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Comment: "Models as Approximations I: Consequences Illustrated with Linear Regression" by A. Buja, R. Berk, L. Brown, E. George, E. Pitkin, L. Zhan and K. Zhang

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1. OVERVIEW

I congratulate Buja et al. on this ambitious and detailed description of a vitally important topic in statistics. The question of how to account for modeling uncertainty is a fundamental problem of statistical inference. I found the Buja et al. papers both challenging and thought-provoking, and I appreciate the opportunity to participate in the discussion. I focus my remarks on the first paper, since the second one largely concerns generalizations that are not the focus of my remarks.

Buja et al. adopt a traditional frequentist perspective. In contrast, I approach the topic from a "calibrated Bayesian" philosophy of statistical inference, where the inference for a particular dataset is Bayesian, but models are chosen to attempt to achieve good frequentist operating statistics (Box, 1980, Rubin, 1984, 2019, Little, 2006, 2011). I also comment on two aspects that receive little attention in the Buja et al. papers, the role of the selection mechanism in statistical modeling, and the perspective of finite population sampling. In the modeling approach to finite population inference, the finite population is assumed to be sampled from an underlying infinite "superpopulation," so what Buja et al. call the "population" I will call the "superpopulation." As an advocate of the calibrated Bayesian approach to survey sampling (Little, 2004, 2012), the topic of Buja et al. is pertinent because, as they note, the Bayesian approach is fundamentally "model-trusting," whereas the competing design-based approach to survey inference is "model-skeptical" and "assumption-lean."

In support of the calibrated Bayes position, I contrast the Buja et al. papers to Szpiro, Rice and Lumley (2010), henceforth SRL, an excellent paper that provides a justification of sandwich estimation of standard errors from a Bayesian perspective. Buja et al. reference SRL, but do not compare it with their work.

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2. SIMPLICITY, NOT MATHEMATISTRY

The Buja et al. papers seem to me quite mathematically formidable, despite the absence of formal regularity conditions. The approach to relaxing assumptions seems to me abstract—I am not looking forward to attempting to explain to practitioners, struggling with the interpretation of a regression coefficient in a logistic regression, that the target slopes are actually projections on a nonparametric space. I argued in my Fisher lecture (Little, 2013) that a primary advantage of the Bayesian approach to statistics is its conceptual simplicity. If, like me, you find the level of mathematical sophistication in the Buja et al. papers challenging, I recommend the fundamental simplicity of the Bayesian perspective in SRL. That is not to say it is easy to implement, but the difficulties lie in developing an appropriate Bayesian model that captures the important scientific aspects of a problem without unnecessary "clutter." This is the "art" of statistics, and it distinguishes it from the field of mathematics.

3. TERMINOLOGICAL TORTURE: "RANDOM" VS. "FIXED" EFFECTS, AND "NONLINEARITY"

I have never resonated with the frequentist interpretation of what is "random" and what is "fixed." Effects in analysis of variance are called "random" if they are regarded as sampled from a population, and "fixed" if they are not; in Buja et al., "fixed" regressors become "random" under potential model misspecification. If X is a treatment indicator, in what sense is it "random"?