unimpeded: A universal parameter estimation, model comparison and tension quantification distributed over every dataset

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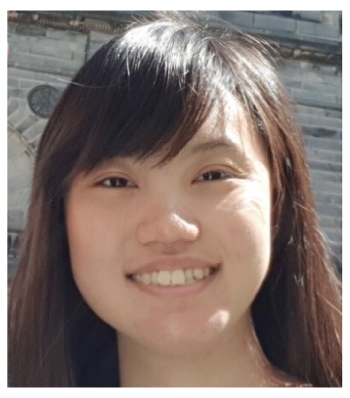


`unimpeded` is a re-usable library of posterior samples, nested sampling [1, 2] runs and machine learning emulators across a grid of cosmological models for detecting cosmological tensions between datasets from the DiRAC allocation (DP192 & 264). It serves as an analogous grid to the Planck Legacy Archive (PLA), but machine learning enhanced and expanded to enable not only parameter estimation (currently available with the MCMC chains on PLA), but also allowing cosmological model comparison and tension quantification. The emulators are implemented with piecewise normalising flows [3] as part of the package `margarine` [4, 5], though alternative density estimation methods can be used. The combination of nested sampling and density estimation allows us to obtain the same posterior distributions as one would have found from a full nested sampling run over all nuisance parameters, but many orders of magnitude faster. This allows users to use the existing results of cosmological analyses without the need to re-run on supercomputers.

The three pillars of Bayesian inference

Parameter Estimation

What do the data tell us about the parameters of a model? e.g. the size or age of a ΛCDM universe

$$\text{Posterior} = \frac{\text{Likelihood} \times \text{Prior}}{\text{Evidence}}.$$

Parameter Estimation

How much do the data support a given model? e.g. ΛCDM vs a dynamic dark energy cosmology

$$\text{Posterior} = \frac{\text{Evidence} \times \text{Prior}}{\text{Normalisation}}.$$

Tension quantification

Do different datasets make consistent predictions from the same model? e.g. Hubble H_0 tension from CMB vs Type 1A supernovae data

$$\mathcal{R} = \frac{\mathcal{Z}_{AB}}{\mathcal{Z}_A \mathcal{Z}_B},$$

Model comparison and tension quantification have become increasingly relevant in recently years because of anomalies, e.g. H_0 and σ_8 tension. Although MCMC chains (currently available on PLA grids) may be used for parameter estimation, model comparison and tension quantification are far more computationally expensive, so more specialist tools like nested sampling are required.

Available Models & Data

`unimpeded` provides a systematic coverage of cosmological models, datasets and their pairwise comparisons. It will be expanded as new datasets and models become available, e.g. ACT, SPT, DESI, DESY5, Union, Patheon+,.... Requests for new datasets are welcome!

Cosmological datasets

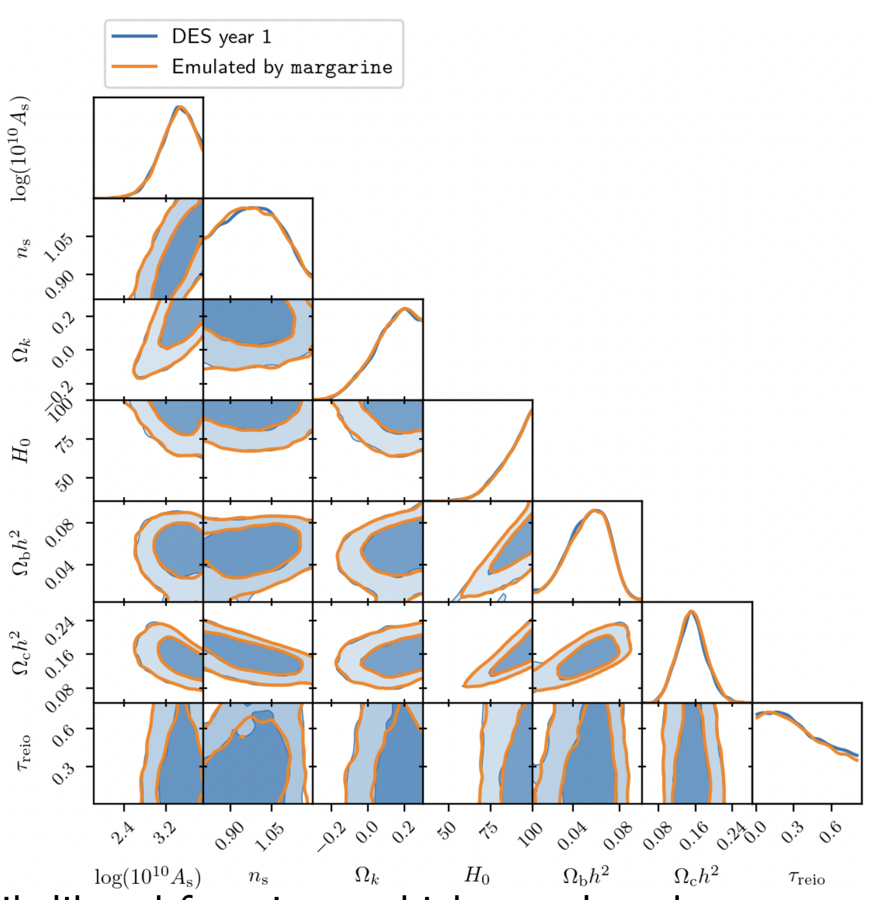
- CMB:(Plik, Camspec, NPIPE, BICEP) ± CMB lensing
- BAO:SDSS, BOSS, eBOSS, Lyα
- SNe: Pantheon, SH0ES
- WL: DESY1

Cosmological models

- ΛCDM : H_0, $\tau_{\rm reio}$, $\Omega_b h^2$, $\Omega_c h^2$, A_s, n_s
- KΛCDM : ΛCDM + Ω_K (varying curvature)
- NΛCDM : Varying $N_{\rm eff}$ and total mass of 3 degenerate ν's
- nΛCDM : Varying total mass of 3 degenerate ν's with $N_{\rm eff}$=3.044
- mΛCDM : Varying $N_{\rm eff}$ with two massless ν and one with m=0.06
- $n_{\rm run}$ΛCDM : ΛCDM + $n_{\rm run}$ (running of spectral index $dn_s/d\ln k$)
- wCDM : ΛCDM + w (constant cosmological equation of state)
- w_0w_aΛCDM : ΛCDM + w_0 + w_a (varying dark energy equation of state, CLP)
- rΛCDM : ΛCDM + r (varying scalar-to-tensor ratio)

Results - Emulators

`unimpeded` provides a library of trained bijectors to be used as priors or emulators [6] or nuisance marginalised likelihoods [5]. Piecewise normalising flows are used with `margarine` to model complex probability densities through bijective transformations between a base distribution and the target distribution. Density estimators, such as Kernel Density Estimators [7, 8] and Masked Autoregressive Flows [9] are used to rapidly calculate reliable and reusable marginal probability densities and marginal Bayesian summary statistics for key signal or cosmological parameters.



This enables the access to the nuisance-free likelihood functions, which greatly reduces computational cost in combining parameters constraints from different datasets. It allows users to use a real 'planck prior' rather than a Gaussian approximation for future cosmological analyses. Here is an example of the DES year 1 dataset (blue filled contours) emulated by `margarine` (orange line) using nested sampling chains, with a p-value of 0.752.

Using unimpeded

`unimpeded` is a Python tool for seamlessly downloading and cacheing chains (API in 'alpha'). It provides both MCMC and nested sampling chains. Data are stored on `zenodo`, with hdf5 storage for fast and reliable download and storage. `unimpeded` is a pip-installable package.

```
pip install unimpeded
```

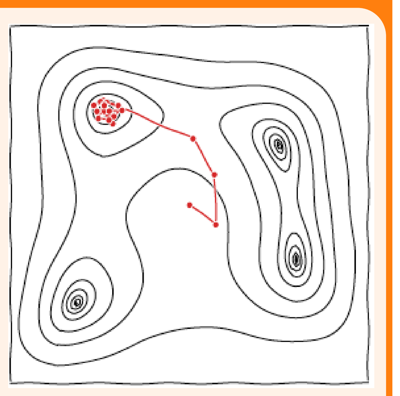
To access any combination of these models and datasets (also the pairwise combinations of datasets, e.g. Planck 2018 CamSpec+DES year 1), simply call the function `unimpeded.get(data, model, method)` and specify the dataset, model and sampling method (ns = nested sampling or mcmc = Metropolis–Hastings MCMC mthods).

```
samples = unimpeded.get(data='planck_2018_CamSpec', model='lcdm',
method='ns')
```

Samplers

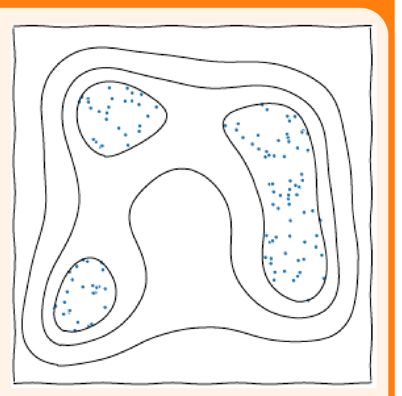
Samples are the fundamental building block of numerical Bayesian inference, encapsulating high-dimensional posterior probability distributions. The samplers used in unimpeded are Metropolis Hastings MCMC and Nested Sampling, using `Cobaya` [10].

Metropolis–Hastings MCMC



- Single "walker"
- Explores posterior
- Fast, if proposal matrix is tuned
- Parameter estimation, suspiciousness calculation
- Channel capacity optimised for generating posterior samples

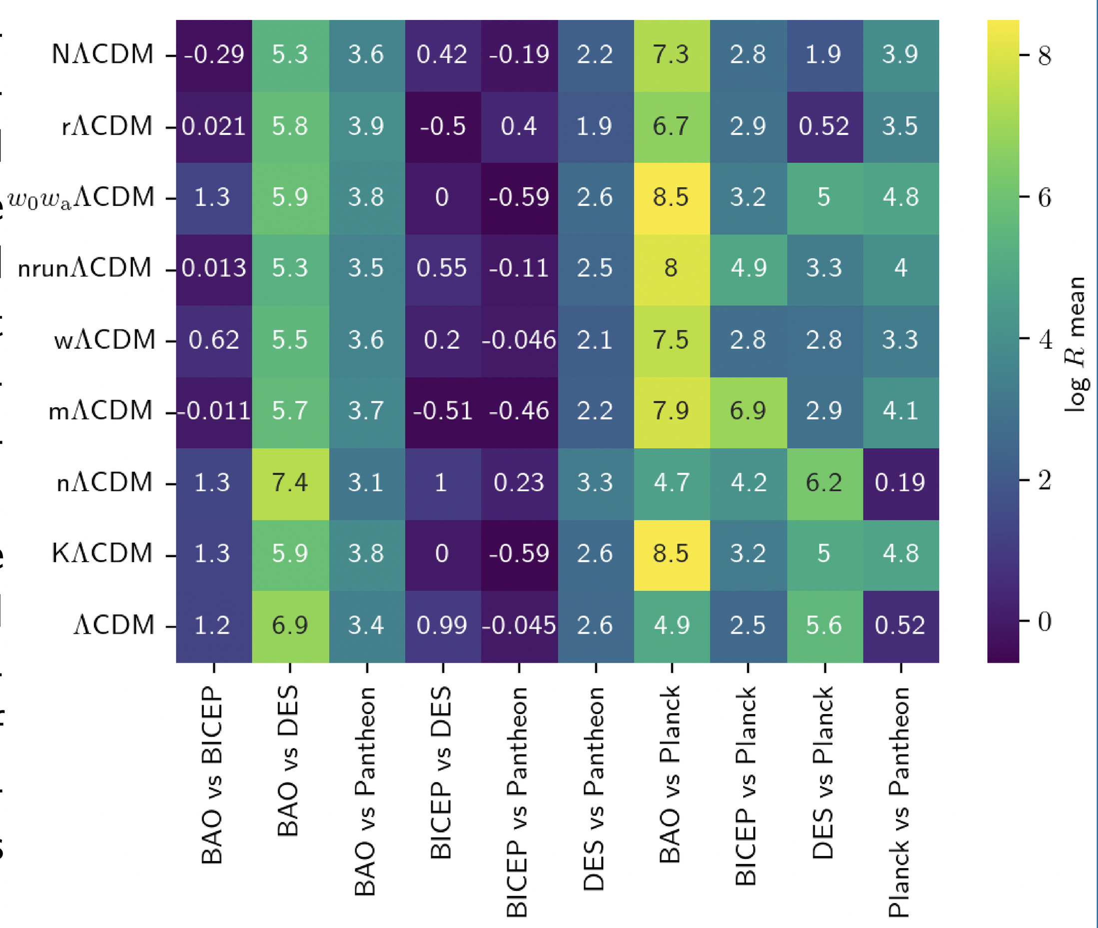
Nested Sampling



- Ensemble of "live points"
- Scans from prior to peak of likelihood
- Slower, no tuning required
- Parameter estimation, model comparison, tension quantification
- Channel capacity optimised for computing partition function

Preliminary Results - Tension Statistics

`unimpeded` acts as a tool for convenient and systematic measurement of tension statistics, and quantifying the Bayesian degree of confidence in comparing and combining datasets across different models. Available tension statistics include the p-value, R statistics [11], the suspiciousness [12], the information ratio from the Kullback-Leibler divergences and the Bayesian model dimensionality. Here is an example of one of the tension statistics ($\log R$) compared between 10 pairwise datasets across 9 cosmological models.



	BAO vs BICEP	BAO vs DES	BAO vs Pantheon	BICEP vs DES	BICEP vs Pantheon	DES vs Pantheon	BAO vs Planck	BICEP vs Planck	DES vs Planck	Planck vs Pantheon
NΛCDM	-0.29	5.3	3.6	0.42	-0.19	2.2	7.3	2.8	1.9	3.9
rΛCDM	0.021	5.8	3.9	-0.5	0.4	1.9	6.7	2.9	0.52	3.5
w_0w_aΛCDM	1.3	5.9	3.8	0	-0.59	2.6	8.5	3.2	5	4.8
nrunΛCDM	0.013	5.3	3.5	0.55	-0.11	2.5	8	4.9	3.3	4
wΛCDM	0.62	5.5	3.6	0.2	-0.046	2.1	7.5	2.8	2.8	3.3
mΛCDM	-0.011	5.7	3.7	-0.51	-0.46	2.2	7.9	6.9	2.9	4.1
nΛCDM	1.3	7.4	3.1	1	0.23	3.3	4.7	4.2	6.2	0.19
KΛCDM	1.3	5.9	3.8	0	-0.59	2.6	8.5	3.2	5	4.8
ΛCDM	1.2	6.9	3.4	0.99	-0.045	2.6	4.9	2.5	5.6	0.52

Github repository for `unimpeded` (top) and this poster (bottom).

References

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