Book Reviews

Journal of the American Statistical Association
December 2011, Vol. 106, No. 496, Book Reviews
DOI: 10.1198/jasa.2011.br1112

A Beginner's Guide to Structural Equation Modeling (3rd ed.).

Randall E. SCHUMACKER and Richard G. LOMAX. New York: Routledge, 2010. ISBN 978-1-841-69891-5. xx + 510 pp. $59.95 (P).

This is an ambitious beginner's guide, running nearly 400 pages of text plus appendices. Its 17 chapters can be grouped together as a sequence of themes. After a brief introductory chapter outlining the major topics and providing a brief history of structural equation modeling (SEM), Chapters 2–5 provide the basics. Chapter 2 focuses on data entry and editing in preparation for use in the latest interactive version of LISREL. This is convenient, because a student version of LISREL 8.8 can be downloaded free and is accessible to all students. Chapter 3 offers a far-ranging discussion of correlation, including alternatives to the Pearson correlation coefficient when data are not continuous and the important idea of nonpositive definite matrices. Chapter 4 covers the basic steps in SEM: model specification, identification, estimation, testing and modification. Chapter 5 offers an extensive discussion of alternative model fit indices and, compared with earlier editions, an important elaboration of power and sample size. The authors also introduce their preferred "four-step" approach to modeling data. Chapters 6–8 and 13–16 present some of the major models that researchers use, including basic regression (Chap. 6), path analysis (Chap. 7), confirmatory factor analysis (Chap. 8), multiple group analysis with structured means (Chap. 13), second-order and multitrait, multimethod factor models (Chap. 14), mixture and multilevel models (Chap. 15), and models with interaction and latent growth curves (Chap. 16). For all of these models, the authors provide simple examples that are easily accessed and offer simple practice problems. The simple examples carefully follow the same five steps, from model specification to modification. Wedged between these chapters are four chapters devoted to developing structural equation models with latent and manifest variables (Chaps. 9 and 10), reporting SEM results (Chap. 11), and validating models (Chap. 12). Throughout the book, illustrations are presented with a minimum of formal algebra, so Appendix A introduces matrix algebra, and Chapter 17 presents the SEM model in matrix format.

This book has a lot to offer. The authors are well known and respected, and the text is well written and carefully linked to LISREL syntax and drop-down menus. Examples are formulated to keep programming details to a minimum while the reader is attempting to grasp complex modeling ideas. There are numerous references to published examples. This edition offers an expanded discussion of statistical power and even includes a primer on Monte Carlo methods. The emphasis on statistical power and model validation is more prominent compared with many other texts.

Having taught a variety of SEM courses over the past decades, and having relied on Bollen's (1989) masterpiece, I have some reservations about adopting this book. First, the book's singular reliance on LISREL—one of its strengths—significantly diminishes its value in classes using other software. Second, I am not entirely comfortable with the sequence of topics, although I think I could make it work. Despite the authors' commitment to hands-on examples, the extended discussion of model fit indices (Chap. 5) precedes any examples that would motivate their use. If I adopted this text, I imagine that I would open the course with moderately detailed examples of published structural equation models, so that the whole idea of alternative models, model fit, and model evaluation would make sense to the novice. In fact, I think I would use just the chi-squared statistic to evaluate models in Chapters 6–9, and then introduce fit indices in a more elaborate comparison of models in Chapters 13–16. Third, to the authors' credit, they attempt to keep the algebra to a minimum, but sometimes a more definitive algebraic framework is necessary to clearly express some specific ideas; for example, the idea of model identification is tough to understand, and I do not think the current three pages on model identification (pp. 56–59) would give my students an adequate grasp of the concept. It is a big step from the indeterminacy of $X + Y = 10$ to the necessary and sufficient conditions of mathematical identification in SEM models. Finally, for some topics, including regression and path models, the authors move from an introduction to model estimation and testing using LISREL with good clarity in the space of a few pages. For other topics, such as multilevel modeling, the same strategy just seems too sketchy to be really useful.

Despite my reservations, I can imagine using this guide in an introductory course in which I rely on the LISREL software. I would probably rearrange the sequence of some of the topics and introduce supplementary material. Beyond that, however, this text would be a good vehicle for engaging students in the process of applying SEM to basic research questions with complex designs and measurement error problems.

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A Comparison of the Bayesian and Frequentist Approaches to Estimation.

Francisco J. SAMANIEGO. New York: Springer, 2010. ISBN 978-1-441-95940-9. xiii + 226 pp. $79.95 (H).

A Comparison of the Bayesian and Frequentist Approaches to Estimation is precisely what the title says. The book presents results, primarily those based on the author's work, aimed at determining when each of the aforementioned approaches to estimation is better. The focus is strictly on point estimation problems. Estimators under consideration are classified as either Bayesian or frequentist based entirely on whether proper prior information is used in their creation. Thus, for example, the sample proportion $\widehat{p}$ is placed in the frequentist category, because it is only Bayesian with respect to an improper Beta(0, 0) prior. Mixture estimators, such as those of the form $\eta\widehat{p} + (1-\eta)p_o$, for example, are classified as Bayesian with respect to some prior estimate and prior weight.

The criterion for deciding between estimators is simple and concise; the better estimator is the one that is closest to the truth, where closeness is measured by decision-theoretic principles. The underlying truth is introduced into the criterion through a distribution, called the true prior. This is an appropriate approach to modeling the underlying truth in an inference problem. Statistical inference problems do not occur in isolation. It may very well be that the same investigator, or other investigators, are also interested in estimation problems similar to the one at hand. Estimation procedures should then be judged on their ability to provide good answers across a range of possibilities. Of course, if one insists that there is only one true value of the parameter, then one can take the true prior to be degenerate.

Samaniego presents a unique approach to comparing the Bayesian and frequentist schools of thought. Previous authors have tackled this comparison by focusing on the differing philosophies and methodologies. Samaniego has the more direct and straightforward goal of determining "which approach should one use in a given problem." Specifically, his goal is to determine a threshold on the class of available priors separating the cases where the Bayesian beats the frequentist, and vice versa. The existence of such a threshold certainly seems obvious. Furthermore, the location of the threshold will depend on the underlying truth, which is clearly unknown. The nature of a review of this work then boils down to a discussion of what Samaniego brings to the estimation problem that is useful to a practitioner. Indeed, his solution to the threshold problem for point estimation is fascinating. Yes, the existence of a threshold is not surprising. No, one cannot know the exact location of the threshold without knowing the underlying truth. The importance of the work is the discovery of how much the location of this threshold points to the advantage of the Bayesian. Only if the Bayesian is both "misguided" *and* "stubborn" in the choice of a prior will the Bayesian estimator lose to the frequentist estimator. It is not enough to be just "misguided" or just "stubborn."

I have only a minor complaint regarding the rules for the comparison. Samaniego argues that a frequentist estimator that can be derived as a Bayesian estimator with respect to a proper prior distribution should fall into the Bayesian category; for example, the minimax estimator of a proportion p is the Bayes estimator under a Beta($\sqrt{n}/2$, $\sqrt{n}/2$) prior. But such a prior depends on the sample size n, and thus reflects more than prior information alone. Although such an estimator is a shrinkage estimator, it is not a Bayesian estimator in the strictest sense. Thus, a general superiority of shrinkage estimators is established in the comparison. Nevertheless, whether or not we classify all shrinkage estimators as Bayesian, the intrigue and utility of the comparison is undiminished.

In the early chapters, Samaniego provides extensive overviews of the decision-theoretic framework, the frequentist approach to estimation, and the Bayesian approach to estimation. I found the coverage of these topics strong and the writing interesting. Although these topics are well represented in the literature, there is still much to recommend in these chapters. The author's writing skills are a large part of what the book has to offer. Samaniego provides a thought-provoking commentary on the coverage of this background material. The threshold problem is introduced in Chapter 4. The comparisons between Bayesian and frequentist estimators start in Chapter 5 with the problem of estimating a scalar parameter under a squared error loss function. Later chapters extend the threshold problem to multivariate parameter estimation and estimation under asymmetric loss. The remaining chapters cover the threshold problem for estimation of nonidentifiable parameters and the threshold problem for estimation in the empirical Bayes framework.

The final chapter provides a call for further study, specifically for an extension of the threshold problem to hypothesis testing and interval estimation. I believe that such a study has much to offer. The point estimation comparisons conducted by Samaniego are based on a concept that is essential, yet can get lost within the theoretical and computational aspects of a problem. The essential concept behind point estimation is to find an answer that is close to the true value of the parameter. Hypothesis testing and confidence interval estimation, where too much of the focus is on how the frequentist and Bayesian philosophies conflict, could serve to be laid bare in this same manner.

I can see *A Comparison of the Bayesian and Frequentist Approaches to Estimation* serving the needs of a special topics course or serving nicely as a reference book for a more general course on Bayesian statistics or mathematical statistics. We are entering an era in which statisticians are becoming less concerned with satisfying a particular dogma and more concerned with getting answers right. This is a important message that has been put forth by Samaniego in various works over the years. This message is wonderfully captured in *A Comparison of the Bayesian and Frequentist Approaches to Estimation*.

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Bayesian Nonparametrics.

N. L. HJORT, C. HOLMES, P. MÜLLER, and S. WALKER (eds.). New York: Cambridge University Press, 2010. ISBN 978-0-521-51346-3. viii + 299 pp. $59.00 (H).

In this book's very first sentence, the authors promise to justify the reader's curiosity about Bayesian nonparametrics. Some 300 pages later, their success is apparent. The book provides a *tour de force* presentation of selected topics in an emerging branch of modern statistical science, and not only justifies the reader's curiosity, but also expands it.

Bayesian nonparametrics (BNP) is an advanced approach to statistical modeling using large (infinitely dimensional) parameter spaces for unknown functions (density, regression, link, response) and for constructing prior distributions over such spaces. Its theoretical origins can be traced back only for about 40 years, whereas the last 10–15 years have brought a rapid development of substantial theoretical results and modeling methodology applied on practical real-world problems in vastly diverse areas.

Before going into details, a summary of my review may be helpful to the potential reader (and a not-so-patient reader of this review). The book brings together a well-structured account of a number of topics on the theory, methodology, applications, and challenges of future developments in the rapidly expanding area of Bayesian nonparametrics. Given the current dearth of books on BNP, this book will be an invaluable source of information and reference for anyone interested in BNP, be it a student, an established statistician, or a researcher in need of flexible statistical analyses. The book focuses on both BNP concepts and methods; however, it is not meant to serve as a "user guide" for the development of BNP models, although studying it would certainly aid such an endeavor. This is not a criticism of the book, but rather an acknowledgment of the fact that BNP is an important growing area of modern statistics that merits a more diverse, high-quality literature.

The material in the book is organized around the following core themes: Dirichlet process priors and posterior asymptotics, BNP models beyond the Dirichlet process, applications in machine learning and computational issues, and applications in biostatistics.

For each theme, established experts in the field (D. Dunson, S. Ghosal, J. Griffin, M. Jordan, A. Lijoi, I. Prünster, F. Quintana, and Y. Teh) were invited to write a chapter of their own or jointly with the editors, and then the editors further discuss and extend each topic in additional chapters. This pairing approach contributes to the coherence of the selected material and to the balance of complementary views and expositions. The selection of the main themes reflects to some degree the background events that led to the publishing of the book. It was a month-long program (a workshop and a conference) on Bayesian nonparametrics organized by the editors and hosted by the Isaac Newton Institute at Cambridge, U.K. in 2007. The seeds from which the core themes of the book grew can be found in the four tutorial lectures given at the event.

The order of the presentation of the topics follows a clear logic of first addressing the basic motivation and the foundational ideas—i.e., Dirichlet process priors and Bayesian posterior inference in large parameter spaces—and then the extensions to more general stochastic priors and their properties, such as completely random measures, beta processes, and hierarchical BNP models, concluding with the applications of BNP models mainly in survival analysis and biostatistics. However, the level of mathematical (and otherwise Bayesian) consideration of infinite-dimensional spaces and the terseness of the exposition necessarily vary among the chapters, so that reading them in a somewhat different order than that listed in the book might help a novice in the area gain familiarity with the material in a smoother way. I would suggest starting with Chapter 7, which, although focusing on biostatistical applications, begins with an accessible introduction to the basics of Bayesian hierarchical modeling using Dirichlet process priors and shows analyses of hierarchically clustered data as they may arise in multiple medical studies, bioinformatics, and epidemiology. Moving after that to Chapter 5 introduces the reader to several extensions of the basic DP mixtures and similar models to more complex specifications with recursive (hierarchical) BNP structures with applications in machine learning, such as natural language processing and computer vision. After this (already broad) exposure to the ideas of Bayesian nonparametrics, one could then resume reading the book from the start.

A look at history is helpful (even necessary) to appreciate the current state in the field of BNP, the beginnings of which can be traced back to the 1960s and the far-reaching ideas of Professor David Blackwell from the Statistics Department at UC Berkeley (a frequentist powerhouse of the time). Soon after came the seminal works by Ferguson (1973, 1974) on Dirichlet process priors and Doksum (1974) on tail-free distributions. Many additional results (duly commented on in the book) were published on the topic of construction of random distributions on spaces of functions (in particular, for applications in survival analysis). However, after the initial success of demonstrating the potential of theoretical results, the computational complexity of the then-available methods for posterior inference seemed to have hindered or even stopped further development. The Markov chain Monte Carlo simulation schemes came to the rescue but not before the 1990s, when the increased availability of computing power allowed statisticians to exploit a variety of simulation algorithms for performing the posterior inference. The complexity of the work with Bayesian nonparametric priors is apparent from the fact that one must construct prior distributions on infinitely dimensional function spaces. In this framework, the standard questions and problems of conventional statistics, such as asymptotic properties and convergence of the posterior distributions, gain importance, and proofs of consistency increase in difficulty.

Bayesian consistency means that the posterior distributions will concentrate on the true model; in other words, the posterior probability of hypotheses containing the truth tends to one. Doob (1949), showed that the Bayesian updating is consistent except possibly on sets of data with prior probability 0. Unfortunately, such null sets may be topologically large and Freedman (1963) showed that inconsistency may lurk even in the simplest nonparametric estimation problems. Although this was an unpleasant result that could have damaged the future of BNP modeling, it turns out that all possible pairs of true parameter values and priors that lead to consistency is very small compared with the whole product space when measured topologically. In other words, what may happen to a given prior distribution is not important if such prior has relevant subjective features and leads to a posterior distribution with good frequentist properties. Yet results like this one serve as a warning that, although Bayesians may agree "with frequentists and among themselves" when sample sizes grow in case of finite-dimensional models, the matters are far more complicated in infinite-dimensional spaces, obliging one to prove the posterior consistency under specific conditions set on the true parameters and the prior.

The first applications of BNP modeling were developed primarily for survival analysis and biostatistical data almost 4 decades ago. Nowadays BNP applications span a wide variety of scientific, medical, financial, and machine learning areas. The recent research activity in BNP at the methodological and theoretical levels seems to be broadening and growing so fast as to risk developing some important segments in isolation of the core areas indicated by the book themes. As a matter of fact, the publishing of this book was motivated in part by the desire to integrate most of the relevant topics of BNP research in a unifying fashion, and to present them in connection with the core field. Successfully accomplishing this task is one of the strengths of the book.

When summarizing the book's material, it is natural to comment on pairs of chapters, because they represent a coupled exposition of the fundamental concepts and results along with their extensions. The first two chapters address the basic motivation and ideas behind Bayesian nonparametric models along with important asymptotic issues and results. The first chapter (by S. Walker) is written in a terse style and may be a challenge for a novice to absorb at once. It describes a view of a Bayesian nonparametric model primarily as a learning tool based on the assumption that the observations are iid draws from some true density. A prior is specified in a way that ensures that the posterior distribution accumulates in suitable neighborhoods of the true density function. The chapter emphasizes the importance of studying the consistency of posterior inference, indicates the usefulness of a decision-theoretic approach in parametric model selection, and outlines a general construction of posterior distributions using loss functions.

Dirichlet process (DP), the flagship prior of Bayesian nonparametrics, is described in a decent amount of detail in the second chapter (by S. Ghosal), including varieties of its construction and properties. The realizations of a Dirichlet stochastic process are almost surely discrete, which follows from its representation using Pólya urn structure and Sethuraman's stick-breaking constructive definition. Discreteness of the DP, although a clear limitation for a direct modeling of data, turns out to be a real boon when used in the mixture setting. If we consider a mixture, $\int k(\cdot \mid \theta)G(\mathrm{d}\theta)$, and specify a DP prior on the mixing distribution, G, then we obtain a DP mixture model, which can serve as a flexible prior for continuous data in cases like density estimation, classification, and regression. Discreteness of the mixing distribution G results in the ties of the values of latent variables, θ, which allows the clustering structure in the data to be captured. A particular emphasis of this chapter is on the problem of posterior consistency and methods for its analysis. In the context of density estimation, an account of Schwartz's theory for deriving proofs of consistency of posterior distribution is presented, which exploits properties of mutual information between the joint density of the observables with respect to the prior and the true density. However, this method of proving consistency is not effective in infinite-dimensional spaces with certain topologies, because it requires truncation of the parameter space, which depends on the sample size. Rates of convergence of the posterior distributions to the truth are also studied, and the analysis is carried out again using the tools and concepts of information theory. In the case of parametric Bayesian models, Bernstein–von Mises theorems assert asymptotic resemblance of the posterior to a normal distribution. The importance of these theorems is reflected in, for example, the justification of the construction of approximately valid confidence sets using Bayesian methods. It would be highly desirable to prove some analogues of these theorems for infinitely dimensional spaces used in BNP; however, very few results in this direction are available to date, and this remains an area of active research.

The second pair of chapters present and discuss BNP models that go beyond a mere use of the DP. The third chapter (A. Lijoi and I. Prünster) starts with a version of de Finetti's representation theorem stating that an infinite sequence of random variables is exchangeable if and only if it is a mixture of sequences of iid random variables. A readable and well presented account on completely random measures (CRM) and their transformations follows. Kingman (1967) introduced and developed the important concept of completely random measures, on spaces of measures that induce mutual independence among random measures on disjoint events. The prototypical BNP prior, the DP is a special case of such normalized random measure with independent increments. Explained and used throughout the chapters is a closely related and important Lévy–Khintchine representation of CRM-s, with a single measure (Lévy intensity) characterizing the CRM. Gamma processes, neutral to the right processes (NTR), beta-Stacey processes, and Pólya trees also are described in this framework with an emphasis on the contributions of J. Pitman and J. F. C. Kingman, including also the most recent results by several authors (too many to mention in here).

The fourth chapter (N. Hjort) mainly deals with the beta processes in the context of survival analysis and presents a version of beta processes that is more constructive than that given in the previous chapter. Included also are sections on hazard regression models, competing risk models and quantile inference. To demonstrate the potential and flexibility of Bayesian nonparametrics in modeling a variety of statistical functions, an analysis of stationary time series is given using a gamma process with independent increments as a prior for the power spectrum measure of the covariance function. A similar approach is described for the case of Bayesian nonparametric treatment of the covariance function in spatial models.

Chapter 5 (by T. Yeh and M. Jordan) describes hierarchies of Bayesian nonparametric prior specifications, such as hierarchical DP (HDP), in which the base distribution of the DP is itself random with another DP as its prior. Applications of HDPs to information retrieval, multipopulation haplotype phasing, and topic modeling are described, including hidden Markov models (HMMs) with countably infinite hidden state spaces in which an HDP is used to model the space of latent states. Advantages of HDP-HMMs models are described for applications in speech recognition and word segmentation. Merits of hierarchical Pitman–Yor (PY) processes, extensions to DPs with two additional parameters (discount and concentration) in which the base distribution of a PY process is a random draw from another PY process, are shown in applications to language modeling and image segmentation.

Chapter 6 (by J. Griffin and C. Holmes) deals with computational issues arising in hierarchical BNP models, with a particular focus on simulations for DP mixture models (DPMs). Models in which the DP mixture kernel is conjugate with the base distribution of the DP are easier to fit than more typical cases of nonconjugacy, in which no analytical solution is available for the integrals arising in the conditional distribution of latent variables (a central part of a DPM model). Poor MCMC mixing is one of the main features of the simulations needed for posterior inference. A number of sampling techniques have been developed using various combinations of Metropolis–Hastings, Gibbs sampling, and slice sampling.

The last pair of chapters cover applications of BNP models to data and problems arising in biostatistics. Chapter 7 (by D. Dunson) starts with a nice overview of the basic features of BNP models with the DP as a nonparametric prior. Applications to biomedical studies in which it is common to combine data across different sources (as in multicenter studies or meta-analyses that combine results of similar studies) are described. The use of dependent DPs (DDPs) as priors is explained for a large class of applications that require modeling of predictor-dependent sets of distributions. The use of DP mixture models in analyses of gene expression data and in a study of polymorphisms and haplotypes is also explained. An account of kernel-weighted mixtures of independent DPs (as basis components) is provided, with an application to reproductive epidemiology.

The final chapter (by P. Müller and F. Quintana) extends the aspect of a DP as a clustering mechanism and examines it as a special case of more general clustering models, such as product partition models and species sampling models. The chapter also describes the use of DDPs in models with categorical predictors in an ANOVA setting, and provides an extension to a DDP ANOVA model for classification. It also discusses the availability of reliable public software as an important contributing factor for enabling wider use of BNP models. The public domain R language is a popular software platform for statistical research and applied work, with an extensive library of user-contributed packages. R packages such as `DPpackage` and `bayesm`, which implement inference for several DP models, are discussed toward the end of the chapter.

In summary, *Bayesian Nonparametrics* provides an up-to-date account of the theory, methods, and applications of BNP and is bound to become a landmark reference in this rapidly growing area of modern statistics in need of more books. If there is an objection to be made explicitly, it would be regarding the choice to print the text on glossy paper, which might diminish the reading experience to some degree. However, this is not an acceptable reason for not including the book in one's own library.

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Choice-Based Conjoint Analysis: Models and Designs.

Damaraju RAGHAVARAO, James B. WILEY, and Pallavi CHITTURI. Boca Raton, FL: Chapman & Hall/CRC, 2010. ISBN 978-1-420-09996-6. xi + 180 pp. $89.95 (H).

Conjoint analysis (CA) and discrete choice experimentation (DCE) have been around for almost four decades, yet very few books have attempted to explore the different study designs available to researchers in these areas. *Choice-Based Conjoint Analysis: Models and Designs* adds to this sparse literature. In particular, the book presents and discusses various design issues that arise in developing concept profiles for DCE studies. It does so in eight chapters. Given the content and the order of presentation, this book is both educational and interesting to read and is suitable for anyone interested in developing a CA/DCE study.

The book is unique, particularly in terms of the breadth and depth of information on experimental designs. The authors did an excellent job providing both contextual and technical details in a form that is both engaging and easy to read. The illustrations are easy to follow and relevant to the related content.

The book opens with an introduction to CA and DCE, along with some historical background and a brief discussion of related statistical models. Chapter 2, "Some Statistical Concepts," provides a crash course in experimental design. It describes different types of designs, with an emphasis on differentiating experimental and treatment designs, block designs, and factorial designs. The chapter then provides a brief, yet sufficient discussion on the estimation approaches for them. It concludes with a note on how to test linear hypotheses in the given context. The first two chapters can serve as "leveling" information, making the remainder of the book readable and useful to both first-timers and expert researchers in the field.

From Chapter 3 onward, the book gets into the details of the design issues. It starts by introducing four generic designs: brands-only designs, attributes-only designs, brand-plus-attributes designs, and brand-plus-attributes with selected two-way interactions models. Examples are provided for each of these designs that present the design matrix in each case, along with illustrations of the choice sets. The chapter concludes by discussing the estimation process and hypothesis testing with these designs. Chapter 4 expands on the design discussion and explores situations in which the attributes in the study are ordered. It explores linear, quadratic, and cubic effects for attributes at two, three, four, and five levels and then discusses the interaction components in the context of linear and quadratic effects. Issues related to Pareto sets and approaches for optimizing the study design are covered as well.

Chapter 5 discusses how researchers can reduce the number of profiles and the size of choice sets of studies. In particular, the authors discuss multiple approaches, including generating subsets with overlapping attributes, balanced incomplete block designs, and cyclic designs. Chapter 6 introduces cross-effects in CA/DCE and discusses them in the context of brand-only models and brand-plus-attributes models. Portfolio choice is also explored, along with a discussion of how Logit models can be used to generalize model portfolios.

The books final two chapters introduce sequential methods (Chap. 7) and mixture designs (Chap. 8). Sequential methods, in which information from previous stages influences the planning and design of subsequent stages, is effective and useful for computer-assisted studies. In this context, Chapter 7 explores symmetric experiments (s^m, 2^m, and 3^m) and two-way interaction and three-way interaction studies. In particular, it provides details of design issues in each of the foregoing contexts, along with the respective estimation processes. Chapter 8 explores mixture designs in which the effects of external factors on subjects' choices are examined in the context of CA and DCE.

The book has a logical structure and a very readable style. In each chapter, the authors first link the focal content to the rest of the book, then progress from a simple design to a more complex one through a series of illustrations, concluding with a discussion of the related estimation processes.

The book is concise, and the examples accompanying the discussion are clear and supported by relevant illustrations. One weakness of the book (at least in the eyes of this reader) is that almost all of the examples provided are in the context of marketing. Although this reflects the prominent role of CA and DCE in marketing, it limits the readership somewhat, making the book most suitable for researchers and graduate students in marketing and somewhat less so for those in statistics, management, and information systems. Although the book does not include exercises, it can be used in graduate courses as a companion to an experimental design textbook.

In conclusion, *Choice-Based Conjoint Analysis: Models and Designs* is a nice addition to the CA/DCE literature and should be useful to researchers and graduate students alike.

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Computation of Multivariate Normal and *t* Probabilities.

Alan GENZ and Frank BRETZ. Berlin: Springer-Verlag, 2009. ISBN 978-3-642-01688-2. viii + 126 pp. $79.95 (P).

This book covers the computation of probabilities associated with the multivariate normal and multivariate *t* distributions. The challenge lies in the multivariate aspect of these computations, which are clearly nontrivial. For example, how does one evaluate numerically the cumulative distribution function of a trivariate normal random vector? Statisticians are used to computing probabilities related to the univariate normal distribution on a calculator or computer, or from tabulated entries in the back of a statistics textbook. But how does one compute similar probabilities for multivariate normal or multivariate *t* distributions? This book synthesizes many results published in statistics journals in recent years on this topic and provides a unique source of information on the computation of these probabilities, which arise very naturally for statistical inference in many modern applications. I believe that it fills a gap in the literature on multivariate statistics.

The book comprises six chapters. Chapter 1 serves as an introduction and covers historical developments, as well as several motivating examples. Chapter 2 deals with various special cases that simplify the computations, such as bivariate and trivariate settings, particular forms of the integration regions associated with the probabilities to be computed, and specific correlation structures of the multivariate distribution. Chapter 3 describes various methods for approximating a problem by easier-to-solve problems. The core of the book is Chapter 4, which presents methods for approximating the integrals describing the sought-after probabilities. Chapter 5 expands on other topics, including linear inequality constraints, singular multivariate distributions, and software implementations. The latter is a very important aspect of this book, giving the reader access to code in `R` and `MATLAB` that can be used to evaluate multivariate normal and *t* probabilities. Two appendices provide detailed description of those commands. Chapter 6 presents various applications of the methods described in the book to multiple-comparison problems, computational finance, and Bayesian statistics.

One application that is not covered and is of particular interest to me is in the field of so-called multivariate unified skew-elliptical distributions, the density of which involves the cumulative distribution function of a multivariate elliptical distribution (see Arellano-Valle and Genton 2010 and references therein). In evaluating such a density or its associated likelihood, the methods described in this book for the computation of multivariate normal and *t* probabilities are essential. Such multivariate unified skew-elliptical distributions appear very naturally in problems involving a selection mechanism, for example, in genetic selection problems. In particular, the exact distribution of the maximum of the n components of an exchangeable multivariate normal random vector involves the multivariate normal cumulative distribution function of dimension $n-1$ (see Arellano-Valle and Genton 2008).

In summary, *Computation of Multivariate Normal and t Probabilities* provides great descriptions of methods for computing multivariate normal and *t* probabilities. With its associated software packages, this book will prove very useful to many statisticians in need of such probabilities for their applications.

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Handbook of Spatial Statistics.

Alan E. GELFAND, Peter J. DIGGLE, Montserrat FUENTES, and Peter GUTTORP (eds.). Boca Raton, FL: Chapman & Hall/CRC, 2010. ISBN 978-1-420-07287-7. xii + 607 pp. $99.95 (H).

As inferred by its title, *Handbook of Spatial Statistics* provides encyclopedic content ranging from history to up-to-date developments in spatial statistics. The key characteristics of data in spatial statistics is the "location" information contained in the data, which can provide additional information for analyzing data or can be of interest itself. As noted in the preface of the book, spatial statistics has grown from several roots rather independently. The stochastic process theory that drives the theoretical building blocks of spatial statistics is developed largely by probabilists. Most statistical methodologies developed in spatial statistics are driven by diverse applications, including mining, engineering, climatology, agriculture and health, and many others.

Among the several books on spatial statistics, *Statistics for Spatial Data*, by Cressie (1993), has served as a "handbook" of spatial statistics since its appearance. The rapid advancement of technology has resulted in an enormous amount of spatial and spatio-temporal data, as well as inexpensive high-performance computing. These changes necessitate the development of new statistical methods in spatial statistics and are driving the need for a "current" reference for those interested in entering into the field. This book is designed to cover all subareas of spatial statistics and meet such needs.

The book's contents mostly provide an overview of subareas in spatial statistics that can be understood at the master's degree level. Most chapters start with the basic concepts and extend the ideas, including recent developments. The book includes several fields of applications that actually lead to the developments of various methodologies in spatial statistics. Readers can see the diversity of applications, as well as how those applications can be grouped within the framework of spatial statistics. Thus, this book is a good starting point for entering each subarea of spatial statistics. Spatial statistics courses at the graduate level are becoming more popular, but few available books on the topic can be used as a textbook. Although this book is not designed as a textbook, I believe that it can serve as a textbook at a graduate level for statistics majors, given that the content is not too difficult for graduate students to follow.

This book consists of cohesive but independent chapters presented in six parts, covering an introduction, continuous spatial variation, discrete spatial variation, spatial point patterns, spatio-temporal processes, and additional topics. The book is edited by active and prolific researchers in spatial statistics and is carefully designed to include all subareas in spatial statistics. Each chapter was written by renowned experts on each subject. The book appears to be the result of a concerted effort by the entire spatial statistics community. Another attractive feature is that each chapter has its own list of contents, which is helpful when searching for a particular topic.

Part I, written by Peter J. Diggle, introduces the history of spatial statistics, starting from the earliest example on probability and extending to current popular statistical modeling of dependent data. Part II, on continuous spatial variation, includes theory and application based on the assumption that the data are a realization of continuous spatial processes. It begins with a chapter that introduces some theoretical background of stochastic processes. Classical approaches used in geostatistics, including modeling variograms and kriging, follow. As a frequentist approach, likelihood-based methods for estimating parameters under the presence of dependence in data are introduced, and statistical methods developed in spectral domain are introduced as an alternative powerful method when the data are observed on a regular grid. Part II also includes a rather brief overview of asymptotic theory developed in spatial statistics. A Bayesian approach, another important tool for handling spatial data, is introduced with general hierarchical modeling, computation, and a data example.

Another important area in spatial statistics is monitoring network design. For example, monitoring environmental processes is critical in the study of climate change. Chapter 10 introduces various network design methods used to monitor such processes. Part II also includes several methods extended from classical approaches for dealing with particular characteristics of data. Chapter 8 introduces a technique for analyzing high- dimensional spatial data by introducing low-dimensional latent processes. Chapter 9 introduces modeling of nonstationary spatial processes, and Chapter 11 introduces non-Gaussian and Bayesian nonparametric approaches for spatial data.

Part III, covering discrete spatial variation, discusses developments in analyzing a finite collection of spatial data that include lattice data, pixel data and areal unit data, and other types of data. Chapters 12 and 13 discuss Markov random fields, the most popular technique for modeling discrete variation, and then conditional and intrinsic autoregressive models, some of the most popular models in Markov random fields. Two application fields, disease mapping and spatial econometrics, are introduced in Chapters 14 and 15.

Whereas Part II covers statistical methodologies for continuous data referenced with spatial locations, Part IV introduces statistical methodologies developed for spatial point patterns in which spatial location becomes random. Analyzing point patterns is based on the theory of point process introduced in Chapter 16. Classical parametric point process models, inference for such models, and multivariate extensions are introduced in Chapters 17, 19, and 21, respectively. Nonparametric methods for describing point patterns are covered in Chapter 18. Chapter 20 provides a useful step-by-step approach for analyzing spatial point patterns with a data example. The last chapter of Part IV, Chapter 22, describes how these methods are applied in spatial epidemiology, particularly for clustering and cluster detection.

Part V covers statistical theory and methodology for spatio-temporal processes. Time can be considered an additional coordinate of spatial processes, but certain spatio-temporal processes can be characterized as dynamic processes, which require a different modeling approach. Different characteristics of spatial data over time lead to the development of various statistical methodologies. Part V starts with a short description of spatio-temporal processes theory in Chapter 23. Dynamic spatial models using spatially varying state-space modeling are introduced in Chapter 24, and spatio-temporal point process models are covered in Chapter 25. Chapter 26 discusses analysis of trajectories in space, and the last chapter of Part V introduces data assimilation, a statistical method for combining numerical model outputs and observations sequentially.

Part VI contains additional topics that are important but somehow did not fit into Parts I–V. The topics include multivariate modeling by constructing valid cross-covariance functions, change of support problems dealing with misaligned data, the ecological bias in analyses using spatially aggregated data to understand individual-level information, and the analysis of spatial surfaces by considering gradient processes.

Although some chapters focus on overly specific or narrow approaches, and some chapters provide a rather short overview, overall *Handbook of Spatial Statistics* is well edited and covers a wide range of topics. providing a very useful reference book for spatial statistics.

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Inference and Prediction in Large Dimensions.

Dennis BOSQ and Delphine BLANKE. West Sussex, U.K.: Wiley, 2007. ISBN 978-0-470-01761-6. x + 316 pp. $100.00 (H).

This book provides a rigorous and thorough account of modern mathematical statistics as applied to the classic problems of prediction, filtering, inference with kernels, and high-dimensional linear processes. The running theme is how finite-dimensional estimates converge to an infinite-dimensional quantity. The book presents many new consistency results for nonparametric estimators, such as kernel plug-in estimators, for both discrete and continuous time processes. This book is meant for theorists interested in asymptotic properties of high-dimensional estimators, typically in nonparametric models. It also may be of interest to practitioners of a theoretical bent who would like to understand the mathematical basis for several commonly used nonparametric prediction models. The book also offers some very nice hidden gems; for those interested in stochastic processes in Hilbert spaces, the sections on Guilbart spaces are very interesting.

The book is nicely divided into sections with clear themes: prediction, inference and projection, kernel models, and linear processes in high dimension. The ordering of these sections is clear, and after the first two sections, the remaining sections can be read independently. The introduction of the problem of prediction using the framework of Blackwell is very appealing, and the authors return to this setting to explain both asymptotics and optimality. They also add some nice geometric insights. The section on inference and projection provides a nice overview of the central theme of the book—how sequences of increasing finite-dimensional models converge to infinite-dimensional processes. The section on kernel estimators contains many results on asymptotic properties of these estimates and would be of great interest to theoreticians in the statistical learning, statistics, and stochastic processes communities. This section also would also be of interest to those interested in analyzing Bayesian nonparametric models. The book's appendices of provide a concise overview of fundamental concepts, such as operator theory, statistical inequalities, stochastic processes, and convergence of stochastic processes.

This book is geared for mathematically advanced researchers interested in mathematical properties on infinite-dimensional models. An advanced graduate student with a very strong background in stochastic processes as well as some mathematical statistics would benefit from this book. References to seminal papers as well as more recent works are provied at the ends of sections. This book is not an introductory text on stochastic processes or asymptotics of estimators. For students with a very strong probability background, some knowledge of statistical estimators should be developed before proceeding with this book.

Inference and Prediction in Large Dimensions is not a light read, but the reader will emerge with a rigorous foundation and appreciation for infinite-dimensional models and nonparametric estimators.

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Large Sample Techniques for Statistics.

Jiming JIANG. New York: Springer, 2010. ISBN 978-1-441-96826-5. xvii + 609 pp. $99.00 (H).

Jiming Jiang's book on large sample techniques is a very welcome addition to the literature. Its strong points include the breadth of covered material, choice of relevant and interesting topics, lucid and attractive style of presentation, and sound pedagogical aspects. Jiang's desire to teach asymptotics and, in particular, to convey the modes of thinking that are essential to developing expertise in large sample techniques is palpable, especially in the book's early chapters. Although I have not had the chance to observe Professor Jiang in the classroom, his book makes it abundantly clear that in addition to being an astute researcher, he is a passionate and thoughtful teacher. Not many books, especially books on mathematical topics, manage to convey thrill and energy, but Jiang does an excellent job on this front. Clearly, much thinking has gone into the book.

Jiang positions his book rather well in the Preface and backs up his claims strongly in the body of the text. His goal is clear right from the start: "Instead of giving a formal, technical proof for every result, we focus on the ideas of asymptotic arguments and how to use the methods developed by these arguments in various less-than-textbook situations." Indeed, it is the "less-than-textbook" situation that represents the crossroads of an aspiring Ph.D. student's career. Accomplishment in textbook situations, as may be reflected by high grades on standard courses, is not sufficient to make the leap to the more nebulous ill-formulated situations that form the domain of a researcher's investigation. It is here that creativity, imagination, and the right kind of training that has equipped the researcher to think critically come into play. Jiang acknowledges the influence of Lehmann's (2004) *Elements of Large Sample Theory*, which also builds from simple concepts to advanced ones.

One technique that Jiang uses is the incorporation of case studies in many of the initial chapters. These specific statistical applications of the methods developed in the chapter accentuate the utility of the presented material. This helps provide context and relevance. The case studies technique was also used effectively by Kosorok (2008) in his book on empirical processes and semiparametric inference.

The first chapter covers "epsilonics" and other background concepts from analysis, using the consistency of the maximum likelihood estimator (MLE) in the iid case and presenting both Cramer's and Wald's arguments. Chapter 4 deals with asymptotic expansions using the classical proof of the asymptotic distribution of the MLE as a case study. Of the first 6 chapters, which provide much of the elementary spadework needed in asymptotic statistics, I particularly liked Chapters 3, 4, and 5. A separate treatment of the "Big O" and "small o" notation might seem like overkill to some, but although well-trained students from Europe or Asia that enter America's statistics Ph.D. programs can skip topics of this sort, I can say, from my own personal experience in dealing with incoming domestic Ph.D. students trying to grapple with Michigan's theoretical statistics course sequence, that a focused treatment of these notions can do them a world of good. Chapter 4 introduces the reader to a wide variety of asymptotic expansions that are central to much of asymptotic analysis without becoming unduly heavy, notationally or otherwise. In fact, I would say that an excellent preparatory course for fresh Statistics Ph.D. students (and especially those with lacunae in their mathematical concepts and backgrounds) could be based in part on the first six chapters of this book.

Turning attention to the later chapters of the book, the reader needs to keep in mind one of the main purposes of this text, namely "to introduce large-sample theory and methods for correlated observations ...." The usual practice in books that deal with asymptotics is basically to emphasize the independent observations case. Consequently, asymptotic results in dependent data scenarios usually need to be obtained from books that specialize in the scenarios of interest. Chapters 8, 9, 10, and 15 are aimed at addressing this gap in many asymptotic texts; in addition, the chapter on bootstrapping devotes a separate section to time series. The chapters on mixed-effects models and small area estimation (Chaps. 12 and 13) reflect some of the author's own research interests. I was very happy to see a separate chapter devoted to empirical processes (Chap. 7). Indeed, empirical processes have become nearly indispensable for dealing with asymptotics for complex semiparametric and nonparametric models, expecially in the domain of "nonstandard" asymptotics (a direction of specialization in my research), which includes problems in which the estimators are typically highly nonlinear functionals of the data and do not admit asymptotic linearizations, and so standard central limit theory fails, and continuous mapping techniques must be brought into play. Thus, there are strong reasons to expose Ph.D. students, even fresh ones, to some empirical process theory—something I have argued for elsewhere as well (Banerjee 2009)—and I was heartened to see that the author feels similarly. The chapter also includes a case study to provide a feel for why such techniques can be useful. Although the book by van der Vaart (1998) covers the modern theory of empirical processes in more detail, the intended audience for this book is quite different (or so it seems to me), and thus a fair comparison cannot be made.

I would expect to see this book used for theoretical masters and Ph.D. courses in Statistics Departments, sooner rather than later. Along with its excellent coverage of the fundamentals in its initial chapters, the book addresses a number of important topics in the latter half as well. I wonder if the author has considered augmenting the book in a later edition (should there be such a plan) with a chapter on asymptotics for likelihood-based inference and related estimation techniques like M and Z estimation. Of course, these are topics I am biased toward, and I realize that not everything can be covered in a single book, and also that there are sufficient available texts that deal with these topics.

All in all, *Large Sample Techniques in Statistics* is an excellent book that I recommend whole-heartedly.

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Large-Scale Inference: Empirical Bayes Methods for Estimation, Testing, and Prediction.

Bradley EFRON. New York: Cambridge University Press, 2010. ISBN 978-0-521-19249-1. xii + 263 pp. $70.00 (H).

The branch of statistics known collectively as multiple comparisons and multiple tests (MCMT) is complex and vexing. By necessity, MCMT makes use of probability perhaps more than any other topic in statistics. Unlike, for example, regression, probability is front and center in all theoretical discussions of MCMT. The arguments can become very slippery, depending on the probabilistic framework that one chooses to adopt, and thus there is enormous controversy over whether, when, how, and why to use MCMT on both the frequentist and Bayesian sides of the fence. In this book, Brad Efron aims squarely at the middle ground between Bayesians and frequentists, hoping to achieve some reconciliation of these controversies through empirical Bayes methods. Typical of Efron's work, the book presents fresh ideas, charts new ground, and lays an impressive theory, much of which he developed single-handedly.

The book's central thrust is that new techniques are needed for handling large-scale testing, cases where the number of tests, N, is in the thousands or even millions. Standard familywise error rate (FWER) controlling methods do not "scale up" well with increasing N, because the Bonferroni p-value threshold α/N becomes harder to achieve as N increases. Efron reviews the vast array of modern false discovery rate (FDR) controlling procedures as viable alternatives and establishes their connection to Bayes and empirical Bayes methods. He then puts forth his own variant, empirical Bayes methods based on empirical null distributions, as a useful alternative to classical FDR-controlling methods that presume a theoretical null [such as N(0, 1)]. Viewed from certain perspectives, Efron's approach to solving the dilemmas of large-scale MCMT works magnificently well. Especially appealing is the way the method "scales up"; whereas standard FDR-controlling methods are known to scale up with N (unlike FWER-controlling methods), they do not necessarily scale up with the sample size n. For tests in general, everything becomes significant with large n; not so Efron's method based on empirical nulls. With larger n the empirical null simply widens, and there are not necessarily any more "significances."

Those who disparage hypothesis testing will love this book. The term "significance" is eschewed in favor of the designation "interesting," and what has been called "insignificant" is called "not interesting" in Efron's terminology. Furthermore, the emphasis is as much on estimation as on determining significant (interesting) cases; local FDRs are estimated, effect sizes are estimated, and the effects of N and correlation structures on these estimates are detailed.

The book starts with a historical perspective on empirical Bayes and James–Stein estimation, setting the stage for their application to multiple comparisons. The book then proceeds to examples, with microarrays providing the main focus, although many other applications are given as well. Classical FWER-controlling procedures are then reviewed, although Efron blithely suggests that readers can skip this chapter. FDR-controlling methods are reviewed next. Efron's seminal contribution of the empirical null is then discussed, along with a chapter devoted to estimation accuracy. Correlation structure has a strong effect on accuracy, and an entire chapter is devoted to correlations, with particular application to microarrays. Delving further into genetics, a chapter devoted to enrichment analysis is provided.

The final two chapters provide interesting departures from the rest of the book. A chapter on relevance of cases gets to the real meat of the controversy of multiple comparisons: What is the relevant "family" within which a set of tests should be considered? Critics of MCMT have long disparaged the subject with the farcical question, "Should the statistician adjust for all tests performed in his or her lifetime?" Efron provides thoughtful advice on the subject. The final chapter focuses of effect size estimation as opposed to simple determination of "interesting" versus "not interesting," and establishes connections with the FDR following the seminal work of Benjamini and Yekutieli's (2005).

We can expect a superb learning experience from Efron, and his pedagogical style delivers. The book is written carefully and thoughtfully, with ample mathematical detail to make the concepts clear. Abundant examples of specific data analyses and simulation studies supplement the mathematical theory, making his points crystal clear. The book is chock full of eye-catching and informative color graphics, and thus is not at all dry. Software (in R) sources are identified so that readers can easily perform the analyses. The technical details and examples are interspersed with "exercises" embedded directly in the text, so that readers can test their knowledge on what they just read in "just-in-time" fashion, rather than waiting to the end of the chapter. The problems are not too difficult. I tried some and gained confidence that I had learned something. Thus, the book will serve well as both a reference book, in which the exercises assist the reader in learning, and as a textbook for a graduate seminar course, where the exercises can be assigned as homework problems.

I feel loathe to criticize this book, given that it is a major tour de force with many exceptional qualities. It delivers on many levels, although I would hesitate to say that "the answer" to the MCMT dilemma lies within. But very good answers to quite general problems are provided, and the framework laid out will be important for future generations of statisticians and scientists. The book does not advance a "grand theory" of MCMT, but then it does not purport to do so. The term "large scale" in the title should fairly warn the reader interested in small-scale applications; a careful reader will see that the methods break down for small N in various ways. Another concern is that the effects of correlation structure on the inferences are disturbing, in that greater correlation suggests a more conservative stance, in opposition to classical approaches. Also, although discreteness is mentioned as a minor technical nuisance, it can be more troublesome than suggested. Finally, there is a danger in overreliance on the FDR-related methods described in the book. Practitioners impressed with the theory and Efron's name may be inclined to apply these methods to publish results, with the implicit assumption that they have the proper statistical blessing. However, these methods are essentially exploratory, and confirmatory follow-up studies are needed to make strong claims; there is a difference between effects that are "interesting" and those that are replicable. The scientific literature has recently experienced an embarrassment of contradictory results, and I worry that nonstatistically minded scientists will miss the exploratory/confirmatory distinction when using these methods.

Efron mentions several books as laying foundational work, including my 1993 book *Resampling-Based Multiple Testing* (jointly written with Stan Young) (Westfall and Young 1993), for which I am very grateful. But I would like to add that the book *Multiple Comparison Procedures* by Hochberg and Tamhane (1987) is still a must-have text, excellent for its broad coverage of pre-FDR MCMT methods and its technical accuracy. Especially notable is the excellent chapter on decision-theoretic approaches, which likely will become a strong contender for "the grand unifying theory of MCMT," covering both large and small N cases with equal facility, as time progresses. Bottom line: I strongly recommend that you read Efron's *Large-Scale Inference*, but while you are at it, read Hochberg and Tamhane's *Multiple Comparison Procedures* as well.

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Multivariate Nonparametric Methods With R: An Approach Based on Spatial Signs and Ranks.

Hannu OJA. New York: Springer, 2010. ISBN 978-1-441-90467-6. xiii + 232 pp. $79.95 (P).

It is well known that the standard moment-based multivariate techniques perform quite satisfactorily for data with a normal distribution, but usually fail in the presence of egregious outliers or heavy-tailed distributions. Puri and Sen (1971) proposed nonparametric methods for multivariate analysis based on marginal signs and ranks, which prove to be robust and more efficient in cases where the standard techniques fail. However, unlike the standard techniques, the methods of Puri and Sen (1971) are not affine-invariant for location-scatter models. This is because the marginal medians, which are closely related to the marginal sign and rank scores, are not affine-invariant. This monograph, part of the *Lecture Notes in Statistics* series, provides a complete overview of multivariate analysis methods based on spatial signs and ranks. It covers a wide range of topics in classical multivariate analysis and presents some deep theoretical results. It also provides a brief review of other related nonparametric multivariate methods for some topics. It may serve as "a general reference for the latest developments in the area." However, the book is not suitable as textbook as the authors claim, because its methods are based solely on spatial signs and ranks, which are too specialized to encompass other popular multivariate nonparametric approaches to which students should be exposed. Further weakening the book's usefulness as a textbook is the lack of proofs, detailed examples, or student exercises.

The text is informally divided into four parts. Part I (Chaps. 1–4) serves as a foundation for the rest of the book. It provides a unified definition for both the theoretical and empirical versions of spatial signs and ranks based solely on the spatial sign function $U(\cdot)$. It shows that multivariate normal distribution models may be progressively extended to elliptical models and location-scatter models by assuming spherical and central symmetry. It gives a unified form for both theoretical and empirical location and scatter functionals and presents an explicit asymptotic distribution for the location and scatter estimates of elliptical models. By introducing the inner centering-standardization technique, it illustrates an affine-invariant extension of the results to location-scatter models and makes the scatter matrix identifiable up to a norming scalar. The central symmetry in a location-scatter model plays a critical role in finding the structure of the first and second moments of the affine-invariant location and scatter statistics, and is necessary for deriving their asymptotic distributions.

Part II (Chaps. 4–10) shifts into statistical inference of the location-scatter models in the case of one independent sample. It uses the location and scatter functionals based on empirical spatial signs and ranks. For estimating location, it proposes an M-estimate of the empirical criterion function for the L_1 median and Hodges–Lehmann median (which turn out to be spatial signs and rank scores), and develops their asymptotic distribution based on the arguments for M-estimates of empirical processes (or more generally, U-processes). For testing location, it uses the asymptotic distribution of spatial signs and rank scores for large sample sizes, as presented in Part I. A simple sign permutation test is proposed for a small sample sizes. The asymptotic relative efficiency of the test is discussed based on the asymptotic distribution of the test statistic under the contiguous alternatives that results from a direct application of LeCam's third lemma (cf. Hájek and Šidák 1967, p. 208). Both of these tests are compared with the classical Hotelling T^2 test. For estimating and testing the scatter matrix, the authors basically repeat the procedure illustrated in Part I, that is, use the empirical covariance matrix of spatial signs and ranks, together with their asymptotic distributions. There is a brief discussion of principle component analysis and canonical correlation analysis, which is related to the scatter matrix in multivariate analysis.

Part III (Chaps. 11 and 12) considers inference based on spatial sign and spatial ranks in a multiple independent-samples setting, and compares it with the classical MANOVA method based on raw scores. Part IV (Chaps. 13 and 14) closes out the text by extending the methods to the multivariate multiple linear regression problem and cluster-correlated data. It considers spatial signs and ranks with L_1 criterion functions for linear regression, where inference for the regression coefficient matrix β involves the design matrix and the affine-invariance requirement that $\hat{\beta}$ is different from that of location estimates in the iid case. For cluster-correlated data, it incorporates the dependence structure into the scatter matrix of the linear model, so that one may use the result for the location-scatter model presented in Part I.

Throughout the book, the reader is provided with numerical examples using the R packages `MNM` and `SpatialNP` for computation based on multivariate nonparametric methods. However, those numerical examples do not bridge the gap between the theory and computational procedure, and the use of R in these examples better serves the purpose of producing computational results than *illustrating* how to use these two R packages.

This monograph is suited for readers with some exposure to classical multivariate methods, nonparametric methods, and computation in R, and preferably familiarity with multivariate medians. My primary criticism of the book is that it lacks worked examples applying the theory. For example, in Section 3.3, an example worked out in detail to show the derivation of the second moment of the sample covariance matrix in the multivariate normal case using Theorem 3.2 (or one its corollaries) would have been very helpful. A secondary criticism is that the notation is not sufficiently rigorous. For example, on page 184 (testing problem I), a formal introduction of $T_i = T(y_i)$ and $T = (T_1, \ldots, T_n)'$ is followed immediately by another almost identical set, $T_i(\beta) = T(y_i - \beta' x_i)$ and $T(\beta) = (T_1(\beta), \ldots, T_n(\beta))'$. Later still another similar set, $T(\epsilon_i)$ and T, is used, and in testing problem II (p. 186), $T(\hat{t}, 0)$ is proposed. Another typical example of the book's abuse of notation is the use of "AVE" for mathematical expression of average, in many cases without indicating the indices over which the average is taken. Sometimes an average can be quite complicated, for example, in the criterion function used to define the Oja median (Sec. 4.5, p. 45), and knowing the indices over which the average is taken provides insight into the order of n (sample size) in it and thus helps identify its asymptotic property.

In summary, *Multivariate Nonparametric Methods With R* is a good reference book for the area of multivariate nonparametric methods based on spatial signs and ranks, although it is not suitable for use as a textbook.

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Pattern Theory: The Stochastic Analysis of Real-World Signals.

David MUMFORD and Agnès DESOLNEUX. Natick, MA: AK Peters, 2010. ISBN 978-1-568-81579-4. xi + 407 pp. $79.95 (H).

This text, intended for a broad audience, gives a very good and thoroughly illustrated exposition of the field of pattern theory, pioneered by Ulf Grenander. The book's main contribution is to engage the reader in a discussion over the choice, use, and development of mathematical tools to tackle challenging problems involving the clarification and understanding of real-world signals. The focus is on the development of stochastic models for real-world signals, able to somehow capture their essential characteristics. In the words of the authors, this is "not a basic introductory graduate text that systematically expounds some area of mathematics" (p. ix). Therefore, the reader should not expect a thorough description of all of the mathematical tools used. Nevertheless, most of the necessary tools are summarily presented throughout the text. The reader also should be aware that this is not a theorem–proof type of book. This is not in contradiction with the use of sophisticated mathematical tools in a careful and technically sound way, which is mastered by the authors and profusely illustrated in the text. Indeed, many of the discussions in the text raise numerous theoretical questions in the realms of pure and applied mathematics that will certainly excite and stimulate students and experienced researchers alike. This book is undoubtedly appropriate for use as the main text in a graduate course; however, it might need to be complemented with background foundational material from other sources as well.

The book is structured in seven chapters. The first chapter (Chapter 0) provides a stepping stone to the rest of the text, setting the tone and motivating the methodological approach. More philosophical in nature, it introduces the reader to the beautiful ideas of pattern theory. The main premise of such methodology is the development of generative stochastic models for the signals of interest, so that samples generated from such models capture the essence of real-world samples, or, in the words of the authors, samples that "look and feel" as real signals. Once such models are developed, inference can in principle be carried out using the Bayes rule, which often raises interesting computational and algorithmic questions. The chapter starts with a gentle introduction to the *Manifesto of Pattern Theory*, which introduces the basic philosophical considerations behind the proposed methodology. The discussion is profusely illustrated with examples of real-world signals, ranging from speech to images and shapes, which are used to construct a basic and natural classification of various types of patterns. The chapter ends by introducing the basic ideas of pattern analysis and synthesis, along with the core algorithmic architectures used for inference in the pattern theory paradigm.

The rest of the book is organized into six relatively independent chapters, roughly ordered by the complexity of the models proposed (in turn intimately related to the complexity of the signals being studied). All chapters are structured similarly, starting with an example from the class of signals of interest. After some discussion of the underlying physical processes that gave rise to these signals, the authors begin to craft a possible model, which usually requires some mathematical tools. These tools are summarily described in "basics" sections in each chapter. These sections are often somewhat "dry," introducing the basic concepts and some fundamental results (generally without proofs or thorough motivation). These (sections) are useful as a refresher if the reader has had earlier, deeper contact with the material. Otherwise it is necessary to gather the necessary background knowledge from other sources. This feature should be considered a strength, not a weakness, of the book, allowing the reader to broaden his or her knowledge in very diverse areas. With this in mind, the intended audience seems to be rather broad, ranging from active researchers (regardless of experience level) wishing to widen their perspective on pattern theory and signal and image processing to first-year graduate students in mathematics, engineering, or statistics wanting to learn how to approach challenging real-world problems in a methodologically sound way. Subsequent short descriptions of the various chapters provide both a rough summary of the contents and illustrate the organization and approach.

Chapter 1 considers models for written text, particularly in the English language. The tools and methodology revolve around the use of Markov chain models. By borrowing concepts from information theory, the authors make use of entropy and mutual information to quantify the quality of the proposed models. The remainder of the chapter presents algorithmic approaches making use of the models developed for parsing and machine translation, through the use of dynamic programming and the Bayes theorem. As in all other chapters, a list of exercises is given at the end. These exercises are particularly useful and instructive, ranging from simple standard problems to the derivation of important results (e.g., the axiomatic derivation of discrete entropy). Chapter 2 considers music signals as an instance of one-dimensional continuous signals. The main mathematical concepts used here are Gaussian models, Fourier analysis, and Poisson processes, introduced in due time throughout the chapter. The authors begin with a simple model for individual musical notes (i.e., signals that are approximately periodic), and go on to develop a more complex model for sequences of notes, making use of Poisson processes. The overall basic model is somewhat too simplistic, but nonetheless captures some of the essential aspects of music signals. A number of possible refinements are informally discussed. The authors conclude with algorithmic considerations, discussing approaches using dynamic programming, and introducing, in a concise but clear way, the *expectation-maximization* algorithm. Both of these chapters are highly accessible and illustrate in a very didactical way the approach of pattern theory.

From Chapter 3 on the authors present, in a thorough and extremely interesting way, numerous problems in which pattern theory has provided (and still provides) state-of-the-art solutions. These chapters closely follow the work conducted in the research groups of the authors and their collaborators, and naturally these chapters are significantly more complex than the preceding ones. Chapters 3 and 4 focus on image analysis in general. Chapter 3 revolves around stochastically modeling shapes in images, starting with object contour models (sharp contrast regions that signal potential boundary shapes). Because such models do not provide good descriptions for shapes, the authors proceed by mathematically formalizing planar shape models. Particularly interesting is the description and use of the *Gestalt laws* of vision and perception, which can be mathematically formalized and give rise to important shape grouping principles. The chapter ends by bringing together almost all of the models introduced up to this point, building a rather complex hierarchical structure. Chapter 4 continues with the topic of image analysis, but now focusing on the problem of image segmentation, namely how to divide the image domain into several regions that correspond to different objects in the scene. This involves modeling both the boundaries of objects and their textures. Several models are presented, based mostly on Markov random fields and exponential models. This chapter also includes a discussion of computational aspects, for instance, how to construct samples from such models or do inference. Unlike in the previous chapters, here several of the foundational mathematical results are presented with instructive proofs, enriching the presentation.

Chapter 5 considers the extremely challenging problem of modeling faces and images of faces. The authors begin by considering the now-classical approach of *eigenfaces* to model lighting variations, and illustrate the dramatic limitations of this model, such as its inability to model deformations of the face template. More adequate models are developed by making use of tools from differential geometry and Lie algebras, which are introduced in a long, but rather clear section. In a similar fashion as before, the chapter ends with the description of a "full face model," which incorporates all of the ingredients introduced so far, and includes a discussion of computational issues that arise when using them.

The sixth and final chapter is, in the words of the authors, "more ambitious then the previous ones" (p. 317). It treats the problem of modeling *general* images of natural scenes. The ultimate goal is to build a probability distribution over the space of all images, such that the corresponding samples are *natural* images (i.e., images of natural scenes). Such a model needs to capture important features, such as translation and scale-invariance. The authors begin by guiding the reader through the ideas of multiscale analysis, ultimately leading to the concepts behind wavelets. Building stochastic models on top of such structures involves a number of challenges of both a technical and a practical nature. Two models are introduced, a model based on translation and scale-invariant Gaussian distributions over a suitably chosen space and a model consisting of superpositions of various "objects" at different scales and positions. These two models should be viewed as a first step toward a general model of natural images, given that many questions and open problems remain, as the presentation makes clear. Unfortunately, unlike in the previous chapters, there is no discussion of computational issues, or of how and when such models can be used in inference tasks.

In summary, *Pattern Theory: The Stochastic Analysis of Real-World Signals* is an inspiring account of the challenges and approaches of pattern theory. The presentation style perfectly matches the content. This book is bound to find a wide and enduring readership and certainly should become one of the main references in the world of pattern theory.

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Simultaneous Inference in Regression.

Wei LIU. Boca Raton, FL: Chapman & Hall/CRC, 2011. ISBN 978-1-439-82809-0. xxi + 270 pp. $89.95 (H).

Although statistical inference in linear regression models based on simultaneous confidence bands has a rich history tracing back to Working and Hotelling (1929), *Simultaneous Inference in Regression* seems to be the first book devoted solely to this issue. Two main topics of the book—construction of the (exact) simultaneous confidence bands and inference in regression models based on these bands—have been the focus of the author's research for nearly the last two decades. It should be stressed that the "regression" in the title refers to parametric regression only, and more involved nonparametric models are not treated. Seven out of the book's eight chapters address standard linear regression under the assumption of normality for the regression parameter estimator. Because this assumption holds, at least asymptotically, for generalized linear and mixed models as well, all developed concepts are applicable to this wider class of parametric models, as discussed in the last chapter on the example of logistic regression.

Simultaneous Inference in Regression is probably less well suited as a course book, but doubtless will be useful for both researcher and practitioners. Practitioners are readily provided with more informative and intuitive inferential tools for linear regression than those promoted in standard textbooks, whereas researchers can profit from the comprehensive literature overview on simultaneous confidence bands and can be inspired by several unsolved problems. The author mentions, but does not provide details on, asymptotic or conservative simultaneous confidence bands available in the literature that links simultaneous inference to study of suprema of Gaussian processes. Instead, he focuses on the exact simultaneous inference, presenting the topic in rather intuitive way from a geometric perspective, generously illustrated with figures. Thus the mathematics involved is accessible, and the reader needs only be familiar with matrix algebra and concepts of estimation and inference in multiple linear regression. Numerous insightful examples help fix the ideas and meaningfully illustrate the advantages of simultaneous inference. The MATLAB programs that implement discussed examples are also provided.

The book starts with a concise and rigorous introduction into main concepts of estimation and inference in linear regression models under the normal error assumption. This assumption is crucial for the confidence bands to be exact, as shown in the next chapter, which deals with a simple linear regression model with only one predictor. This chapter presents in an elegant way the basic principles of the simultaneous confidence bands construction, which are subsequently generalized. Three types of simultaneous confidence bands—hyperbolic, two-segment, and three-segment—for a regression line over a general interval of covariate values are discussed in terms of polar coordinates of a bivariate t-distributed random variable and compared using the average width and minimum area confidence set criteria. In general, calculation of critical values for all bands involves a one-dimensional integration and the simultaneous confidence level is exact, given normality of the errors. Presented examples stress the differences between a simultaneous confidence set over the whole covariate region (the confidence band of Scheffé 1953) and a simultaneous confidence band restricted to a plausible range of covariate values. At the end of the chapter, other types of simultaneous confidence bands are discussed briefly, but unfortunately, little is said about Bayesian confidence sets.

Even though all bands developed for simple linear regression with one predictor can be directly generalized for the multiple linear regression, Chapter 3 explicitly treats only hyperbolic and constant width confidence bands, in which the values of predictor variables are restricted either to a rectangular or an ellipsoidal region. Again, critical values can be obtained exactly, similar to the one covariate case; however, if the covariates are restricted to a rectangular region, then construction of a simultaneous confidence band requires multidimensional integration. To circumvent this, the author promotes a simulation-based approach to obtain the critical values in lieu of approximate formulas (e.g., those of Sun and Loader 1994). This chapter is missing a comparison and some discussion of the introduced confidence bands. For example, the simultaneous confidence bands over an ellipsoid covariate region are easier to obtain (with just a one-dimensional integration involved), but if and when these should be preferred in practice is not explained. In addition, the two-dimensional black-and-white plots in this and subsequent chapters are not very informative and sometimes impossible to interpret.

Next three chapters highlight the advantages of inference based on simultaneous confidence bands and are the most interesting chapters for practitioners. The author contrasts standard F-tests for assessing part of a regression model and for comparing two or more regression models with tests based on simultaneous confidence bands. Although such F-tests are equivalent to tests based on simultaneous confidence bands over the whole predictor region, simultaneous confidence sets naturally provide more information. For example, a simultaneous confidence band quantifies the magnitude of the difference between two regression models if the equality of these two models is tested. Moreover, the inference based on simultaneous bands also can be performed over a certain restricted covariates region, which is often more reasonable in practice.

Chapter 7 deals with simultaneous confidence bands and inference for polynomial regression. Again, the author opts to obtain the exact critical values by simulations. The ideas developed in this chapter seem to be a plausible starting point toward nonparametric regression, which is not mentioned, however.

The last chapter is devoted to simultaneous inference in logistic regression. The main idea is to make use of the asymptotic normality of the maximum likelihood estimators. Naturally, the inference becomes approximative. However, at least a part of the chapter could have been easily written directly in terms of the exponential family distribution without loss of clarity.

The book introduces various types of simultaneous confidence bands for parametric regression over a (restricted) covariates region and corresponding inference procedures. The author advocates the use of exact critical values obtained either by a one-dimensional integration or by a simulation approach, instead of available approximative results. It should be noted that this simulation approach is not related to bootstrap or certain MCMC procedures. A similar technique has been used by, for example, Ruppert, Wand, and Carroll (2003, sec. 4.3.1) for inference in (empirical) Bayesian nonparametric regression. To obtain critical values either by numerical integration or simulation, practitioners will certainly need an easy-to-use implementation in a preferably free software. Even though the author provides MATLAB programs, I feel that a package in the free statistical software R would make the techniques presented in the book much more accessible. Another important practical question that merits more attention, is the robustness of the presented simultaneous confidence bands against deviations from normality assumption.

In summary, *Simultaneous Inference in Regression* definitely fills a significant niche, providing practitioners with powerful inference tools for parametric regression and stimulating further research in this important area.

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Statistical Inference: An Integrated Bayesian/Likelihood Approach.

Murray AITKIN. Boca Raton, FL: CRC Press, 2010. ISBN 978-1-420-09343-8. xvii + 236 pp. $89.95 (P).

This book attempts to establish a new foundational paradigm for statistical inference. The motivation for this new paradigm is the controversy around model selection, and the author proposes an alternative approach for statistical hypothesis testing and model selection based on comparisons of posterior distributions of likelihoods under competing models. This interesting book on model selection provides a nice review of the frequentist, likelihood, and Bayesian approaches to inference and model comparison. However, I remain skeptical about the author's claim that his proposed method is superior to the existing methods, for reasons explained later.

The first chapter lays out several theoretical perspectives regarding statistical inference, with an emphasis on how Bayesian methods allow one to deal with nuisance parameters most sensibly. The most commonly cited difficulties with the Bayesian approach—the role of priors and the importance of parameterization—are not discussed until Chapter 2, where the author largely dismisses these problems. In this chapter, the author presents the basis for his approach to model selection. This approach chooses between two models based on the posterior expectation of the likelihood ratio for these two models. Although the rest of the book is basically traditional Bayesian statistics (with the exception of the treatment of sample surveys), this method for model selection is unique to this book. [The article in which the author first proposed this approach Aitkin (1991) should be of interest to a potential reader, particularly because it contains a rather extensive discussion.] The author argues that neither frequentist approaches nor model selection based on the Bayes factor are comparable to his approach. However (based on a result from Dempster), he notes that the usual p-value is recovered from his approach when applied to simple versus simple hypothesis testing, and that his approach coincides with the use of Bayes factors for model assessment when comparing nested models. It seems rather odd to try to persuade Bayesians to adopt a new approach because it provides a connection between the posterior distribution and p-values, given that most would generally dismiss p-values. It also seems odd to criticize the use of Bayes factors and yet note that the new approach coincides with Bayes factors when comparing nested models.

After the second chapter, the author applies his approach to model selection to a variety of problems. The first application is to two-sample problems and the connection to the two-sample t-test. This material is highly predictable to anyone with sufficient background to understand the first two chapters, although it does illustrate the author's approach. Following this is a very nice, if slightly out of place, treatment of sample surveys from the finite population perspective. Although this chapter does not illustrate the use of the posterior expectation of the likelihood ratio (hence it being slightly out of place), it does illustrate the use of the Bayesian bootstrap and explores the frequentist operating characteristics of the methods via simulations.

The next two chapters return to the theme of model selection in two commonly encountered situations: regression modeling and analysis of binomial/multinomial data. The material on regression is surprisingly light and extends the approach to the two-sample problem in a straightforward manner; however, the treatment of contingency tables is interesting in terms of the attention given to the role of fixed margins.

The next-to-last chapter discusses model diagnostics. After a brief discussion of frequentist approaches, the author provides an odd critique of posterior predictive checks. He notes in passing that Hjort, Dahl, and Steinbakk (2006) concluded that such checks are not well calibrated; however, the discrepancy measure that those authors proposed is exactly of the type that the proponents of posterior predictive checks would advise against using (namely, comparing the sample mean to its expected value). The author develops his own critique based on the idea that, if y_{new} is a draw from a predictive distribution, then if $p(y_{\text{new}}|y)$ is computed, this probability (which is just a number) should convey uncertainty and thus should be treated as a random variable. Then the basic method of model selection is used to determine whether a collection of iid observations should be treated as arising from a given continuous distribution or from a multinomial distribution. A simulation study then examines the frequentist behavior of the resulting approach.

The final chapter discusses more complex data types (hierarchical models and mixture models) in the context of the author's approach to model selection.

The book contains surprisingly little on model averaging-based approaches or Bayesian nonparametrics, both of which are considerably stronger approaches to the problem of model selection from a Bayesian perspective. Nonetheless, this is an interesting book on model selection.

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Statistical Power Analysis With Missing Data: A Structural Equation Modeling Approach.

Adam DAVEY and Jyoti SAVLA. New York: Routledge, 2010. ISBN 978-0-805-86370-3. xiii + 369 pp. $42.50 (P).

The need for power analysis, or, more specifically, sample size determination, cannot be overestimated. As Cohen (1988) helped applied researchers realize—particularly researchers in the social and behavioral sciences—studies often are either wastefully overpowered or, much more commonly, tremendously underpowered so as to be predestined to find few if any results. Thus, attention to the methods necessary for planning research is generally quite welcome. This is especially true given the increased complexity of the methods used in applied research, for commensurate with increases in methodological complexity come increased challenges in determining the required sample size to use those methods sensibly. For these reasons—furthering awareness of the importance of power as well as the facilitation of power analysis for complex models—this book is a positive addition to a still relatively small body of resources on the subject.

After an introduction to power, the book is divided into three main sections. The first section, Fundamentals, acquaints the reader with the traditional LISREL framework, provides an overview of missing data, and discusses power estimation for structural equation modeling (SEM) within the typical maximum likelihood framework. The second section, Applications, starts with a brief presentation of power methods relevant for testing means and covariances and then moves into longitudinal (i.e., growth curve) models, dealing with different patterns of missingness, and then Monte Carlo approaches to power with missing data. The third (and considerably shorter) section, Extensions, provides a glimpse into issues of model fit, reliability of variables, auxiliary variables, and future directions. Finally, the book's references are followed by appendices containing more than 100 pages of sample code, with the SPSS, SAS, and STATA code meant mainly for power-related computations and the LISREL, Mplus, and AMOS code written for structural modeling purposes. This material is in addition to the considerable amount of sample code embedded within each chapter to help the reader with the necessary computations for the types of models presented.

As is clear from the book's overall tone, the authors genuinely wish to be helpful to the applied researcher. In addition to the extensive sample code, the book has a nicely accessible writing style, illustrative explanations and complementary figures, and many examples and hands-on exercises. Good writing is good teaching, and clearly these authors are good teachers, especially for an audience of applied researchers across a variety of social and behavior science disciplines, including (but not limited to) psychology, sociology, education, communication, management, nursing, and social work.

As with any first edition, this book has room to grow. The authors openly acknowledge this in various places, and any reviewer could certainly single out his or her pet areas where future expansion would be desirable. I would like to make a broader request (although possibly no less self-serving): The book's title—*Statistical Power Analysis With Missing Data: A Structural Equation Modeling Approach*—does not quite match its content, and I hope future content can be reshaped to achieve a better match. More specifically, although the title implies that an SEM framework will be used to facilitate power analysis with missing data, in fact the book is really about doing power analysis in SEM when there are missing data. The distinction is more than semantic. The former implies a broader treatment of power analysis, whereas the latter is confined to those models customarily found in an SEM framework. Because the book's current content is more of the latter, it really sets itself up to be for readers already invested in SEM; this in turn makes the whole introduction to the LISREL framework unnecessary. If you are going to introduce the reader in great detail to the LISREL model for the purposes of doing power analysis with missing data, it should not be just for models familiar to those who do SEM; rather, the reader's considerable investment in the beginning of the book should pay dividends across a broader family of general linear models. Specifically, just as Enders (2010) has recommended an SEM paradigm for dealing with missing data in such common scenarios as repeated-measures ANOVA and multiple regression (e.g., using full-information maximum likelihood estimation), this book likewise should deliver by making clear how to do power analysis with missing data for such familiar models. The logical pedagogical development in the book's content would thus parallel standard social science statistical training, using the SEM paradigm to take the reader from t-tests and ANOVA through multiple correlation and regression, possibly to multivariate measured variable methods, and then to the more common types of structural equation and latent variable models, such as confirmatory factor analysis and latent growth curves. I look forward to the authors applying their considerable didactic skills to such an expanded treatment, thus greatly enhancing their readers' ability to conduct power analysis with missing data across a wider variety of common analytic scenarios.

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Testing Statistical Hypotheses of Equivalence and Noninferiority (2nd ed.).

Stefan WELLEK. Boca Raton, FL: Chapman & Hall/CRC Press, 2010. ISBN 978-1-439-80818-4. xvi + 415 pp. $99.95 (H).

This second edition is a modest but welcome revision of the original. The book's title has been augmented to distinguish the case of "equivalence," normally associated with two-sided tests of an interval null, with "noninferiority," normally associated with related one-sided tests. Useful additions to this revised edition include a new closing chapter on tests for "relevant differences" and a switch from SAS and Fortran to R as the book's main computational engine. The book's outlook remains decidedly frequentist, and asymptotic arguments are used generously throughout. Bayesian approaches, quite natural for interval nulls that one hopes to accept rather than reject, are not covered. For these, the reader must turn to the books by Spiegelhalter, Abrams, and Myles (2004) and Berry et al. (2011).

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