

# nestcheck: error analysis, diagnostic tests and plots for nested sampling calculations

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#### Software

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## Summary

Nested sampling (Skilling, 2006) is a popular Monte Carlo method for Bayesian analysis which, given some likelihood and prior, provides both samples from the posterior distribution and an estimate of the Bayesian evidence. Due to the distinctive manner in which the nested sampling algorithm explores the parameter space, it produces posterior samples with different statistical properties to those generated from alternative techniques such as Markov chain Monte Carlo (MCMC)-based approaches. As a result, posterior inferences and estimates of their associated uncertainties require methods specific to nested sampling.

nestcheck is a Python package for analysing samples produced by nested sampling, and estimating uncertainty on posterior inferences. Most importantly, nestcheck contains fast and well-tested implementations of the error analysis methods introduced in (Higson, Handley, Hobson, & Lasenby, 2018a) and the diagnostic tests and plots described in (Higson, Handley, Hobson, & Lasenby, 2018b). The code has been profiled for computational efficiency and uses fast numpy functions and parallelisation with concurrent.futures. The diagnostic plots make use of the matplotlib (Hunter, 2007) and fgivenx (Handley, 2018) packages.

nestcheck can analyse samples from the popular MultiNest (Feroz & Hobson, 2008; Feroz, Hobson, & Bridges, 2008; Feroz, Hobson, Cameron, & Pettitt, 2013) and PolyChord (W. J. Handley, Hobson, & Lasenby, 2015a, 2015b) packages, and functions for loading samples from other software packages with different formats can easily be added. nestcheck is also compatible with samples produced by the dynamic nested sampling algorithm (Higson, Handley, Hobson, & Lasenby, 2017), and its functions for storing and manipulating nested sampling output are used by the dyPolyChord (Higson, 2018a) and perfectns (Higson, 2018b) dynamic nested sampling packages.

nestcheck is designed to allow nested sampling software users to quickly calculate results and uncertainty estimates, as well as to apply diagnostics for checking their software has explored the posterior correctly. It was used for the diagnostic tests and plots in (Higson et al., 2018b), and for error analysis in (Higson et al., 2017) and (Higson, Handley, Lasenby, & Hobson, 2018). An earlier version of the code was used in the analysis of black hole mergers in (Chua et al., 2018). The source code for nestcheck has been archived to Zenodo (Higson, 2018c).

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### References

Chua, A. J. K., Hee, S., Handley, W. J., Higson, E., Moore, C. J., Gair, J. R., Hobson, M. P., et al. (2018). Towards a framework for testing general relativity with extreme-mass-ratio-inspiral observations. *Monthly Notices of the Royal Astronomical Society*, 478(1), 28–40. doi:10.1093/mnras/sty1079

Feroz, F., & Hobson, M. P. (2008). Multimodal nested sampling: An efficient and robust alternative to Markov Chain Monte Carlo methods for astronomical data analyses. *Monthly Notices of the Royal Astronomical Society*, 384(2), 449–463. doi:10.1111/j.1365-2966.2007.12353.x

Feroz, F., Hobson, M. P., & Bridges, M. (2008). MultiNest: an efficient and robust Bayesian inference tool for cosmology and particle physics. *Monthly Notices of the Royal Astronomical Society*, 398(4), 1601–1614. doi:10.1111/j.1365-2966.2009.14548.x

Feroz, F., Hobson, M. P., Cameron, E., & Pettitt, A. N. (2013). Importance Nested Sampling and the MultiNest Algorithm. arXiv preprint arXiv:1306.2144. Retrieved from https://arxiv.org/abs/1306.2144

Handley, W. (2018). fgivenx: A Python package for functional posterior plotting. *Journal of Open Source Software*, 3(28), 849. doi:10.21105/joss.00849

Handley, W. J., Hobson, M. P., & Lasenby, A. N. (2015a). PolyChord: Nested sampling for cosmology. *Monthly Notices of the Royal Astronomical Society: Letters*, 450(1), L61–L65. doi:10.1093/mnrasl/slv047

Handley, W. J., Hobson, M. P., & Lasenby, A. N. (2015b). PolyChord: next-generation nested sampling. *Monthly Notices of the Royal Astronomical Society*, 15, 1–15. doi:10.1093/mnras/stv1911

Higson, E. (2018a). dy PolyChord: dynamic nested sampling with PolyChord. doi: 10.5281/zenodo.1328175

Higson, E. (2018b). Perfectns: Perfect dynamic and standard nested sampling for spherically symmetric likelihoods and priors. doi:10.5281/zenodo.1327591

Higson, E. (2018c). Nestcheck: Error analysis, diagnostic tests and plots for nested sampling calculations. doi:10.5281/zenodo.1329513

Higson, E., Handley, W., Hobson, M., & Lasenby, A. (2017). Dynamic nested sampling: an improved algorithm for parameter estimation and evidence calculation. arXiv preprint arXiv:1704.03459. Retrieved from https://arxiv.org/abs/1704.03459

Higson, E., Handley, W., Hobson, M., & Lasenby, A. (2018a). Sampling errors in nested sampling parameter estimation. *Bayesian Analysis*, 13(3), 873–896. doi:doi:10.1214/17-BA1075

Higson, E., Handley, W., Hobson, M., & Lasenby, A. (2018b). Diagnostic Tests for Nested Sampling Calculations. arXiv preprint arXiv:1804.06406. Retrieved from https://arxiv.org/abs/1804.06406

Higson, E., Handley, W., Lasenby, A., & Hobson, M. (2018). Bayesian Sparse Reconstruction: a brute-force approach to astronomical imaging and machine learning. *in preparation*.

Hunter, J. D. (2007). Matplotlib: A 2D graphics environment. Computing in Science and Engineering, 9(3), 90–95. doi:https://doi.org/10.1109/MCSE.2007.55

Skilling, J. (2006). Nested sampling for general Bayesian computation. Bayesian Analysis, 1(4), 833–860. doi:10.1214/06-BA127