

Monte Carlo Strategies in Scientific Computing, by Jun S. LIU, New York: Springer-Verlag, 2001, ISBN 0-387-95230-6, xvi + 343 pp., \$69.95.

The strength of this book is in bringing together advanced Monte Carlo (MC) methods developed in many disciplines. This intent is clear from the outset: "Many researchers in different scientific areas have contributed to its development. . . communications among researchers in these fields are very limited. It is therefore desirable to develop a relatively general framework in which scientists in every field. . . can compare their Monte Carlo techniques and learn from one another." Throughout the book are examples of techniques invented, or reinvented, in different fields that may be applied elsewhere. This is occasionally embarrassing to those of us who are statisticians. Consider this statement: "Using the HMC to solve statistical inference problems was first introduced by Neil (1996). This effort was only 10 years behind that in physics and theoretical chemistry. In contrast, statisticians were 40 years late in using the Metropolis algorithm."

The book serves "three audiences: researchers specializing in the study of Monte Carlo algorithms; scientists who are interested in using advanced Monte Carlo techniques; and graduate students. . . second-year graduate-level course on Monte Carlo methods."

Chapter 1 gives an overview and a variety of applications. These include the Ising model, molecular structure simulation, bioinformatics, target tracking, hypothesis testing for astronomical observations, Bayesian inference of multilevel models, missing-data problems.

Chapter 2 covers basic MC methods and begins sequential methods, including exact sampling for chain-structured models, and sequential importance sampling and rejection control, with applications in solving a linear system, missing data, and populations genetics.

Chapter 3 expands on sequential methods. The common thread is that each observation from a multivariate distribution is generated sequentially from approximate conditional distributions. The ratio between the joint density (of dimensions generated so far) and the approximation is an importance sampling weight and is a martingale; for high-dimensional problems, this tends to diverge, with most observations having weights near 0 and a few having high weight. Remedies include a variety of pruning and enrichment (also known as Russian roulette and splitting) and resampling techniques. Applications include growing a polymer, missing data, nonlinear filtering, and (in Chap. 4) molecular simulation, population genetics, motif patterns in DNA sequences, counting 0-1 tables with fixed margins, parametric Bayes analysis, approximating permanents, target tracking, and digital communications.

Chapter 5 introduces Markov chain Monte Carlo (MCMC) methods, with Metropolis-Hastings and a number of generalizations, including multipoint, reversible jumping, and dynamic weighting rules. Chapters 6-8 treat MCMC methods based on the Gibbs sampler, including data augmentation, cluster algorithms, partial resampling, slice sampler, metropolized Gibbs, hit-and-run, random-ray, collapsing and grouping, the Swendsen-Wang algorithm as data augmentation, transformation groups, and generalized Gibbs. Applications include Gaussian random fields, texture synthesis Bayesian probit regression, stochastic differential equations, hierarchical Bayes, finding motifs in protein or DNA sequences, Ising and Potts models, inference with multivariate t distributions, and parameter expansion for data augmentation.

Chapter 9 considers hybrid MC and a connection to molecular dynamics algorithms used in structural biology and theoretical chemistry. Also covered are some strategies for improving efficiency, including surrogate transition, window, and multipoint methods, and applications in Bayesian analysis and stochastic volatility.

Chapters 10 and 11 discuss recent methods for efficient MC sampling, including temperature-based methods (simulated tempering, parallel tempering, and simulated annealing), reweighting methods (umbrella sampling and multicanonical sampling) and evolution-based methods (adaptive direction sampling and conjugate gradient MC). Chapters 12 and 13 cover theory for Markov chains and their convergence rates.

The book focuses on relatively more difficult MC applications where "directly generating independent samples from the target distribution π is not feasible." It omits discussion of some relatively simple MC techniques that are valuable in applications where direct generation is feasible and which could be adapted for other applications; e.g. stratified sampling (the "stratified sampling" technique discussed here is unusual and of limited value) post-stratification, and defensive mixture designs in importance sampling (Hesterberg 1995).

The treatment of importance sampling (IS) could be improved. The book describes the original motivation for IS—focusing attention on "important" regions—then indicates:

Another scenario for resorting to IS is when we want to generate i.i.d. random variables from π but doing so directly is infeasible. In this case we may generate random samples from a different, but similar, trivial distribution $g(\cdot)$, and then correct the bias by using the importance sampling procedure. Similar to the rejection method, a successful application of importance sampling in this case requires that the sampling distribution of g be reasonably close to π ; in particular, that g has a longer tail than π . Note that finding a good trial distribution g can be a major—and sometimes impossible—undertaking in high-dimensional problems. (new paragraph) Alternately, we can opt for *correlated* samples produced by running a Markov chain whose stationary distribution is π . . . (MCMC).

But MCMC and IS need not be mutually exclusive; MCMC is a way to generate samples from a distribution, whereas IS is a way to use samples from one distribution to provide estimates for another distribution. MCMC outputs could be used as the design ("trial") distribution, or for one or more components in a mixture design. The case in which one MCMC component has π as the stationary distribution is a defensive mixture, with that component providing a guaranteed level of robustness (for any number of dimensions), whereas other components may focus on tails or other regions of particular interest.

IS is particularly useful when there are multiple target distributions. An example of this is in Bayesian analysis to test the sensitivity of results to changes in the prior, because the same set of samples can be used for many target distributions.

The formula for relative efficiency under IS (page 36) is incorrect in a way that has fundamental implications for how IS is used. The formula indicates that the effective sample size is always smaller than the actual sample size, but the reverse may be true and is the basis for the use of IS as a variance reduction technique. For example, if $\pi \sim N(0, 1)$, $h = I(x > 3)$, and $g \sim N(3, 1)$, then the formula implies an effective sample size of $.00012n$, whereas the actual effective sample size is $218n$. (The author does note that the "approximation can be substantially off" if a "remainder" term is large.) Here and elsewhere the book suggests that a good IS design is one that closely matches the target π ; but the real goal is estimating not π , but quantities such as $E_{\pi}(H)$. What matters is not how closely g tracks π , but rather how the differences affect estimation for quantities of interest. An optimal g is heavier than π in the tails of quantities of interest, for example, $g^* \propto |H - E_{\pi}(H)|\pi$ for univariate H , or see Hesterberg (1991) for multivariate quantities and practical guidelines. This distinction could also be exploited for pruning and splitting triggered not on the raw importance sampling weight, but rather on the ratio of that weight to an estimated optimal weight conditional on variates generated so far.

The book describes an adaptive importance sampling procedures whereby the design g is adapted to closely track the target π . Another approach (Moy 1965) is to adapt for accurate estimation of quantities of interest.

In summary, *Monte Carlo Strategies in Scientific Computing* offers a large (and sometimes bewildering) variety of methods and examples. Those interested in using MC to solve difficult problems will find many ideas, collected from a variety of disciplines, and references for further study. Although the treatment of importance sampling could be improved, that does not detract from the bulk of the material presented.

The book has 263 references, including 35 by the author. There are 51 end-of-chapter exercises for use as a text. Included are four appendices; the first two, on basic probability theory and statistical modeling and inference, could be omitted, because a reader without that background could not read this book. I found few errata; no web site for errata is listed. The 6-page index is skimpy; for example, it is missing 14 of 46 items listed in the table of contents.

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In All Likelihood: Statistical Modeling and Inference Using Likelihood, by Yudi PAWITAN, New York: Oxford University Press, 2001, ISBN 0-19-850765-8, xiii + 528 pp., \$70.00.

As the title indicates, this book discusses using the likelihood function for both modeling and inference. It is written as a textbook with a fair number of examples. The author conveniently provides code using the statistical package R for all relevant examples on his web site. He assumes a list of prerequisites that would typically be covered in the first year of a master's degree in statistics (or possibly in a solid undergraduate program in statistics). A good background in probability and theory of statistics, familiarity with applied statistics (such as tests of hypotheses, confidence intervals, least squares and p values), and calculus are prerequisites for using this book.

The author presents interesting philosophical discussions in Chapters 1 and 7. In Chapter 1 he explains the differences between a Bayesian versus frequentist approach to statistical inference. He states that the likelihood approach is a compromise between these two approaches and that it could be called a Fisherian approach. He argues that the likelihood approach is non-Bayesian yet has Bayesian aspects and that it has frequentist features but also some nonfrequentist aspects. He references Fisher throughout the book. In Chapter 7 the author discusses the controversial informal likelihood principle, "two datasets (regardless of experimental source) with the same likelihood should lead to the same conclusions." It is hard to be convinced that how data were collected does not affect conclusions.

Chapters 2 and 3 provide definitions and properties for likelihood functions. Some advanced technical topics are addressed in Chapters 8, 9, and 12, including score function, Fisher information, minimum variance unbiased estimation, consistency of maximum likelihood estimators, goodness-of-fit tests, and the EM algorithm. Six chapters deal with modeling. Chapter 4 presents the basic models, binomial and Poisson, with some applications. Chapter 6 focuses on regression models, including normal linear, logistic, Poisson, non-normal, and exponential family, and deals with the related issues of deviance, iteratively weighted least squares, and the Box-Cox transformations. Chapter 11 covers models with complex data structure, including models for time series data, models for survival data, and some specialized Poisson models. Chapter 14 examines quasi-likelihood models, Chapter 17 covers random and mixed effects models, and Chapter 18 introduces the concept of nonparametric smoothing.

The remaining chapters put more emphasis on inference. Chapter 5 deals with frequentist properties including bias of point estimates, p values, confidence intervals, confidence intervals via bootstrapping, and exact inference for binomial and Poisson models. Chapter 10 handles nuisance parameters using marginal and conditional likelihood, modified profile likelihood, and estimated likelihood methods. Chapter 13 covers the robustness of a specified likelihood. Chapter 15 introduces empirical likelihood concepts, and Chapter 16 addresses random parameters.

This book works fine as a textbook, providing a nice introduction to a variety of topics. For engineers, this book can also serve as a good initial exposure to possibly new concepts without overwhelming them with details. But when applying a specific topic covered in this book to real problems, a more specialized book with greater depth and/or more practical examples may be desired.

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Calculated Bets, by Steven SKIENA, Cambridge, UK: Cambridge University Press, 2001, ISBN 0-521-00962-6, xv + 232 pp., \$17.95.

This is a nontechnical book written for the general audience that deals with mathematical modeling, computers, and gambling. The author, Steven Skiena, a professor of computer science at the State University of New York

at Stony Brook, has also written two popular technical books on algorithm design and computational mathematics. He has come up with a fairly instructive and entertaining book. It is short, readable, and contains plenty of figures and illustrations to help the readers understand the technical side of mathematical modeling.

Although the book's main theme is the application of mathematical modeling to gambling systems, its main thread is a story about a computer scientist's fascination with the sport of jai alai and its betting system and the subsequent creation of a computer model to predict the outcomes of jai alai matches. In Chapter 1, the author recounts his early visits to a fronton (the arena where jai alai is played and betting is held) in Florida as a child and how the visits piqued his interest in the sport. Chapter 2 describes jai alai and its betting system in detail. The story then takes us to the author's attempt in high school to predict National Football League results using a computer program, and later to his simulation of jai alai matches during his graduate school years. The author then gives an account of the development of his mathematical model, which not only predicts the results of jai alai matches, but also provides betting options that yield positive returns. He then discusses how the model fared when it was actually put to the test.

The story of the development of the computer program is quite interesting in itself. The author makes it more so by sprinkling it with informative and often-amusing anecdotes and facts, ranging from profiles of his graduate students who worked on the project to why many computer programmers hate Microsoft. In similar fashion, the technical topics and concepts that arise from the modeling are introduced and discussed as short and relevant digressions from the main story. The number of topics covered is fairly substantial, including Monte Carlo simulations, efficient programming by parsing, neural networks, and probabilistic and statistical concepts such as curve-fitting, correlation and martingale system. His treatments of these topics are often brief, but sufficient to convey the basic ideas to the general reader.

After the story of his computer model on jai alai ends, the author provides a guide on how to bet on jai alai, complete with tables of different types of bets with their probabilities of winning and expected payoffs. At the end of the book, he suggests some possible projects that readers can undertake on their own using the mathematical modeling techniques discussed in the book.

Although on the whole the book is well written, it has one major deficiency from the standpoint of the general reader. A large portion of the book is devoted to jai alai betting and the jai alai as a sport, and because the U.S. fan base of jai alai is small, the book may not appeal to a wide audience. The typical reader may prefer to see mathematical modeling applied to more popular betting schemes, such as the lottery or horse-racing.

As a statistician, I paid particular attention to the author's explanations of the book's statistical concepts. I believe that I am not the only one who disagrees with the author's "layperson" definitions of the mean or average and of the standard deviation: "The mean or the average is a statistical measure of the most likely value in a sequence. . ."; "... the standard deviation measure(s) the consistency of values in a sequence" (pp. 137-138). Also, his use of the term "degrees of freedom" to synonymously mean the number of parameters in linear regression (p. 143) is misleading and is, from a strictly technical standpoint, wrong. Despite these flaws, the book does a fairly good job describing technical topics in the simplest possible language.

My overall assessment of *Calculated Bets* is that it is a must read if the reader is both a jai alai fan and a nonmathematician/nonstatistician/noncomputer scientist wishing to learn more about the technical aspects of computer modeling related to gambling. (I think the book should be more aptly titled *Calculated Bets in Jai Alai*.) Nontechnical-type readers who do not fall into this category will nevertheless find it worth reading. As for statisticians and engineers and computer scientists, they should read this book only if they wish to learn more about jai alai betting.

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Mind on Statistics, by Jessica M. UTTS and Robert F. HECKARD, Pacific Grove, CA: Duxbury, Thomson Learning, 2002, ISBN 0-534-35935-3, xxi + 568 pp. + CD, \$93.95.

Any time an introductory statistics book tries to move in some different directions, not so much in topics but in order, presentation, and style, that book will have some strong advocates and some less than enthusiastic supporters.



<http://www.springer.com/978-0-387-95230-7>

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