Nonparametric models can be checked[1]

Andrew Gelman

28 Feb 2013

Muller and Mitra present an excellent motivation and overview of Bayesian nonparametric models, and in fact their article could have gone on longer, to include models such as Bayesian additive regression trees (Chipman, George, and McCulloch, 2010) which have the potential to revolutionize the practice of causal inference by allowing researchers to directly model potential outcomes (Hill, 2011), avoiding the traditional and often counterproductive focus on average treatment effects and restricted domains of inference. And I am sure there are many other areas of application where Bayesian nonparametrics can allow for scientific advances by allowing researchers to focus on modeling phenomena of interest rather than getting distracted by issues of identification and functional forms.

Bayesian data analysis can be fruitfully considered (Gelman et al., 1995) as an iteration of three steps: (1) model building, (2) inference, and (3) model checking. Compared to traditional Bayesian methods, nonparametric Bayes represents an additional modeling investment in step 1, with the gains coming in step 2 (more accurate models and predictions) and in step 3 (better fit to data).

For all their flexibility, however, nonparametric models are still models. They have assumptions and their fit to data can be checked by comparing observed data to hypothetical replicated datasets simulated from the fitted model (Rubin, 1984, Gelman, Meng, and Stern, 1996). The good news is that, in an environment in which models are fit using posterior simulations, it is typically trivial (in both the mathematical and computational senses) to simulate replicated datasets. Based on our own experiences, we think the most effective model checks are graphical—but this is no problem either, as such checks are a simple step forward beyond the graphical displays of inferences and data that are becoming standard best practice in nonparametric inference (as illustrated, for example, in Figures 1, 7, and 9 of the paper under discussion). The same sorts of displays that are informative about data can directly be used to explore model fit by comparison to simulated replications.

References

Chipman, H., George, E., and McCulloch, R. (2010). BART: Bayesian additive regression trees. *Annals of Applied Statistics* 4, 266-298.

[1] Discussion of "Bayesian nonparametric inference – why and how," by Peter Muller and Riten Mitra, for *Bayesian Analysis*. We thank the National Science Foundation for partial support of this work.

Gelman, A., Carlin, J. B., Stern, H. S., and Rubin, D. B. (1995). *Bayesian Data Analysis*. London: Chapman and Hall.

Gelman, A., Meng, X. L., and Stern, H. S. (1996). Posterior predictive assessment of model fitness via realized discrepancies (with discussion). *Statistica Sinica* 6, 733-807.

Hill, J. L. (2011). Bayesian nonparametric modeling for causal inference. *Journal of Computational and Graphical Statistics* 20, 217-240.

Rubin, D. B. (1984). Bayesianly justifiable and relevant frequency calculations for the applied statistician. *Annals of Statistics* 12, 1151-1172.