

SEPTEMBER 2025  
VOL. 32 NO. 3



INTERNATIONAL SOCIETY FOR BAYESIAN ANALYSIS

# THE ISBA BULLETIN

OFFICIAL BULLETIN OF THE INTERNATIONAL SOCIETY FOR BAYESIAN ANALYSIS

## SOFTWARE HIGHLIGHT

Luca Porta Mana

[pgl@portamana.org](mailto:pgl@portamana.org)

### INFERNO INFERENCE IN R WITH BAYESIAN NONPARAMETRICS

A very important kind of inference in research fields such as medicine is *population inference*, often also called “density inference” or “density regression”. Its general goal is to infer the frequency distribution of some variates in a population. This is different, for instance, from *functional regression*, where the goal is to infer the functional relationship – assumed to exist – between a set of predictor variates and a target or “predictand” variate. In population inference the existence of a functional relation cannot be assumed; in fact there may not even be a clear distinction between predictor and predictand variates. A clinician may want to know the probability of a medical condition given a symptom, but also that of a symptom given a medical condition. And neither need be fully determined by the other. De Finetti’s theorem (see e.g. [Bernardo and Smith, 2000](#), §§ 4.2, 4.3, 4.6) lies at the heart of population-inference methods; a particularly discussion is given by Lindley & Novick (1981).

Many researchers in important fields, such as medicine, sadly still use  $p$ -values and frequentist statistics to do *population inference*, despite their intrinsic flaws. Some researchers use Bayesian methods but limit themselves to parametric ones, which make possibly unrealistic statistical assumptions.

Until a couple decades ago such practices could somehow be justified by pragmatic reasons:

- Better methods were computationally too expensive.
- The population-inference problems were low-dimensional; one could *visually* check whether the method or assumptions were appropriate to the problem, and change them otherwise, or consider the results as simply qualitative.

But today, in many cases, the reasons above cannot meaningfully be given anymore:

- Bayesian methods, even nonparametric, have become computationally feasible for many inference problems.
- Many population-inference problems today involve tens or hundreds of variates of different kinds, and are therefore very high-dimensional. It is impossible to visually check whether frequentist results or parametric assumptions are acceptable, or by how much they err. Results may therefore be affected by large errors ([Draper, 1995](#)), whose existence is often not even reported.

There is one reason that can still be given today for not using Bayesian methods, especially parametric ones, in population inference: *lack of user-friendly software*. Clinicians who’d be curious to try out Bayesian analysis of their studies simply can’t, because that would require the study of Markov-chain Monte Carlo techniques, of programming languages to implement them, and of a plethora of debated methods and acquired visual skills to “assess convergence”. Most clinicians don’t have time to learn all this even if they wanted to.

Available packages for Bayesian nonparametrics focus moreover on the problem of *regression*, that is, the inference of a functional relationship – assumed to exist – between a set of predictor variates and

a target or “predictand” variate. These packages are not appropriate to *population inference*, where no functional relationships exist a priori, and where often there is no a priori division between predictor and predictand variates. In clinical studies one may be interested in calculating the probability of an effect or symptom given a condition, and of a condition given an effect or symptom.

The R-package **inferno** was built to try to fill the need for this kind of software.

(Walker, 2010)

## References

- J.-M. Bernardo and A. F. Smith. *Bayesian Theory*. Wiley series in probability and mathematical statistics. Wiley, New York, repr. edition, 2000. doi: 10.1002/9780470316870. First publ. 1994.
- D. Draper. Assessment and propagation of model uncertainty. *J. R. Stat. Soc. B*, 57(1):45–70, 1995. doi: 10.1111/j.2517-6161.1995.tb02015.x. See also discussion and reply in Spiegelhalter et al. (1995).
- N. L. Hjort, C. Holmes, P. Müller, and S. G. Walker, editors. *Bayesian Nonparametrics*. Cambridge series in statistical and probabilistic mathematics. Cambridge University Press, Cambridge, 2010. doi: 10.1017/CBO9780511802478.
- D. V. Lindley and M. R. Novick. The role of exchangeability in inference. *Ann. Stat.*, 9(1):45–58, 1981. doi: 10.1214/aos/1176345331.
- D. J. Spiegelhalter, A. P. Grieve, D. V. Lindley, D. V. Lindley, J. B. Copas, A. J. G. Cairns, C. Chatfield, G. Box, D. Cox, J. W. Tukey, A. E. Raftery, M. Aitkin, G. A. Barnard, P. Donnelly, A. S. C. Ehrenberg, A. E. Gelfand, B. K. Mallick, A. Gelman, X.-L. Meng, C. A. Glasbey, G. J. Gibson, R. Glendinning, U. Hjorth, R. E. Kass, L. Wasserman, M. Lavine, D. Madigan, B. M. Pötscher, J. W. Pratt, A. F. de Vos, B. J. Worton, A. Zellner, and D. Draper. Discussion of the paper by Draper. *J. R. Stat. Soc. B*, 57(1):71–97, 1995. doi: 10.1111/j.2517-6161.1995.tb02016.x. See Draper (1995).
- S. G. Walker. Bayesian nonparametric methods: motivation and ideas. In Hjort et al. (2010), chapter ch. 1, pages 22–34. 2010. doi: 10.1017/CBO9780511802478.002.