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dyPolyChord: dynamic nested sampling with PolyChord

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Software

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Summary

Nested sampling (Skilling, 2006) is a popular numerical method for calculating Bayesian evidences and generating posterior samples given some likelihood and prior. The initial development of the algorithm was targeted at evidence calculation, but implementations such as `MultiNest` (Feroz & Hobson, 2008; Feroz, Hobson, & Bridges, 2008; Feroz, Hobson, Cameron, & Pettitt, 2013) and `PolyChord` (W. J. Handley, Hobson, & Lasenby, 2015a, 2015b) are now used extensively for parameter estimation in scientific research (and in particular in astrophysics); see for example (Chua et al., 2018; DES Collaboration, 2018). Nested sampling performs well compared to Markov chain Monte Carlo (MCMC)-based alternatives at exploring multimodal and degenerate distributions, and the `PolyChord` software is well-suited to high-dimensional problems.

Dynamic nested sampling (Higson, Handley, Hobson, & Lasenby, 2017) is a generalisation of the nested sampling algorithm which dynamically allocates samples to the regions of the posterior where they will have the greatest effect on calculation accuracy. This allows order-of-magnitude increases in computational efficiency, with the largest gains for high dimensional parameter estimation problems.

`dyPolyChord` implements dynamic nested sampling using the efficient `PolyChord` sampler to provide state-of-the-art nested sampling performance. Like `PolyChord`, `dyPolyChord` is optimized for calculations where the main computational cost is sampling new live points. For empirical tests of `dyPolyChord`'s performance, see the dynamic nested sampling paper (Higson et al., 2017); these tests can be reproduced using the code at https://github.com/ejhigson/dns.

`dyPolyChord` uses a version of the dynamic nested sampling algorithm designed to minimise the computational overhead of allocating additional samples, so this should typically be a small part of the total computational cost. However this overhead may become significant for calculations where likelihood evaluations are fast and a large number of MPI processes are used (the saving, loading and processing of the initial exploratory samples is not currently fully parallelised). It is also worth noting that `PolyChord`'s slice sampling-based implementation is less efficient than `MultiNest` (which uses rejection sampling) for low dimensional problems, although for calculations using `dyPolyChord` this is may be offset by efficiency gains from dynamic nested sampling. See (W. J. Handley et al., 2015b) for more details.

`dyPolyChord` output files are in the same format as those produced by `PolyChord`. The package is compatible with Python, C++ and Fortran likelihoods, and is parallelised with MPI. In addition to `PolyChord`, `dyPolyChord` requires `mpi4py` (Dalcin, Paz, Kler, & Cosimo, 2011), `nestcheck` (Higson, 2018a, Higson, Handley, Hobson, & Lasenby (2018a), Higson, Handley, Hobson, & Lasenby (2018b)), `scipy` (Jones, Oliphant, Peterson, & Others, 2001) and `numpy` (T. E. Oliphant, 2006). Two alternative publicly available dynamic

nested sampling packages are `dynesty` (pure Python, see https://github.com/joshspeagle/dynesty for more information) and `perfectns` (pure Python, spherically symmetric likelihoods only) (Higson, 2018b).

`dyPolyChord` was used for the numerical tests in the dynamic nested sampling paper (Higson et al., 2017), and parts of its functionality and interfaces were used in the code for (Higson et al., 2018a). It has been applied to sparse reconstruction, including of astronomical images, in (Higson, Handley, Lasenby, & Hobson, 2018). The source code for `dyPolyChord` has been archived to Zenodo (Higson, 2018c).

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