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Multilevel Analysis: Techniques and Applications.

Joop HOX. Mahwah, NJ: Lawrence Erlbaum, 2002. ISBN 0-8058-3218-1. x + 304 pp. $69.95 (H); ISBN 0-8058-3219-X. $32.50 (P).

Over the last decade, much attention has been given to the analysis of data that have a nested or hierarchical structure. As various disciplines have recognized the usefulness of these types of analyses, the need for an introductory text on the subject has become more apparent. *Multilevel Analysis: Techniques and Applications* provides an intuitive understanding of the topic while building on a basic foundation of classical multiple regression.

This book is an introduction to multilevel analysis for applied researchers. Multilevel analyses include such models as random-coefficient models, empirical Bayes models, and hierarchical linear models (Laird and Ware 1982; Strenio, Weisberg, and Bryk 1983; Wolfinger 1996; Goldstein 1987; Bryk and Raudenbush 1992). In general, these models all fall under the classification of mixed models. This book is not as detail oriented as, say, the text by Brown and Prescott (2001) or that of Littell, Milliken, Stroup, and Wolfinger (1996). Brown and Prescott (2001) were more thorough in their treatment of topics and give a light theoretical background to topics. Littell et al. (1996) provided discussions that are primarily geared for SAS users. This book is more conceptual and would be a nice supplement to a text such as the one by Brown and Prescott or that by Littell et al.

At times, the author is too conceptual and does not provide enough meat to allow the reader to truly get a feel for the topics at hand. As a case in point, he devotes an entire chapter to estimation and hypothesis testing. In this chapter he discusses the concepts of generalized least squares, maximum likelihood, and restricted maximum likelihood, but does not introduce a likelihood expression or a model. The text by Brown and Prescott also addresses these topics, but it provides a more intuitive treatment by demonstrating how these procedures work. Although Brown and Prescott's book would serve nicely as a textbook for a first mixed-models course, *Multilevel Analysis* would not be appropriate as a stand-alone text.

Hox's writing style is to present a dataset (generally resulting from sociological work) along with the types of questions that a sociologist might ask. Models for the data are presented in increasing order of complexity, beginning with an intercept-only model and ending with more sophisticated models that include various levels of random effects and their associated interactions. Analysis-of-variance tables are provided along the way, allowing the reader to gain valuable intuition into the problem. For each topic presented, Hox provides a nice array of references that delve into more specialized issues associated with the topic at hand.

The datasets discussed are provided on the web in SPSS system and portable formats. Most of the analyses presented in the text are carried out in the HLM and MlwiN software packages. As a SAS user, I was curious to see whether I could reproduce the presented analyses in SAS. With the aid of the text by Littell, Milliken, Stroup, and Wolfinger (1996, chaps. 2, 3, 4, and 7), I was able to reproduce the analysis-of-variance tables quite easily.

The text comprises 14 chapters and a short appendix that describes the datasets analyzed in the text. In the first two chapters, Hox motivates the need for multilevel analysis and presents a basic introduction to the multilevel regression model. The multilevel model is presented simply as an extension of the classical multiple regression model. Chapters 3–11 present various applications of the multilevel regression model, including models for longitudinal data, dichotomous data and proportions, meta-analysis, and multivariate outcomes. Chapter 10 is devoted to sample size and power analyses for the multilevel regression model. It is difficult to gain much insight into these topics from the text alone. The approach is more of a literature review on the topics instead of a set of "how-to" explanations. Chapter 11 provides an excellent discussion of profile likelihood, bootstrapping estimates and standard errors, and Bayesian estimation methods. As in the rest of the book, the discussions are nontechnical, but a reader facing these topics for the first time would gain some intuition about the methodologies.

The remaining three chapters are devoted to multilevel structural-equation modeling. These chapters are somewhat more advanced, and the reader will need at least some familiarity with topics such as factor analysis and path analysis to follow the discussion. One of the main issues involved with multilevel structural models is that of estimating between-groups and within-groups covariance matrices. When the data are not balanced, this task can be quite complicated. Hox describes a pseudobalanced approach to estimation proposed by Muth'en (1989), and then illustrates the approach with an example. Analyses are done using standard structural equation modeling software, as well as a more specialized software package, MPLUS. Also addressed in this chapter are issues involving goodness of fit and the calculation of standardized coefficients. Chapters 13 and 14 take much of the material in Chapter 12 and extend it to path and latent-curve models. Again, the reader is expected to be at least somewhat familiar with these types of models.

Overall, *Multilevel Analysis: Techniques and Applications* is very well organized and is a nice resource to supplement other texts that give a more thorough treatment to mixed models. The literature review on each of the topics is quite expansive within the realm of social sciences. I especially recommend this book to practitioners and consultants who work in social-science-related disciplines, although it is also handy for anyone that works with mixed models.

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Sequential Monte Carlo Methods in Practice.

Arnaud DOUCET, Nando DE FREITAS, and Neil GORDON (eds.). New York: Springer-Verlag, 2001. ISBN 0-387-95146-6. 581 pp. $79.95 (H).

Sequential Monte Carlo or particle filtering is an important new advance in statistical computing and practice. It provides an efficient way of estimating unobservables in hidden Markov and nonlinear filtering problems. The new ideas are rich enough to be applied in routine Bayesian calculations, for generating self-avoiding paths, in chemistry problems, and much else.

To fix ideas, consider an underlying unobserved Markov chain $X_0, X_1, X_2, \ldots$ with transition probability $P(x_t|x_{t-1})$. One observes a corrupted version $Y_0, Y_1, Y_2, \ldots$, with specified distribution $P(y_t|x_t)$. The problem is to sequentially predict X_t given $Y_0, Y_1, Y_2, \ldots$. These problems arise in nonlinear time-series analysis (the linear, Gaussian version is the celebrated Kalman filter), in real-time image analysis (the observed image is corrupted by distortion, overlap, and noise), and in hidden Markov modeling as widely used in finance, biology, and elsewhere. Even if $P(x_t|x_{t-1})$ and $P(y_t|x_t)$ are completely specified, the problems of practical computation in even mildly realistic situations are overwhelming.

Gordon, Salmond, and Smith (1993) introduced a new idea that gives good answers in practice. Roughly, this replaces classical distributions with weighted sets of particles. The classical probability calculations for updating are replaced by a stochastic dynamics in which particles with small weight are eliminated and particles with larger weights are replicated, evolve, and are reweighted. At each stage, the total number of particles remains fixed. The procedures are straightforward to implement and have become very widely used in engineering circles.

Sequential Monte Carlo Methods in Practice is a remarkable, successful effort at making these ideas available to statisticians. It gives an overview, presents available theory, gives a splendid development of various bells and whistles important in practical implementation, and finally gives a large number of detailed examples and case studies.

The book is the result of a collaboration of a large group of authors (57 by my count). A handful are well-known statisticians, but many are engineers of various sorts or computer scientists. The authors and editors have been careful to write in a unified, readable way.

Following a useful introduction and overview, the algorithms are clearly set out. Then basic (and not so basic) properties are proved in a pair of theoretical articles. The mathematical problems are new and challenging; I never found the development too heavy-handed. Next come 12 chapters on strategies for implementing and speeding up the basic algorithms. Almost all of these are filled with examples, links to basic theory, and new theory (and problems). I found the chapter by Liu, Chen, and Logvinenko particularly illuminating. It abstracts the ideas so that one can see that they are broadly applicable. In particular, if $(Z_1, Z_2, \ldots, Z_n)$ is a vector, then one may sample by first choosing Z_1, then Z_2 given Z_1, and so on. This sequential procedure allows many of the ideas described earlier to be applied. As a special case, a very early application appeared in simulating self-avoiding walks in physics and chemistry.

The final 12 chapters are detailed applications. These range through terrain navigation, shape recognition, neural networks, signal estimation, robot localization, time series models, freeway monitoring, chip manufacture, target tracking, robotics, tracking and guidance, and target recognition. The authors here are leading practitioners, and most chapters introduce new ideas. The book has a unified index and a very complete bibliography.

Particle filters open up new problems for probabilists, new estimation areas for statisticians, and new opportunities for solving problems. It really is revolutionary. I find it remarkable that the editors and authors have combined to produce an accessible bible that will be studied and used for years to come.

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Gordon, N. J., Salmond, D. J., and Smith, A. F. M. (1993), "Novel Approach to Nonlinear/Non-Gaussian Bayesian State Estimation," *Communications, Radar, and Signal Processing*, 140, 107–113.

Numerical Methods of Statistics.

John F. MONAHAN. New York: Cambridge University Press, 2000. ISBN 0-521-79168-5. xiv + 428 pp. $74.95 (H).

The suitability of a book as a textbook for any course depends on the depth and breadth of material covered. In the Preface, Monahan states that the book grew out of notes for a graduate-level course in statistical computing that he has taught for 20 years. This sounds familiar in that Kennedy and Gentle (1980) made a similar comment in the preface to their book. It seems fitting that *Numerical Methods of Statistics* appears roughly 20 years later. It is for the user to decide whether it is a suitable replacement for Kennedy and Gentle's text, which now appears to have become a classic. Lange (1998), in the preface to his book, commented on the difficulty of finding a suitable text for teaching a graduate-level course on statistical computing. Thus, any effort toward fulfilling this need is to be commended.

One reason for this dearth of books is that the area of statistical computing has been constantly changing during the last two decades. Because statistical methodology developed during this period involves heavy use of computers and computational algorithms, more and more statisticians are expected to gain expertise in a variety of numerical techniques. Modern applications range from Markov chain Monte Carlo in Bayesian applications to computations associated with nonparametric function estimation, such as those using wavelets. Perhaps this is an expected natural progression of knowledge in an area of study in statistics. However, the effect of this has been that the interface between statistics and computing has now become blurred to such an extent that almost anyone being trained as a statistician has to become an expert in one or more aspects of computing. A clear example of this situation is the area of biostatistics. One might claim that some biostatisticians today have more expertise in the use of certain computational algorithms than do mainstream statisticians.

It is inevitable that many statistics departments have been attempting to accommodate these changes by strengthening statistical computing instruction in their curricula. This requires that adequate materials (preferably in the form of textbooks) are available for instructors. Lange (1998) in his preface, documented that the classic book of Kennedy and Gentle (1980) has become outdated. The appearance of the book of Thisted (1988) may have fulfilled this need only partially, mainly because it does not examine some computational methods that are now used extensively [e.g., Markov chain Monte Carlo (MCMC)]. Monahan's goal, however, is not too different; as he explains, it is "to prepare doctoral students with the computing tools needed for statistical research." Thus the book's intended target is clear.

Chapters 1 and 2 provide the obligatory introductions to algorithms, programming languages, and computer arithmetic. The author, by recounting a personal experience in which an algorithm for the iterative computation of the Hodges–Lehmann estimator was stuck in a loop, emphasizes the need for care when constructing iterative procedures. The discussion of floating-point computations is an essential part of any text on numerical computing, and an understanding of this material is extremely important in this day of point-and-click computing. Starting with a nice introduction to number systems, Monahan introduces the fundamental material in a matter of a few pages. Although the discussion here is somewhat similar to that of Thisted (1988), I found the presentation here more useful for someone new to numerical computation using a language like Fortran. Monahan ends the discussion on computer arithmetic by offering some prescriptions for limitations on accuracy imposed by floating point representation of numbers.

Chapters 3–6 address computations associated with linear algebra. The standard algorithms for solving either systems of linear equations or eigenanalysis problems are presented using a rather traditional approach. For understandable reasons, linear algebra computations have made the greatest advances in computational statistics over the years. Many statisticians may question the need for detailed knowledge of the implementation of such algorithms (e.g., QR decomposition), particularly because these are rather well implemented in software systems, such as S-PLUS. Also, Fortran implementations of LINPACK/LAPACK routines are available through popular libraries, such as IMSL and NAG. The need, one might argue, is to emphasize their applications in statistics rather than their implementation, particularly for those training to be statisticians.

Monahan attempts to balance the two perspectives, using examples to illustrate how various algorithms work (as well as their applications), and including discussions on such topics as accuracy and conditioning. I found the discussion here to be a bit broader than in the book of Thisted (1988), who covered these topics in a single large chapter. I found it a bit strange that conjugate gradient methods are covered in Chapter 5 as an application to the least squares problem rather than as a general optimization algorithm in statistics in Chapter 8. As in the book of Thisted (1988), iterative methods (e.g., Gauss–Seidel) are discussed fittingly in Chapter 4. The treatment here leaves something to be desired, however. Thisted, for example, discussed several possible statistical applications of these methods. Such a discussion here could be useful to encourage more applications of these algorithms. I believe that Monahan takes such an approach in presenting the complex singular-value decomposition in Chapter 6.

As in the earlier chapters, Monahan provides quite a number of useful Fortran programs to illustrate the algorithms discussed (e.g., sweep). As Monahan himself states, many of the presentations follow those in the texts by Stewart (1973) and Golub and Van Loan (1984, 1989, 1990). This might be a blessing for readers who were never formally introduced to the expert presentations of matrix-algebra algorithms in these superb texts.

Chapter 7 presents an excellent exposition of function interpolation, smoothing, and approximation. Monahan covers this material separately from numerical integration, whereas Kennedy and Gentle (1980) and Thisted (1988) presented these topics in sections introducing numerical quadrature. Perhaps this