

# unimpeded: A Public Nested Sampling Database for Bayesian Cosmology

Dily Duan Yi Ong <sup>1,2,3</sup>¶ and Will Handley <sup>1,2</sup>

<sup>1</sup> Kavli Institute for Cosmology, Madingley Road, Cambridge, CB3 0HA, UK <sup>2</sup> Astrophysics Group, Cavendish Laboratory, J.J. Thomson Avenue, Cambridge, CB3 0HE, UK <sup>3</sup> Newnham College, Sidgwick Avenue, Cambridge, CB3 9DF, UK ¶ Corresponding author

DOI: [10.xxxxxx/draft](https://doi.org/10.xxxxxx/draft)

Software

- [Review](#) 
- [Repository](#) 
- [Archive](#) 

Editor: [Open Journals](#) 

Viewers:

- [@openjournals](#)

Submitted: unsubmitted

Published: unpublished

License

Authors of papers retain copyright and release the work under a Creative Commons Attribution 4.0 International license ([CC BY 4.0](#)).

## Summary

Bayesian inference is central to modern cosmology. While parameter estimation is achievable with unnormalised posteriors traditionally obtained via MCMC methods, comprehensive model comparison and tension quantification require Bayesian evidences and normalised posteriors, which remain computationally prohibitive for many researchers. To address this, we present *unimpeded*, a publicly available Python library and data repository providing DiRAC-funded (DP192 and 264) pre-computed nested sampling and MCMC chains with their normalised posterior samples, computed using Cobaya (Torrado & Lewis, 2021) and the Boltzmann solver CAMB (Lewis et al., 2000; Lewis & Bridle, 2002). *unimpeded* delivers systematic analysis across a grid of eight cosmological models (including  $\Lambda$ CDM and seven extensions) and 39 modern cosmological datasets (comprising individual probes and their pairwise combinations). The built-in tension statistics calculator enables rapid computation of six tension quantification metrics. All chains are hosted on Zenodo<sup>1</sup> with permanent access via the *unimpeded* API, analogous to the renowned Planck Legacy Archive (Dupac et al., 2015) but utilising nested sampling (Skilling, 2006) in addition to traditional MCMC methods.

## unimpeded

*unimpeded* addresses these challenges directly. It provides a pip-installable tool that leverages the *anesthetic* package (W. Handley, 2019) for analysis and introduces a seamless Zenodo integration for data management. The nested sampling theory and methodology are detailed in (Ong & Handley, 2025). Its main features are:

- A Public Nested Sampling Grid:** The package provides access to a pre-computed grid of nested sampling chains and MCMC chains for 8 cosmological models (standard  $\Lambda$ CDM and seven extensions), run against 39 datasets (comprising individual probes and their pairwise combinations). This saves the community significant computational resources and provides a common baseline for new analyses. Evidence and Kullback-Leibler divergence can be calculated jointly with *anesthetic* for model comparison and quantifying the constraining power of datasets and models, respectively. The scientific results from this grid are presented in (Ong & Handley, 2025).
- Archival and Reproducibility via Zenodo:** *unimpeded* automates the process of archiving analysis products. The `DatabaseCreator` class bundles chains and metadata, uploading them to a Zenodo community to generate a permanent, citable Digital Object Identifier (DOI). The `DatabaseExplorer` class allows public user to easily download and analyse these chains, promoting open science and effortless reproducibility. Figure 1 illustrates the *unimpeded* ecosystem, detailing its three core functions. For data

<sup>1</sup><https://zenodo.org/>

generation, it configures YAML files for HPC nested sampling. It then archives the chains on Zenodo, ensuring reproducibility with permanent DOIs, and finally provides an interface for post-processing analysis and visualisation with *anesthetic*. The following example demonstrates downloading chains:

```
from unimpeded.database import DatabaseExplorer

# Initialise DatabaseExplorer
dbe = DatabaseExplorer()

# Get a list of currently available models and datasets
models_list = dbe.models
datasets_list = dbe.datasets

# Choose model, dataset and sampling method
method = 'ns' # 'ns' for nested sampling, 'mcmc' for MCMC
model = "klcdm" # from models_list
dataset = "des_y1.joint+planck_2018_CamSpec" # from datasets_list

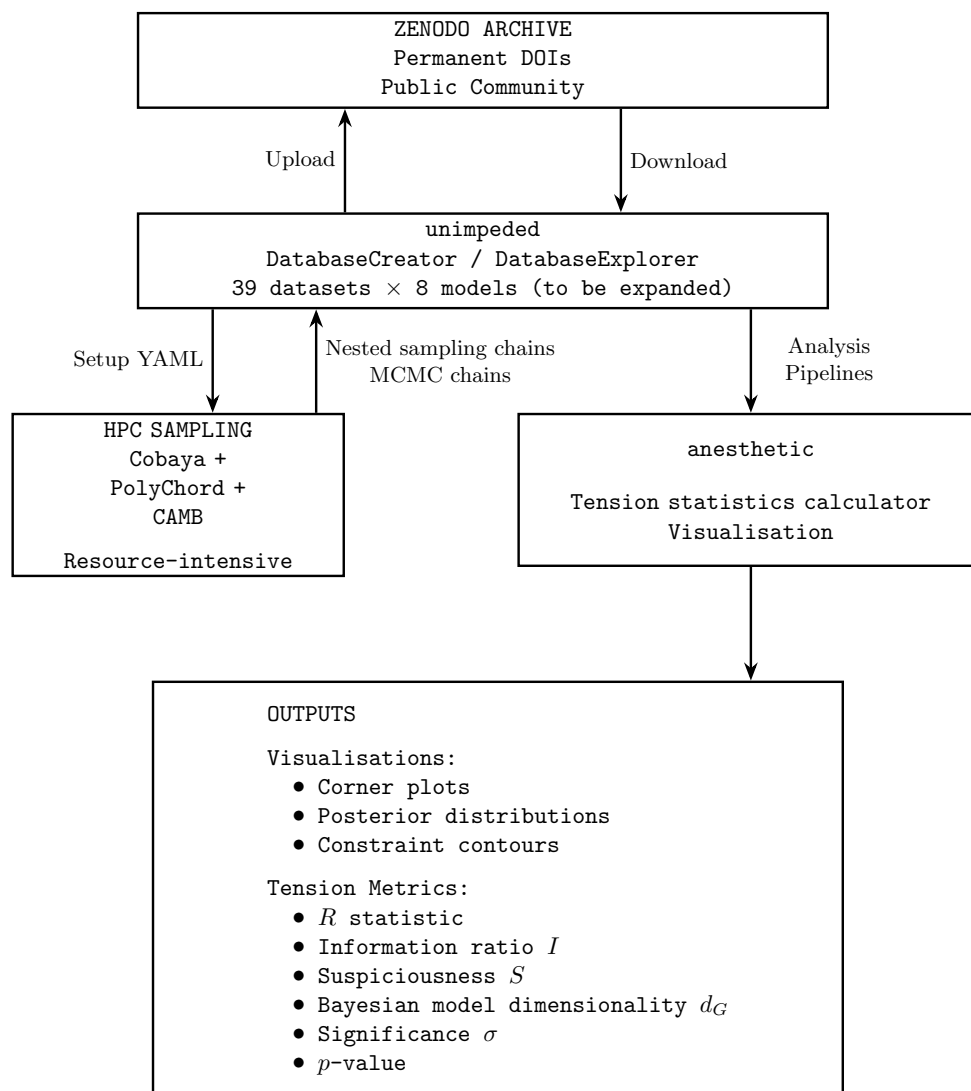
# Download samples chain
samples = dbe.download_samples(method, model, dataset)

# Download Cobaya and PolyChord run settings
info = dbe.download_info(method, model, dataset)
```

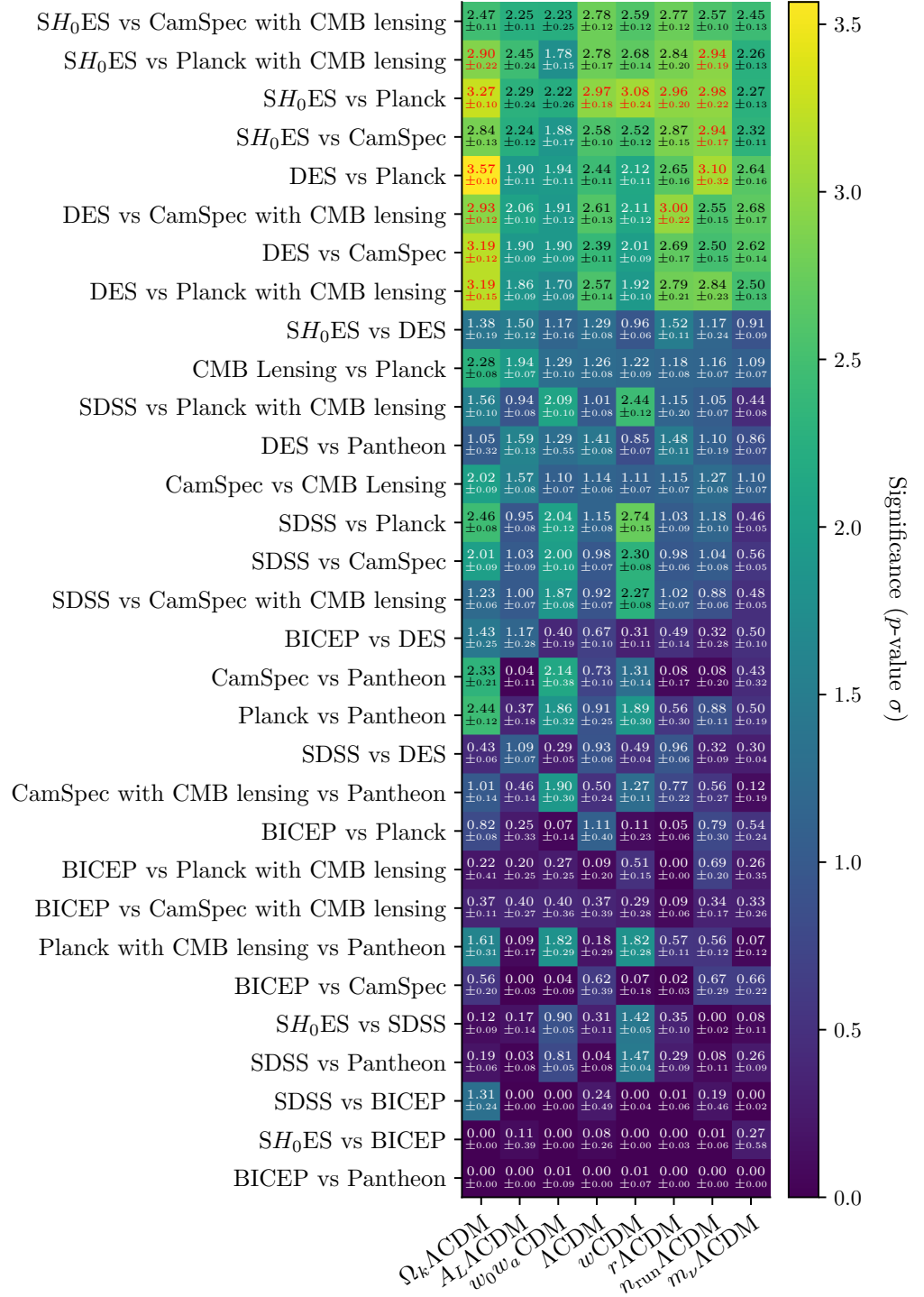
1. **Tension Statistics Calculator:** With the nested sampling chains and the built-in tension statistics calculator, six tension quantification metrics with different characteristics are available, including the  $R$  statistic, information ratio  $I$ , suspiciousness  $S$ , Gaussian model dimensionality  $d_G$ , tension significance in units of  $\sigma$ , and p-value. Each of them has unique characteristics optimised for different tasks, thoroughly discussed in (Ong & Handley, 2025). *unimpeded* implements these statistics with the necessary correction to account for discarded prior volume (W. Handley & Lemos, 2019; Will Handley & Lemos, 2021; Ong & Handley, 2025). Figure 2 demonstrates the tension calculator output showing p-value derived tension significance ( $\sigma$ ) for 31 pairwise dataset combinations across 8 cosmological models, sorted by significance to highlight the datasets in tension. Caution should be exercised when combining them. The following minimal example demonstrates the usage:

```
from unimpeded.tension import tension_calculator

tension_samples = tension_calculator(method='ns',
                                       model='lcdm',
                                       datasetA='planck_2018_CamSpec',
                                       datasetB='des_y1.joint',
                                       nsamples=1000)
```



**Figure 1:** The unimpeded ecosystem and workflow. At the centre, unimpeded manages data archival and retrieval through Zenodo, providing permanent DOIs and public access to pre-computed chains. For data generation, unimpeded configures YAML files for resource-intensive HPC nested sampling using Cobaya, PolyChord, and CAMB. For analysis, users download chains via DatabaseExplorer and leverage anesthetic for visualisation (corner plots, posterior distributions, constraint contours) and tension quantification (six metrics:  $R$  statistic, information ratio  $I$ , suspiciousness  $S$ , Bayesian model dimensionality  $d_G$ , significance  $\sigma$ , and  $p$ -value).



**Figure 2:** Tension analysis heatmap produced by unimpeded and anesthetic displaying p-value derived tension significance ( $\sigma$  values) for 31 pairwise dataset combinations across 8 cosmological models. Rows are sorted by significance, with the most problematic dataset pairs (highest tension) at the top. This demonstrates unimpeded’s capability to systematically quantify tensions and their model dependence.

While tools like getdist (Lewis, 2019) are excellent for MCMC analysis, and frameworks like CosmoSIS (Zuntz et al., 2015) or MontePython (Brinckmann & Lesgourgues, 2019) are used

for running simulations with samplers like Cobaya (Torrado & Lewis, 2021), unimpeded fills a unique niche. It is not a sampler but a high-level analysis and database management tool that extends the capabilities of its underlying engine, *anesthetic*, to create a public, reproducible, and statistically robust nested sampling resource for the cosmology community.

The package is fully documented, tested, and available for installation via the Python Package Index (PyPI). A Jupyter notebook tutorial is also available to help users get started.

## Acknowledgements

We thank the developers of the open-source packages that this work relies upon, including *anesthetic*, *numpy*, *scipy*, *pandas*, and *corner.py*. This work was performed using the Cambridge Service for Data Driven Discovery (CSD3), operated by the University of Cambridge Research Computing Service, provided by Dell EMC and Intel using Tier-2 funding from the Engineering and Physical Sciences Research Council (capital grant EP/P020259/1), and DiRAC funding from the Science and Technology Facilities Council ([www.dirac.ac.uk](http://www.dirac.ac.uk)).

## References

- Brinckmann, T., & Lesgourgues, J. (2019). MontePython 3: boosted MCMC sampler and other features. *Physics of the Dark Universe*, 24. <https://doi.org/10.1016/j.dark.2018.100260>
- Dupac, X., Arviset, C., Fernandez Barreiro, M., Lopez-Caniego, M., & Tauber, J. (2015, December). The Planck Legacy Archive. *Science Operations 2015: Science Data Management*. <https://doi.org/10.5281/zenodo.34639>
- Handley, W. (2019). *anesthetic*: nested sampling visualisation. *Journal of Open Source Software*, 4(37), 1414. <https://doi.org/10.21105/joss.01414>
- Handley, W., & Lemos, P. (2019). Quantifying tension: interpreting the DES evidence ratio. *Physical Review D*, 100(4). <https://doi.org/10.1103/PhysRevD.100.043504>
- Handley, Will, & Lemos, P. (2021). Quantifying the global parameter tensions between ACT, SPT, and Planck. *Physical Review D*, 103(6). <https://doi.org/10.1103/PhysRevD.103.063529>
- Lewis, A. (2019). GetDist: a Python package for analysing Monte Carlo samples. *arXiv e-Prints*. <https://arxiv.org/abs/1910.13970>
- Lewis, A., & Bridle, S. (2002). Cosmological parameters from CMB and other data: A Monte Carlo approach. *Physical Review D*, 66(10), 103511. <https://doi.org/10.1103/PhysRevD.66.103511>
- Lewis, A., Challinor, A., & Lasenby, A. (2000). Efficient Computation of Cosmic Microwave Background Anisotropies in Closed Friedmann-Robertson-Walker Models. *The Astrophysical Journal*, 538, 473–476. <https://doi.org/10.1086/309179>
- Ong, D. D. Y., & Handley, W. (2025). Tension statistics for nested sampling. *arXiv e-Prints*. <https://arxiv.org/abs/2511.04661>
- Skilling, J. (2006). Nested sampling for general bayesian computation. *Bayesian Analysis*, 1(4), 833–859. <https://doi.org/10.1214/06-BA127>
- Torrado, J., & Lewis, A. (2021). Cobaya: Code for Bayesian analysis of hierarchical physical models. *Journal of Cosmology and Astroparticle Physics*, 2021(05), 057. <https://doi.org/10.1088/1475-7516/2021/05/057>
- Zuntz, J., Paterno, M., Jennings, E., Rudd, D., Manzotti, A., Dodelson, S., Bridle, S., Sehrish,

S., & Kowalkowski, J. (2015). CosmoSIS: Modular cosmological parameter estimation. *Astronomy and Computing*, 12, 45–59. <https://doi.org/10.1016/j.ascom.2015.05.005>