downloadable posterior samples (MCMC or Nested Sampling) \bullet
- Downloadable machine Learning-powered "emulators" for fast reuse (e.g. Planck-like priors)
- Powered by DiRAC, hosted on Zenodo, pip-installable, available on GitHub
- Turns weeks or months of supercomputer time into seconds on your laptop

III README S Code of conduct MIT license

, unimpeded: Universal model comparison & parameter estimation distributed over every dataset

unimpeded:	Universal model comparison & parameter estimation distributed over every dataset
Author:	Dily Ong & Will Handley
Version:	0.2.4
Homepage:	https://github.com/handley-lab/unimpeded
Documentation:	http://unimpeded.readthedocs.io/

Dily Ong (dlo26@cam.ac.uk)





11/21



CosmoVerse@Istanbul 2025

unimpeded

unimpeded: Models and Datasets Coverage

- 10 cosmological models + 60 datasets & pairwise combinations (to be expanded)
- Mix-and-match any model/dataset, plus pairwise combinations

Cosmological models

- $\Lambda CDM : H_0, \tau_{reio}, \Omega_b h^2, \Omega_c h^2, A_s, n_s$
- $K \wedge CDM : \Lambda CDM + \Omega_K$ (varying curvature)
- NACDM : Varying $N_{\rm eff}$ and total mass of 3 degenerate ν 's
- $n\Lambda CDM$: Varying total mass of 3 degenerate ν 's with N_{eff} =3.044
- $m\Lambda CDM$: Varying N_{eff} with two massless ν and one with m=0.06
- $n_{run} \Lambda CDM : \Lambda CDM + n_{run}$ (running of spectral index $dn_s/d \ln k$)
- wCDM : Λ CDM + w (constant cosmological equation of state)
- $w_0 w_a \Lambda CDM : \Lambda CDM + w_0 + w_a$ (varying dark energy equation of state, CLP)
- $r \wedge CDM$: $\wedge CDM + r$ (varying scalar-to-tensor ratio)



Cosmological datasets

- CMB:(Plik, Camspec, NPIPE, BICEP) \pm CMB lensing
- BAO:SDSS, BOSS, eBOSS, Ly α , DESI
- SNe: Pantheon, SH0ES
- WL: DESY1

CosmoVerse@Istanbul 2025

unimpeded



uimpeded: Easy Access to Complex Results

• Pip-installable

pip install unimpeded

- Open-source
 - unimpeded on Github
 - Chains and emulators on Zenodo
- Simple API in python for seamless download
- Easily access pre-computed results with a few lines of Python

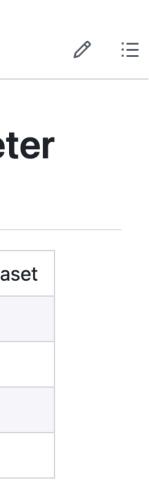
README Solution Code of conduct

[°] unimpeded: Universal model comparison & parameter estimation distributed over every dataset

unimpeded:	Universal model comparison & parameter estimation distributed over every datas
Author:	Dily Ong & Will Handley
Version:	0.2.4
Homepage:	https://github.com/handley-lab/unimpeded
Documentation:	http://unimpeded.readthedocs.io/

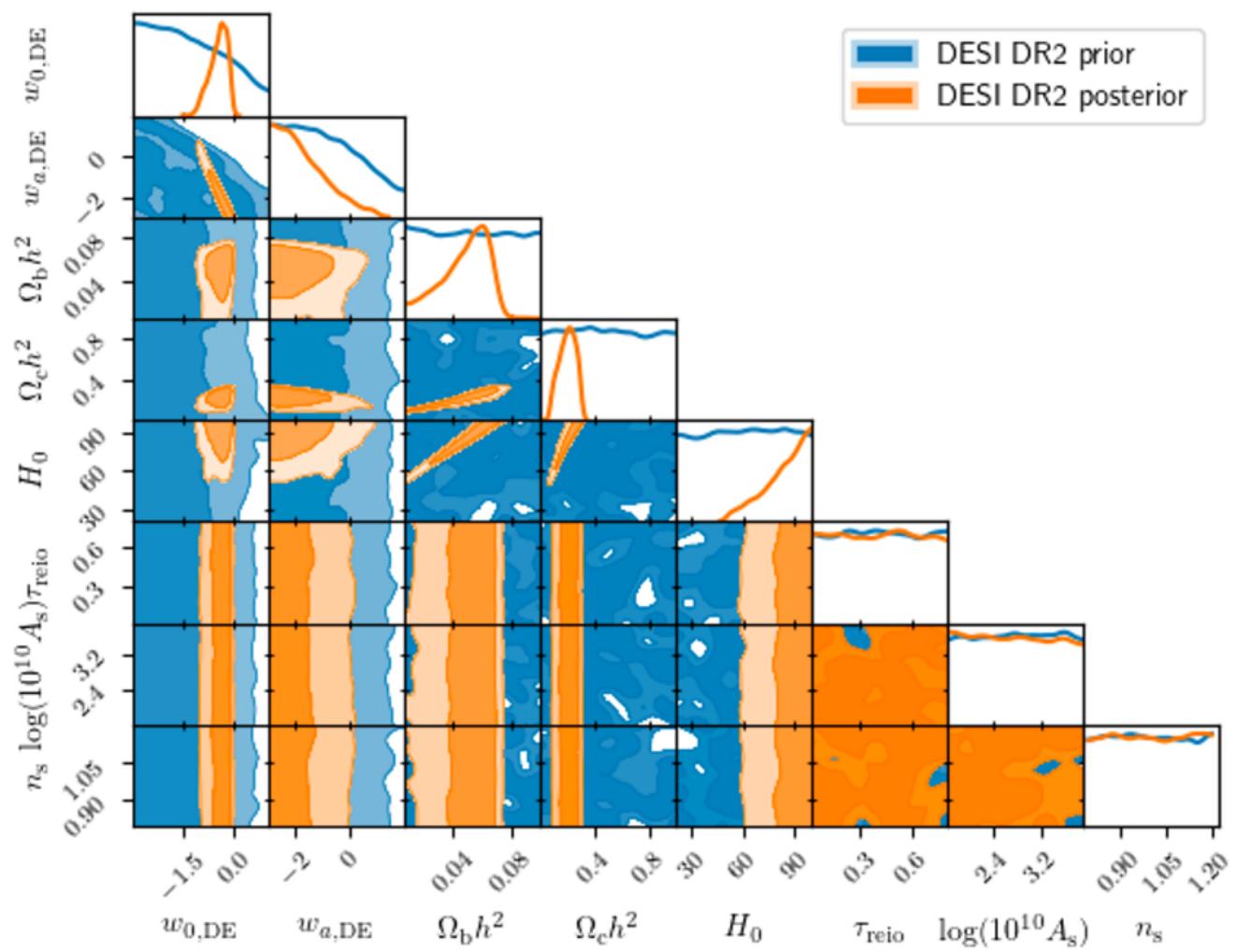
```
1 from unimpeded.database import
      DatabaseExplorer
_{2} dbe = DatabaseExplorer()
3 planck = dbe.download_samples(
      method='ns', model='walcdm',
      dataset='planck_2018_CamSpec')
6 sdss = dbe.download_samples(
      method='ns', model='walcdm',
      dataset='bao.sdss_dr16')
9 planck_sdss = dbe.download_samples(
      method='ns', model='walcdm',
10
      dataset='bao.sdss_dr16+
11
      planck_2018_CamSpec ')
```

unimpeded





unimpeded: Posterior samples



- Posteriors from nested sampling runs and MCMC runs
- Pre-computed results by HPC, accessible in your laptop in seconds, not weeks/months!
- Example:
 - DESI DR2 dataset using the w_0 w_aACDM cosmology model
 - Posteriors are clearly more constrained than the priors for several parameters.

unimpeded



unimpeded: Five Key Tension Statistics

- Information Ratio: $\log I = D_A + D_B D_{AB}$ (KL-divergence-based)
- Suspiciousness: $\log S = \log R \log I$ (prior-independent tension)
- *p*-value sigma: Approximate "number of sigma" separation
- Bayesian Model Dimensionality: $\frac{d}{2} = \begin{bmatrix} P \\ P \end{bmatrix}$ parameter count)

• **R statistics** : $R = \frac{Z_{AB}}{Z_A Z_B} = \frac{P(A \mid B)}{P(A)} = \frac{P(B \mid A)}{P(B)}$ (measure confidence in combining datasets)

$$P(\theta) \left(\log \frac{P(\theta)}{\pi(\theta)} - D \right)^2 d\theta$$
 (effective constrained)

unimpeded

CosmoVerse@Istanbul 2025



unimpeded: A Global View of Tensions

Tension statistics across 10 models (y-axis) and 29 pairwise datasets (x-axis)

	c^{∞}	
p =	/	$\chi_d^2(x) \mathrm{d}x$
و	$J_{d-2\log d}$	

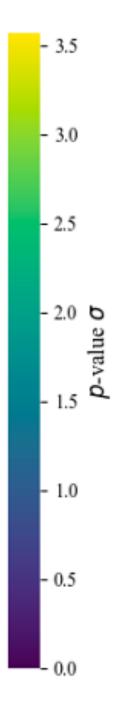
• $\sigma > 2$ in red

$$\sigma = \sqrt{2} \mathrm{Erfc}^{-1}(p).$$

ACDM -	0.31 ±0.11	0.08 ±0.26	1.29 ±0.08	2.78 ±0.12	2.58 ±0.10	2.78 ±0.17	2.97 ±0.18	0.24 ±0.49	0.93 ±0.06	0.92 ±0.07	0.98 ±0.07	$\underset{\pm 0.08}{\textbf{1.01}}$	$\underset{\pm 0.08}{\textbf{1.15}}$	0.04 ±0.08	0.67 ±0.10	0.37 ±0.39	0.62 ±0.39	0.09 ±0.20	1.11 ±0.40	0.00 ±0.00	2.61 ±0.13	2.39 ±0.11	2.57 ±0.14	2.44 ±0.11	$\underset{\pm 0.08}{\textbf{1.41}}$	0.50 ±0.24	0.73 ±0.10	0.18 ±0.29	0.91 ±0.25
KACDM -	0.12 ±0.09	0.00 ±0.00	1.38 ±0.19	2.47 ±0.11	2.84 ±0.13	2.90 ±0.22	3.27 ±0.10	1.31 ±0.24	0.43 ±0.06	1.23 ±0.06	2.01 ±0.09	1.56 ±0.10	2.46 ±0.08	0.19 ±0.06	1.43 ±0.25	0.37 ±0.11	0.56 ±0.20	0.22 ±0.41	0.82 ±0.08	0.00 ±0.00	2.93 ±0.12	3.19 ±0.12	3.19 ±0.15	3.57 ±0.10	1.05 ±0.32	1.01 ±0.14	2.33 ±0.21	1.61 ±0.31	2.44 ±0.12
NACDM -	0.01 ±0.04	0.00 ±0.00	1.16 ±0.08	2.49 ±0.32	1.79 ±0.14	2.69 ±0.31	2.20 ±0.15	0.01 ±0.05	0.59 ±0.06	0.65 ±0.07	0.51 ±0.07	0.59 ±0.06	0.60 ±0.07	0.23 ±0.12	0.74 ±0.12	0.21 ±0.31	0.32 ±0.13	0.56 ±0.12	0.22 ±0.24	0.00 ±0.00	2.55 ±0.14	2.08 ±0.08	2.41 ±0.12	2.54 ±0.12	0.98 ±0.09	0.19 ±0.24	0.15 ±0.22	0.35 ±0.25	0.58 ±0.18
mΛCDM -	0.05 ±0.10	0.24 ±0.60	1.15 ±0.07	2.19 ±0.15	2.20 ±0.21	2.35 ±0.10	2.94 ±0.27	1.88 ±0.53	0.82 ±0.05	0.81 ±0.06	0.75 ±0.07	1.01 ±0.07	1.18 ±0.10	0.24 ±0.13	0.63 ±0.07	0.68 ±0.22	0.33 ±0.30	0.68 ±0.20	0.16 ±0.33	0.01 ±0.09	2.38 ±0.11	2.35 ±0.11	2.37 ±0.13	2.26 ±0.11	$\underset{\pm 0.08}{\textbf{1.25}}$	0.62 ±0.17	0.59 ±0.33	0.95 ±0.22	0.69 ±0.50
nrun∧CDM -	0.00 ±0.02	0.01 ±0.06	1.17 ±0.24	2.57 ±0.10	2.94 ±0.17	2.94 ±0.19	2.98 ±0.22	0.19 ±0.46	0.32 ±0.09	0.88 ±0.06	$\underset{\pm 0.08}{\textbf{1.04}}$	1.05 ±0.07	1.18 ±0.10	0.08 ±0.11	0.32 ±0.28	0.34 ±0.17	0.67 ±0.29	0.69 ±0.20	0.79 ±0.30	0.00 ±0.00	2.55 ±0.15	2.50 ±0.15	2.84 ±0.23	3.10 ±0.32	1.10 ±0.19	0.56 ±0.27	0.08 ±0.20	0.56 ±0.12	0.88 ±0.11
rACDM -		0.00 ±0.03			2.87 ±0.15	2.84 ±0.20	2.96 ±0.20	0.01 ±0.06	0.96 ±0.06	1.02 ±0.07	0.98 ±0.06	1.15 ±0.20	$\underset{\pm 0.09}{\textbf{1.03}}$	0.29 ±0.09	0.49 ±0.14	0.09 ±0.06	0.02 ±0.03	0.00 ±0.00	0.05 ±0.06	0.00 ±0.00	3.00 ±0.22	2.69 ±0.17	2.79 ±0.21	2.65 ±0.16	1.48 ±0.11	0.77 ±0.22	0.08 ±0.17	0.57 ±0.11	0.56 ±0.30
wACDM -	1.42 ±0.05	0.00 ±0.00	0.96 ±0.06	2.59 ±0.12	2.52 ±0.12	2.68 ±0.14	3.08 ±0.24	0.00 ±0.04	0.49 ±0.04	2.27 ±0.08	2.30 ±0.08	2.44 ±0.12	2.74 ±0.15	1.47 ±0.04	0.31 ±0.11	0.29 ±0.28	0.07 ±0.18	0.51 ±0.15	0.11 ±0.23	0.01 ±0.07	2.11 ±0.12	2.01 ±0.09	1.92 ±0.10	2.12 ±0.11	0.85 ±0.07	1.27 ±0.11	1.31 ±0.14	1.82 ±0.28	1.89 ±0.30
nACDM -	0.08 ±0.11	0.27 ±0.58	0.91 ±0.09	2.45 ±0.13	2.32 ±0.11	2.26 ±0.13	2.27 ±0.13	0.00 ±0.02	0.30 ±0.04	0.48 ±0.05	0.56 ±0.05	0.44 ±0.08	0.46 ±0.05	0.26 ±0.09	0.50 ±0.10	0.33 ±0.26	0.66 ±0.22	0.26 ±0.35	0.54 ±0.24	0.00 ±0.00	2.68 ±0.17	2.62 ±0.14	2.50 ±0.13	2.64 ±0.16	0.86 ±0.07	0.12 ±0.19	0.43 ±0.32	0.07 ±0.12	0.50 ±0.19
								0.00 ±0.00																					
AACDM -	0.17 ±0.14	0.11 ±0.39	1.50 ±0.12	2.25 ±0.11	2.24 ±0.12	2.45 ±0.24	2.29 ±0.24	0.00 ±0.00	1.09 ±0.07	1.00 ±0.07	1.03 ±0.09	0.94 ±0.08	0.95 ±0.08	0.03 ±0.08	1.17 ±0.28	0.40 ±0.27	0.00 ±0.03	0.20 ±0.25	0.25 ±0.33	0.00 ±0.00	2.06 ±0.10	1.90 ±0.09	1.86 ±0.09	1.90 ±0.11	1.59 ±0.13	0.46 ±0.14	0.04 ±0.11	0.09 ±0.17	0.37 ±0.18
SHOES + CamSpec with SHOES + Planck with CMB lensing spec with SDSS + Planck with CMB lensing planck p																													
SHOES+C	all	SHOES	× * -		51	055×0	au	SDSS'	< *		BIG	EP+C	au	BICEP	* *	5	DESTO	au	DES	* *	Cam	Spec wit	n Pl	anck wit	II -				

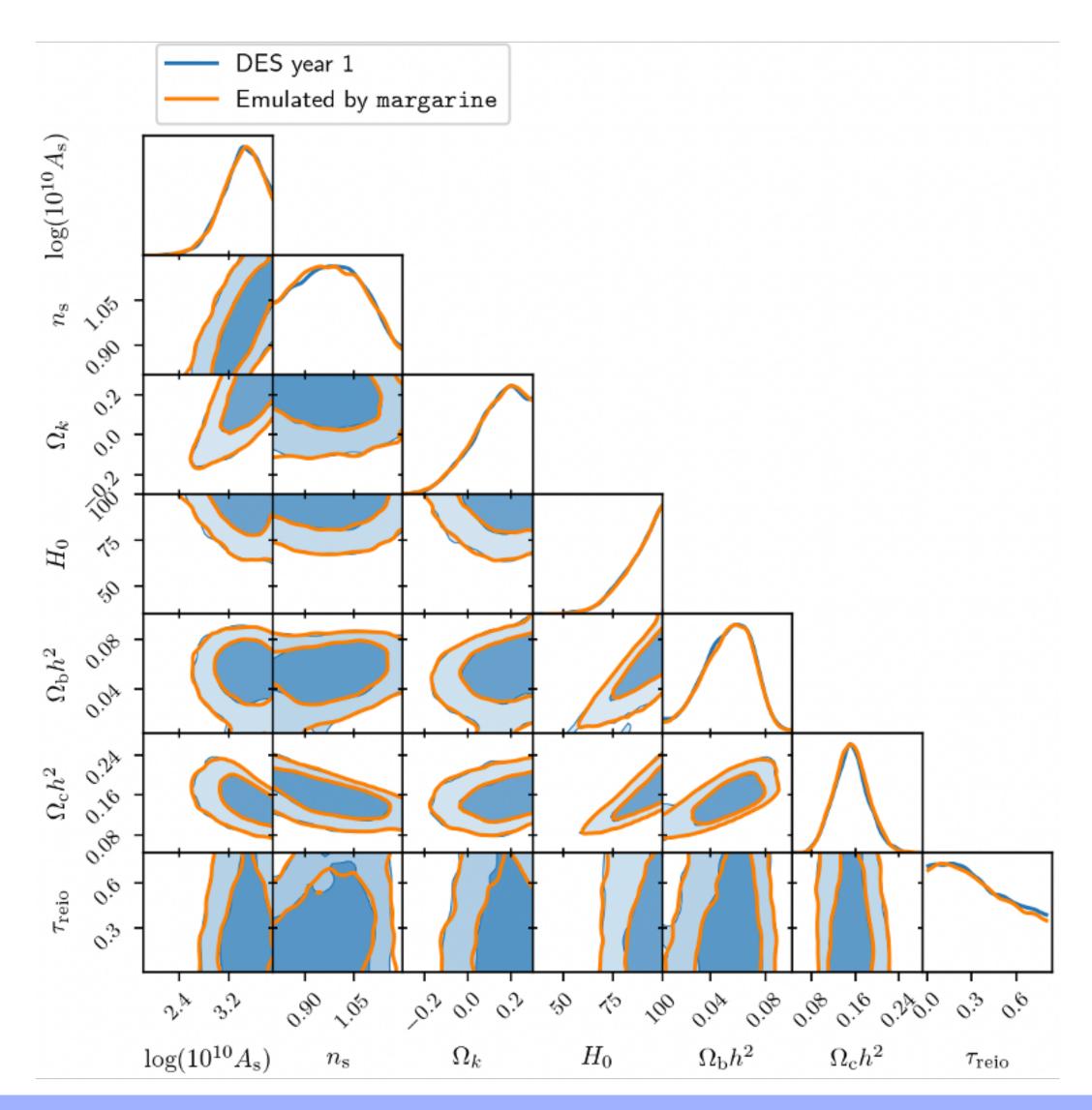
A systematic, quantitative search for tensions across a grid of models and data

CosmoVerse@Istanbul 2025





unimpeded: Machine learning emulators



Dily Ong (dlo26@cam.ac.uk)

- Machine learning emulators
- Emulate marginalised likelihoods or \bullet posteriors.
- Benefits:
 - Dramatically speeds up inference for re-use in new analyses
 - Provides a fast and flexible alternative to full MCMC/NS runs
 - Provides a real 'planck prior' rather than a Gaussian approximation



What's next?

- Future of unimpeded:

 - Integrating more advanced ML and Simulation-Based Inference techniques.
- Join Us!
 - please get in touch!
 - The code is open-source on GitHub.
- About Me:
 - I'd be delighted to discuss my work further.

• Expanding the grid with DiRAC 17 to include next-generation datasets (DESI, Euclid, etc.).

• We are actively seeking α-testers and collaborators. If this tool could be useful for your research,

I am a final-year PhD student and am currently exploring postdoctoral opportunities for next year.

unimpeded

CosmoVerse@Istanbul 2025



What's next?

- Future of unimpeded:

 - Integrating more advanced ML and Simulation-Based Inference techniques.
- Join Us!
 - please get in touch!
 - The code is open-source on GitHub.
- About Me:
 - I'd be delighted to discuss my work further.

• Expanding the grid with DiRAC 17 to include next-generation datasets (DESI, Euclid, etc.).

• We are actively seeking α-testers and collaborators. If this tool could be useful for your research,

Thank you!

I am a final-year PhD student and am currently exploring postdoctoral opportunities for next year.

unimpeded



Bonus Slide: Prior range

Parameter	Prior range	Baseline	
$\omega_{\rm b} \equiv \Omega_{\rm b} h^2 \ldots \ldots$	[0.005, 0.1]		Bary
$\omega_{\rm c} \equiv \Omega_{\rm c} h^2 \ldots \ldots$	[0.001, 0.99]		Cold
$100\theta_{MC}$	[0.5, 10.0]		100>
au	[0.01, 0.8]		Thon
Ω_K	[-0.3, 0.3]	0	Curv
$\sum m_{\nu}$	[0, 5]	0.06	The s
$m_{\nu, \text{ sterile}}^{\text{eff}}$	[0,3]	0	Effec
W_0	[-3.0, -0.3]	-1	Dark
W_a	[-2, 2]	0	As al
$N_{\rm eff}$	[0.05, 10.0]	3.046	Effec
$Y_{\rm P}$	[0.1, 0.5]	BBN	Fract
$A_{\rm L}$	[0, 10]	1	Amp
$n_{\rm s}$	[0.9, 1.1]		Scala
$n_{\rm t}$	$n_{\rm t} = -r_{0.05}/8$	Inflation	Tens
$dn_{\rm s}/d\ln k$	[-1, 1]	0	Runn
$\ln(10^{10}A_{\rm s})$	[2.7, 4.0]		Log
$r_{0.05}$	[0,2]	0	Ratio

Definition

yon density today dark matter density today \times approximation to r_*/D_A (CosmoMC) mson scattering optical depth due to reionization vature parameter today with $\Omega_{tot} = 1 - \Omega_K$ sum of neutrino masses in eV ctive mass of sterile neutrino in eV k energy equation of state^{*a*}, $w(a) = w_0 + (1 - a)w_a$ bove (perturbations modelled using PPF) ctive number of neutrino-like relativistic degrees of freedom (see text) ction of baryonic mass in helium plitude of the lensing power relative to the physical value lar spectrum power-law index ($k_0 = 0.05 \text{Mpc}^{-1}$) sor spectrum power-law index ($k_0 = 0.05 \text{Mpc}^{-1}$) ning of the spectral index power of the primordial curvature perturbations ($k_0 = 0.05 \text{ Mpc}^{-1}$) o of tensor primordial power to curvature power at $k_0 = 0.05 \text{ Mpc}^{-1}$

Planck 2013 results. XVI. Cosmological parameters





Bonus Slide: Zenodo

zenodo	unimpeded:	Q Communities My dashboard
		324 result(s) found
Versions		February 9, 2025 (v1) Dataset Gpen
View all versions		unimpeded: mlcdm planck_2018_CamSpec Ong, Dily
Access status		cosmological model:mlcdm, dataset:planck_2018_CamSpec
Open	321	Uploaded on February 10, 2025
Restricted	3	February 9, 2025 (v1) Dataset Gen
Resource types		unimpeded: wlcdm des_y1.joint+planck_2018_plik Ong, Dily
Dataset	279	cosmological model:wlcdm, dataset:des_y1.joint+planck_2018_plik
> Publication	40	Uploaded on February 11, 2025
> Image	2	February 9, 2025 (v1) Dataset Gen
Poster	1	unimpeded: rlcdm bao.sdss_dr16+sn.pantheon Ong, Dily
Presentation	1	cosmological model:rlcdm, dataset:bao.sdss_dr16+sn.pantheon
Software	1	Uploaded on February 10, 2025

Files (316.5 MB)		
Name	Size	Dow
mcmc_wlcdm_des_y1.joint+planck_2018_plik.csv md5:63243fd154170721340d6b126d3cb51d 🚱	134.2 MB	Preview
mcmc_wlcdm_des_y1.joint+planck_2018_plik.yaml md5:3a75b2be0d65788b98bc7ac674170508	17.4 kB	
ns_wlcdm_des_y1.joint+planck_2018_plik.csv md5:b33ed2091153ce302f4970905fa29218 @	182.2 MB	Preview
ns_wlcdm_des_y1.joint+planck_2018_plik.prior_info md5:85010fb0ba899aad91d5650e1abf1a7e @	48 Bytes	
ns_wlcdm_des_y1.joint+planck_2018_plik.yaml md5:9d2e88284645351fed2338593c290040 🚱	17.8 kB	

