anesthetic: nested sampling visualisation

Will Handley¹, ², ³

¹ Astrophysics Group, Cavendish Laboratory, J.J.Thomson Avenue, Cambridge, CB3 0HE, UK ² Kavli Institute for Cosmology, Madingley Road, Cambridge, CB3 0HA, UK ³ Gonville & Caius College, Trinity Street, Cambridge, CB2 1TA, UK

Summary

anesthetic is a Python package for processing nested sampling runs, and will be useful for any scientist or statistician who uses nested sampling software. anesthetic unifies many existing tools and techniques in an extensible framework that is intuitive for users familiar with the standard Python packages, namely NumPy, SciPy, Matplotlib and pandas. It has been extensively used in recent cosmological papers (W. Handley and Lemos 2019a, 2019b).

Nested sampling

Nested sampling (Skilling 2006) is an alternative to Markov-Chain-Monte-Carlo techniques (Hastings 1970). Given some data \(D\), for a scientific model \(M\) with free parameters \(\theta\), Bayes theorem states:

\[
P(\theta|D) = \frac{P(D|\theta)P(\theta)}{P(D)}
\]

Traditional MCMC approaches ignore the Bayesian evidence \(P(D)\) and instead focus on the problem of generating samples from the posterior \(P(\theta|D)\) using knowledge of the prior \(P(\theta)\) and likelihood \(P(D|\theta)\). Nested sampling reverses this priority, and instead computes the evidence \(P(D)\) (the critical quantity in Bayesian model comparison (Trotta 2008)), producing posterior samples as a by-product. Nested sampling does this by evolving a set of live points drawn from the prior under a hard likelihood constraint which steadily increases, causing the live points to contract around the peak(s) of the likelihood. The history of the live-point evolution can be used to reconstruct both the evidence and posterior samples, as well as the density of states and consequently the full partition function.

Current publicly available implementations of nested sampling include MultiNest (Feroz, Hobson, and Bridges 2009), PolyChord (W. J. Handley, Hobson, and Lasenby 2015a, 2015b; Higson 2018), DNest (Brewer and Foreman-Mackey 2018) and dynesty (Speagle 2019), all of which have been incorporated into a wide range of cosmological (Lewis and Bridle 2002; Zuntz et al. 2015; Brinckmann and Lesgourgues 2019) and particle physics (The GAMBIT Scanner Workgroup: 2017) codes.

aNESThetic

anesthetic acts on outputs of nested sampling software packages. It can:
Figure 1: Marginalised posterior plots produced by anesthetic. The x axes indicate the fraction of normal matter, dark matter and dark energy respectively, whilst the y-axis is the amplitude of mass fluctuation in our late-time universe. The three measurements were performed using measurements of baryonic acoustic oscillations, large scale structure and the cosmic microwave background (W. Handley and Lemos 2019a). It is an open cosmological and statistical questions whether the LSS and CMB are consistent with one another.

1. Compute inferences of the Bayesian evidence (Trotta 2008), the Kullback-Leibler divergence (Kullback and Leibler 1951) of the distribution, the Bayesian model dimensionality (W. Handley and Lemos 2019b) and the full partition function.
2. Dynamically replay nested sampling runs.
3. Produce one- and two-dimensional marginalised posterior plots (Figure 1).

A subset of computations from item 1 is provided by many of the nested sampling software packages. anesthetic allows you to compute these independently and more accurately, providing a unified set of outputs and separating these computations from the generation of nested samples.

Item 2 is useful for users that have experienced the phenomenon of ‘live point watching’ – the process of continually examining the evolution of the live points as the run progresses in an attempt to diagnose problems in likelihood and/or sampling implementations. The GUI provided allows users to fully reconstruct the run at any iteration, and examine the effect of dynamically adjusting the thermodynamic temperature.

Finally, it is important to recognise that the functionality from item 3 is also provided by many other high-quality software packages, such as getdist (Lewis 2015), corner (Foreman-Mackey 2016), pygtc (Boquet and Carter 2016), dynasty (Speagle 2019) and MontePython (Brinckmann and Lesgourgues 2019). anesthetic adds to this functionality by:

- Performing kernel density estimation using the state-of-the-art fastkde (O’Brien et al. 2016) algorithm.
- Storing samples and plotting grids as a weighted pandas.DataFrame, which is more consistent with the scientific Python canon, allows for unambiguous access to samples and plots via their reference names, and easy definition of new parameters.
- Using a contour colour scheme that is better suited to plotting distributions with uniform probability, which is important if one wishes to plot priors along with posteriors.

The source code for anesthetic is available on GitHub, with its automatically generated documentation at ReadTheDocs and a pip-installable package on PyPi. An example
interactive Jupyter notebook is given using Binder (Jupyter et al. 2018). Continuous integration is implemented with Travis and Circle.

Acknowledgements

Bug-testing was provided by Pablo Lemos.

References

Bocquet, Sebastian, and Faustin W. Carter. 2016. “Pygtc: Beautiful Parameter Covariance Plots (Aka. Giant Triangle Confusograms).” *The Journal of Open Source Software* 1 (6). https://doi.org/10.21105/joss.00046.

Brewer, Brendon, and Daniel Foreman-Mackey. 2018. “Dnest4: Diffusive Nested Sampling in C++ and Python.” *Journal of Statistical Software, Articles* 86 (7): 1–33. https://doi.org/10.18637/jss.v086.i07.

Brinckmann, Thejs, and Julien Lesgourgues. 2019. “MontePython 3: Boosted MCMC Sampler and Other Features.” *Physics of the Dark Universe* 24: 100260. https://doi.org/10.1016/j.dark.2018.100260.

Feroz, F., M. P. Hobson, and M. Bridges. 2009. “MULTINEST: an efficient and robust Bayesian inference tool for cosmology and particle physics.” *Monthly Notices of the Royal Astronomical Society* 398 (October): 1601–14. https://doi.org/10.1111/j.1365-2966.2009.14548.x.

Foreman-Mackey, Daniel. 2016. “Corner.py: Scatterplot Matrices in Python.” *The Journal of Open Source Software* 24. https://doi.org/10.21105/joss.00024.

Handley, Will, and Pablo Lemos. 2019a. “Quantifying tension: interpreting the DES evidence ratio.” *arXiv E-Prints*, February, arXiv:1902.04029. http://arxiv.org/abs/1902.04029.

Handley, Will, and Pablo Lemos. 2019b. “Quantifying dimensionality: Bayesian cosmological model complexities.” *arXiv E-Prints*, March, arXiv:1903.06682. http://arxiv.org/abs/1903.06682.

Handley, W. J., M. P. Hobson, and A. N. Lasenby. 2015a. “POLYCHORD: nested sampling for cosmology.” *Monthly Notices of the Royal Astronomical Society* 450 (June): L61–L65. https://doi.org/10.1093/mnrasl/slv047.

Handley, W. J., M. P. Hobson, and A. N. Lasenby. 2015b. “POLYCHORD: next-generation nested sampling.” *Monthly Notices of the Royal Astronomical Society* 453 (November): 4384–98. https://doi.org/10.1093/mnras/stv1911.

Hastings, W. K. 1970. “Monte Carlo Sampling Methods Using Markov Chains and Their Applications.” *Biometrika* 57 (1): 97–109. https://doi.org/10.2307/2334940.

Higson, Edward. 2018. “dyPolyChord: Dynamic Nested Sampling with PolyChord.” *Journal of Open Source Software* 3 (29): 916. https://doi.org/10.21105/joss.00965.

Jupyter et al. 2018. “Binder 2.0 - Reproducible, Interactive, sharable Environments for Science at Scale.” In. Proceedings of the 17th Python in Science Conference. https://doi.org/10.25080/Majora-4af1f417-011.

Kullback, S., and R. A. Leibler. 1951. “On Information and Sufficiency.” *Ann. Math. Statist.* 22 (1): 79–86. https://doi.org/10.1214/aoms/1177729694.
Lewis, Anthony. 2015. “Getdist Github Repository.” https://github.com/cmbant/getdist.

Lewis, Antony, and Sarah Bridle. 2002. “Cosmological parameters from CMB and other data: A Monte Carlo approach.” Phys. Rev. D66: 103511. https://doi.org/10.1103/PhysRevD.66.103511.

O’Brien, Travis A., Karthik Kashinath, Nicholas R. Cavanaugh, William D. Collins, and John P. O’Brien. 2016. “A Fast and Objective Multidimensional Kernel Density Estimation Method: FastKDE.” Computational Statistics & Data Analysis 101: 148–60. https://doi.org/10.1016/j.csda.2016.02.014.

Skilling, John. 2006. “Nested Sampling for General Bayesian Computation.” Bayesian Analysis. 1 (4): 833–59. https://doi.org/10.1214/06-BA127.

Speagle, Joshua S. 2019. “dynesty: A Dynamic Nested Sampling Package for Estimating Bayesian Posteriors and Evidences.” arXiv E-Prints, April, arXiv:1904.02180. http://arxiv.org/abs/1904.02180.

The GAMBIT Scanner Workgroup.. 2017. “Comparison of Statistical Sampling Methods with Scannerbit, the Gambit Scanning Module.” The European Physical Journal C 77 (11): 761. https://doi.org/10.1140/epjc/s10052-017-5274-y.

Trotta, R. 2008. “Bayes in the sky: Bayesian inference and model selection in cosmology.” Contemporary Physics 49 (March): 71–104. https://doi.org/10.1080/00107510802066753.

Zuntz, J., M. Paterno, E. Jennings, D. Rudd, A. Manzotti, S. Dodelson, S. Bridle, S. Schrish., and J. Kowalkowski. 2015. “CosmoSIS: Modular cosmological parameter estimation.” Astronomy and Computing 12 (September): 45–59. https://doi.org/10.1016/j.ascom.2015.05.005.