Bayesian Statistics: An Introduction (3rd ed.) by Peter M. Lee. London: Arnold Publishers, 2004. 351 + xv pp. $17.95. ISBN 0340814055.

Bayesian statistics has made great strides in recent years, due partly to better understanding of priors (e.g., automatic or reference priors that can be used in the absence of subjective prior information), partly due to the introduction of Markov Chain Monte Carlo (MCMC) techniques for drawing samples from the posterior distribution even when the sample space is huge, and partly due to the power of hierarchical Bayes models for describing very complex problems in a natural way. Added to this, the result of a Bayesian analysis naturally provides what scientists really would like to know, whereas the interpretation of the results of a standard frequentist analysis is often unnatural and confusing, especially to working scientists, but even to many of those with statistical training. No longer is the Bayesian approach regarded with suspicion or disdain by most classically trained statisticians; rather, some of the most cutting-edge work in statistics is being done by statisticians of all stripes using the Bayesian point-of-view. This is a tribute to the power of modern Bayesian methods. The present book is the third update of a book that has become something of a standard in introductory texts on the subject. It is not much different from the second edition, the new material being a chapter on hierarchical Bayes and an expansion of the chapter on MCMC (which was added in the second edition). However, the basic approach and most of the topics remain virtually unchanged from the second edition.

I personally learned a great deal from the earlier editions of this book when I was discovering the power of Bayesian methods in my own work. The selection of topics is basic, including chapters on inference for normally distributed data and for data having other distributions (e.g., binomial, Poisson and other sorts), hypothesis testing (an area in which the numerical results can differ substantially from those provided by standard hypothesis tests, particularly for point null hypotheses), two-sample problems, and Bayesian results on correlation, regression and analysis of variance. A chapter on "other topics" discusses some of the salient features of Bayesian analysis that differ from standard statistical discussions, such as the important Likelihood Principle (which standard methods often violate), the Stopping Rule Principle (which under mild conditions insulates Bayesian methods from the problems that arise in standard hypothesis testing when the experimenter is allowed to stop optionally and conditionally on the results so far) and the role of decision theory. The chapter on hierarchical Bayes discusses the surprising Stein "paradox," whereby the obvious estimator for a vector parameter under square-error loss is inadmissible in classical decision theory; better estimators can be found naturally using a hierarchical Bayes model. Finally, a chapter on MCMC rounds out the book; MCMC has revolutionized Bayesian statistics over the past fifteen years by providing a practical method for obtaining results, especially integrals, by posterior simulation. (In spirit these interpretation is different: Standard statistics regards parameters as fixed and data as random variables, and averages or simulates over the data, whereas Bayesian statistics regards parameters as random variables and the observed data as fixed, and averages or simulates over the parameters.) The chapter on MCMC introduces most of the standard techniques (with slice sampling as a notable exception) using examples coded in the free computer language R.

The book has much to recommend it, but I do have some problems with it. For one thing, much of the book is devoted to exact or asymptotic results, often using so-called conjugate priors that with standard error distributions produce posterior distributions that remain in the conjugate family and are analytically tractable. For example, using a normal prior on the location variable in normal inference problems with a known data variance results in a normal posterior distribution, so results are easily calculated. But, for all the importance of such analytical techniques, they are too restrictive for the vast majority of real-world problems, which generally require posterior simulation using MCMC to get practical results. A student reading this book might get an exaggerated idea of the role that these analytical techniques play in practical problems and might regard MCMC techniques as an afterthought, whereas the truth is quite the opposite. It is for this reason that I no longer use it as a textbook in my Bayesian course, which I teach using simulation as the main calculational technique, introducing exact analytical results after discussing problems from a simulation point of view. My aim has been to prepare the students to tackle real-world problems in their chosen field after this one-semester graduate course. The post-course experience of my students attests to the success of this approach.

Thus, I am of two minds when recommending this book. Certainly I learned much from the first edition, so it can be useful for self-study by a mature scientist who is aware of its limitations; but I would be careful about using it as a textbook in a course, at least without balancing it with other material (e.g., the highly-regarded but more advanced book by Gelman, Carlin, Stem and Rubin) or with lectures that placed more emphasis on simulation methods.

WILLIAM H. JEFFERYS
Harlan J. Smith Centennial Professor in Astronomy, Emeritus
Department of Astronomy
1 University Station, C1400
University of Texas at Austin
Austin, TX 78712-0259

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