A First Course in Monte Carlo.

George FISHMAN. Stamford, CT: Thomson Learning, 2006. ISBN 0-534-42046-X. xi + 414 pp. \$102.95.

Monte Carlo methods have revolutionized scientific computing. For example, Monte Carlo methods have become the research statistician's version of a laboratory experiment, used to evaluate the finite sample properties of a statistical method. Modern Monte Carlo algorithms have made some resampling statistical methods commonplace, such as Markov chain Monte Carlo (MCMC) methods in Bayesian analysis, bootstrapping, and permutation analysis. The Monte Carlo experiment has become the tool of choice for engineers, operations researchers, and other physical scientists to study complex systems. In light of these developments, it would be difficult to overstate the impact that Monte Carlo methods have had on scientific discovery.

Fishman's book is a welcome addition on this revolutionary topic. Being an established researcher with broad interests in Monte Carlo methods and having already written a well received textbook on the subject (Fishman 1997), he is well qualified to write such a text.

A First Course in Monte Carlo (henceforth AFCMC) distinguishes itself from the crowded area of excellent books on Monte Carlo (e.g., Chen, Shao, and Ibrahim 2000; Fishman 1997; Liu 2001; Robert and Casella 1999) and computational statistics (e.g., Givens and Hoeting 2005; Lange 1999) by being a dedicated textbook. An appropriate audience for a course using AFCMC would be mathematically advanced undergraduate or beginning graduate students in engineering, mathematics, operations research, statistics, or other quantitatively oriented sciences.

AFCMC starts with an introductory chapter that gives an overview of topics and notation. The author emphasizes the ubiquity of the Monte Carlo method by giving a list of applications that, although impressively long and varied, "hardly does justice to the breadth and application of the Monte Carlo method" (p. 2). Some of these applications are used later in the text as the basis for exercises and examples. Being a Monte Carlo enthusiast, I particularly enjoyed this quote from Chapter 1 that stresses the importance of the position that Monte Carlo holds within the field of scientific computing (p. 1):

... it is no exaggeration to say that the [Monte Carlo] method provided one, if not the first example of the computer's potential for solving large-scale complex problems.

After the introductory chapter, the second through ninth chapters are titled "Independent Monte Carlo," "Sample Generation," "Pseudorandom Number Generation," "Variance Reduction," "Markov Chain Monte Carlo," "MCMC Sample-Path Analysis," "Optimization via MCMC," and "Advanced Topics in MCMC." My only minor criticism of the structure of the book is that I would put the chapter "Pseudorandom Number Generation" before "Sample Generation."

Perhaps the most emphatically positive aspect of the book is its early discussion of algorithmic efficiency and the assessment of Monte Carlo error, which appears in the second chapter. This sets a tone for the remainder of the book where algorithms are evaluated critically, usually in sections labeled "cost considerations" or "lessons learned." Also, formulas for Monte Carlo error estimates typically accompany the estimation method, promoting good Monte Carlo practice. For example, I believe that a student having used AFCMC as a textbook would not fall into the common trap of reporting Monte Carlo results to six significant digits when the Monte Carlo sample size only affords two.

The book is comprehensive in its treatment of Monte Carlo techniques, using independently generated samples (referred to as independent Monte Carlo). Throughout, the book favors generality and abstraction, presenting general algorithms first and special cases later. For example, the book first introduces the general approximation of an integral using a weighted Monte Carlo estimator, while basic Monte Carlo estimation of an expectation is presented later. In Fishman's treatment of independent Monte Carlo, he covers several interesting advanced techniques in the "Variance Reduction" chapter. These include antithetic control variates, Rao–Blackwellization, and quasirandom number generation.

The discussion of Markov chain Monte Carlo that follows is comprehensive with respect to algorithms. However, the book only introduces the minimal amount of Markov chain background theory necessary for development of the algorithms. Again, AFCMC favors generality, introducing the general Metropolis–Hastings algorithm first, followed by special cases such as coordinate updating, and the independent and random-walk algorithms. Notably, the book introduces several concepts from Markov chain Monte Carlo theory such as geometric, uniform, and polynomial convergence, again highlighting the book's emphasis on algorithmic efficiency. The subsequent chapter on "MCMC Sample-Path Analysis" offers a pragmatic approach to combining multiple independent chains, and also discusses burn-in and the batch means method for estimating Monte Carlo standard errors.

The chapter on "Optimization via MCMC" has a nice treatment of simulated annealing, including practical recommendations with regard to choosing nominating kernels and cooling schedules. More advanced strategies that employ multiple chains, such as genetic algorithms and simulated tempering, are also covered. Perhaps the most interesting aspect of this chapter is an intricate example about protein folding.

All algorithms in the book are developed mathematically and then presented in pseudocode, which the author generally names with an acronym for future reference. This naming convention can make the text difficult to wade through at first, but probably reduces confusion in the long run. Excepting the chapter on "Pseudorandom Number Generation," all chapters end with practical exercises that require programming.

As for criticisms, I only have a few. First, for better or worse, most statistics and biostatistics departments do not have a class devoted entirely to Monte Carlo. Instead, however, most departments do have a general course in statistical computing. Although AFCMC would be ideal for the Monte Carlo portion of such a course, it does not include other relevant topics. Second, the exposition of the book often emphasizes mathematics and could be improved by more detailed description relative to algorithms. However, the brevity, clarity, and correctness of Fishman's writing is a strength of the text.

In summary, AFCMC is comprehensive, promotes good Monte Carlo practices, evaluates algorithms critically, and motivates Monte Carlo methods effectively with several interesting applications. It is not hard to envision that it will become a default textbook for courses devoted to Monte Carlo methods.

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Simulation Techniques in Financial Risk Management.

Ngai Hang CHAN and Hoi Ying WONG. Hoboken, NJ: Wiley, 2006. ISBN 0-471-46987-4. xvii + 220 pp. \$89.95. Digital: \$89.95.

Simulation Techniques in Financial Risk Management addresses the main techniques needed by practitioners who deal with financial risk management problems. The book covers the basics of stochastic processes and stochastic calculus enough to allow the reader to understand their connection with the simulation techniques required in financial risk management questions. The main problems in financial risk management are introduced together with the basic techniques in simulation. The advanced part of the book introduces topics in financial risk management and simulation. Throughout the book, examples and case studies perfectly illustrate the application of the techniques presented.

The contents and the high quality of the book make it suitable for use in an upper undergraduate or graduate course in simulation and risk management. Exercises conclude each chapter. Solutions to selected exercises are provided at the end of the book. This feature makes this text attractive as a course textbook. Given the immediate applicability of the techniques presented and the nature of the questions addressed, the text should also be useful for practitioners looking for answers to very well defined questions in financial risk management.

In financial risk management, closed analytical formulas are often not available or are not easy to implement. Simulation makes some of these problems possible to address. In risk management, knowledge from several disciplines is necessary: finance, statistics, probability, and computer science. This is a book on simulation, where the necessary background from other disciplines is reviewed with applications to risk management in mind.

The prerequisites are an undergraduate course in probability and the basic notions from finance. Although it covers the basics of simulation and risk management, the book also provides insights into current academic research. An example of this is the use of extreme value theory in the computation of valueat-risk. I consider this book to be a very useful addition to the literature on quantitative risk management.

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Pattern Recognition Algorithms for Data Mining.

Sankar K. PAL and Pabitra MITRA. Boca Raton, FL: Chapman & Hall/CRC, 2004. ISBN 1-584-88457-6. xxix + 280 pp. \$89.95.

Pattern Recognition Algorithms for Data Mining (PRADM) reads more like a computer science book than a classical statistics text. The text contains very few formulas; most of the ideas are explained in English text. Important algorithms are expressed so as to make coding implementations as easy as possible. Although the lack of theorems and proofs may make some readers feel there is little to sink their teeth into, I did not feel as if I were missing much. However, the general level of detail is such that PRADM is not a good stand-alone resource. The text provides an excellent introduction to the topics it covers, giving context and making the material easy to learn. Because of these aspects, I think this book will primarily be used for self-study. If used as a textbook for a course, it would require significant supplementation. PRADM also runs a higher risk of becoming dated than most books. By trying to give a picture of the current state of the field and not being self-contained, its value as a reference 10 years from now may be limited.

Each chapter takes on a different topic. PRADM starts with chapters on data compression, unsupervised learning, and support vector machines. Then comes the meat of the book: four (of eight total) chapters on rough/fuzzy classification and clustering tools. A typical chapter starts by introducing its topic, along with a lengthy literature review. If you do not know much on the topic, the introductions provide context and references. A couple of algorithms are then usually presented, including at least one by the authors. The performance of these algorithms is then compared, usually in favor of the authors' methods.

What works well about this book? It is different from typical statistics texts. For instance, it views run times for algorithms as an important metric, because as datasets get larger, some methods become infeasible to run. This consideration is absent in much of the statistics literature. Although the literature reviews and backgrounds for each chapter are brief, they are excellent in providing context. Indeed, this may be the greatest strength of the book. Finally, fuzzy rules are not something considered widely in the statistics literature; PRADM makes a case that they should be.

Where does PRADM come up short? In trying to cover as much as they do in the space allotted, a number of the algorithms are hard to figure out from the descriptions in the book; added length or more examples would help clarify. Some theoretical results would also illuminate the successes and limitations of the methods. Are either of these fatal flaws? No, but they are limitations that the potential reader of the book should be aware of.

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Robust Statistical Methods With R.

Jana JUREČKOVÁ and Jan PICEK. Boca Raton, FL: Chapman & Hall/CRC, 2006. ISBN 1-58488-454-1. xi + 197 pp. \$79.95.

This book is an outgrowth of the course "Robust Statistical Methods" that is part of the Master's degree program in statistics at Charles University in Prague. As anyone who has taught a graduate level course in robust statistics knows, there are few texts on robust statistics other than the classic books by Huber (1981) and Hampel, Ronchetti, Rousseeuw, and Stahel (1986). Hence, this book is a welcome addition. Other well regarded books on robust statistics tend to be more specialized, such as Reider (1994), which principally deals with the asymptotic theory for robust statistics, or Rousseeuw and Leroy (1987), which is a more applied text aimed at promoting the use of high breakdown point methods.

Despite the title and the cover description of the text as one "with an emphasis on practical application" and "computational aspects," the text is more aptly described as providing a classical theoretical treatment of robust statistics, supplemented with some illustrative examples. The layout of the chapters and the presentation is similar to that in Huber (1981), with different emphases on the various topics and a little less overall general theory.

Chapter 1 presents the advanced mathematical tools needed for a theoretical treatment of robust statistics. Among other topics, it covers the general concepts of statistical functionals, Fisher consistency, distances between probability measures, and the Gâteaux, the Fréchet, and the Hadamard or compact derivatives.

Chapter 2 presents the basic concepts of robust statistics, such as the influence function, the sensitivity curve, qualitative robustness, maximum bias, and the breakdown point. It also discusses robustness measures based on the influence function, namely the gross error sensitivity and the local shift sensitivity, which in the text are referred to as the global and local sensitivities, respectively.

Chapter 3 treats M estimates, L estimates, and R estimates for real valued parameters of a univariate distribution. Aside from general derivations for the influence functions of the M and L estimates, the focus is on the univariate location problem. The results here for the M estimates of location, such as their asymptotic normality and their breakdown points, primarily apply to the monotonic M estimates of location with fixed scale, and are illustrated in more detail for the mean, the median, and Huber's class of M estimates of location. The chapter also gives an overview of redescending M estimates of location, as well as studentized versions of the M estimates of location. Among topics discussed for the L estimates of location are their asymptotic normality and their breakdown points, with the results being illustrated for the trimmed and the Winsorized means. The section on R estimates primarily focuses on the Hodges–Lehmann estimate of location.

Chapters 4 and 5 discuss robust regression and robust multivariate statistics, respectively. The treatment of robust estimation in these topics is not as in-depth as that given in the rest of the book. Rather, these chapters represent more of a survey of topics in the areas. Chapter 4 gives an overview of the properties of M estimates, GM estimates, and L estimates of regression. In addition, it defines the S estimates and MM estimates of regression, provides a short discussion on high breakdown point regression, and treats various other topics such as one step versions of robust regression estimates, robust estimates of the residual scale, and regression rank scores. Chapter 5 is fairly short. Its coverage of robust multivariate statistics is limited to a two page section on high breakdown point estimates, with an emphasis on the multivariate S estimates.

Chapter 6 can be viewed as an appendix to Chapter 3. It provides a theoretical treatment of the asymptotic properties for M estimates, L estimates, and Restimates for a real valued parameter. Again, the primary focus is on the univariate location problem. The final chapter of the book, Chapter 7, considers goodness-of-fit tests for the error distribution in a linear model.

The ends of Chapters 1, 3, 4, and 7 provide illustrative examples of the theory and methods in the respective chapter, along with a section on the use of R to implement them. The text also contains an appendix that serves as a primer for the R language. The complements and problems given at the end of each chapter tend to be, with a few exceptions, theoretical exercises rather than applied or methodological.

The text is relatively short, 180 pages plus an up-to-date bibliography, and so cannot be expected to provide a comprehensive treatment of the subject of robust statistics. Although the book does cover a fair amount of the classical theory of robust statistics, one important topic that is not presented is the general treatment of multiparameter problems. There is also no direct discussion on tuning robust estimates. The coverage of scale problems, redescending M estimates, multivariate procedures, and high breakdown point methods is very sparse. In general, more contemporary topics, that is, post Huber (1981) and Hampel et al. (1986), are not covered as well as the classical topics.

The choices of topics covered in any text tend to be a reflection of the authors' own interests, and this is especially true of this book. For example, some topics given a relatively extensive treatment are the tail behavior of estimates and moment convergence for M estimates and L estimates of location. The text