topics course. Each chapter concludes with a "Problems" section, contributing to its usefulness in this direction. Finally, I strongly recommend this book to anyone interested in long-memory time series. Both researchers and beginners alike will find this text extremely useful.

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## Matrix Algebra: Theory, Computations, and Applications in Statistics.

James E. GENTLE. New York: Springer, 2007. ISBN 978-0-387-70872-0. xxii + 528 pp. $89.95.

This book arose as an update of *Numerical Linear Algebra for Applications in Statistics* (Gentle 1998). The author also mentions that many sections of the book evolved from his class notes. This book could serve as a text for a course in matrices for statistics (a course that I taught last year) or, more generally, a course in statistical computing or linear models. As such, it certainly will be difficult to cover the entire book in one course, but this can be a useful reference book for such a course or, more generally, as a reference for any statistician who uses matrix algebra extensively.

This leads to the obvious question of whether we really need yet another book on this topic. What really distinguishes this book from the many other textbooks is its computational orientation. For example, in many linear algebra for statistics textbooks, the "classical" Gram–Schmidt orthogonalization is not distinguished from the "modified" Gram–Schmidt orthogonalization, which is clearly a superior way to implement it. The classical method is not as stable and should not be used. The author first discusses this issue on page 27, and then justifies it on page 432. As another example, in the preamble, the author claims that "on the computer, a straightforward evaluation of $\sum_{x=1}^{\infty} x$ converges!" To some readers, this statement might appear to contain a typo, where $x$ should be replaced by $\frac{1}{x}$, until she or he reads up to Section 10.2 to see the author's point. For the "theory" part, the informal style of presentation makes this book unique. There is a natural development of the material that the reader can follow easily. Neither definitions nor facts are highlighted by such words as "Definition," "Theorem," and so on. Although a lack of definition or theorem numbers requires that the author refer to results by page number, in this style of presentation the definitions, facts, and proofs are inserted naturally into the text. I found this style appealing, but some readers might find it unfamiliar.

As the title suggests, the book emphasizes the areas of linear algebra that are important for statisticians, with the kinds of matrices encountered in statistical applications receiving special attention. The book comprises three parts featuring the areas mentioned in the book's title: theory of linear algebra (Part I), applications in data analysis (Part II), and numerical methods and software (Part III).

Part I, comprising Chapters 1–7, gives a broad overview of the linear algebra needed by most statisticians. Chapter 1 introduces vectors, and Chapters 2 and 3 develop matrices and basic theories of vectors and matrices. Chapter 3 extends over almost 100 pages covering a wide range of topics in matrix theory. Chapter 4 covers vector/matrix differentiation and integration; the reader is assumed to be familiar with the partial differentiation of scalar functions. Chapters 5–7 are more applied in nature and prepare the reader for the computational aspects discussed in later chapters. Chapter 6 discusses several important topics related to the solution of linear systems, which are very relevant to the applications in data analysis mentioned in Chapter 9.

Part II is concerned with data analysis. Chapter 8 discusses special matrices and operations useful in data analysis, and Chapter 9 addresses selected applications. This chapter covers several important topics, including principal components, optimal designs, multivariate random number generation, and stochastic processes. Several books have been published on each of these subtopics, and it is not possible to discuss them in detail; however, that the author addresses some of the numerical issues involved in these topics in a single book is commendable.

Part III, consisting of the final three chapters, covers some of the important details of numerical computations. Chapter 10 provides some basic information on how data are stored and manipulated in a computer. Chapter 11 covers numerical linear algebra, with several computational considerations discussed in detail. Chapter 12 is devoted to discussing programming languages, such as Fortran and C, as well as software like Matlab and R.

The prerequisites for reading this book are minimal. Only some basic background in mathematics and statistics is necessary. Some level of computer literacy also is required. But mature readers with advanced undergraduate-level courses in linear algebra and calculus, as well as in statistical data analysis and computing, will be better equipped to read this book.

The author clearly states that no typographical distinction is made between scalars and vectors. Boldface notation for vectors would have helped to clarify expressions such as $z = ax + y$ (eq. 2.1, p. 10). Similarly, all vectors are denoted as column vectors, although the author sometimes intentionally writes them as horizontal lists of their elements (but the meaning is clear from the context). Although the author explicitly mentions this in the preamble and in Appendix A, I personally prefer notational consistency; for example, in the expression $\mathrm{vec}(A) = (a_1^{\mathrm{T}}, a_2^{\mathrm{T}}, \ldots, a_M^{\mathrm{T}})$ of equation 3.5 (p. 45), I think it would have been better to put one more transpose at the end.

Some readers might find some chapters a little dense. Some more illustrative examples in Chapters 3 and 4 might have been useful. If this book is considered as a textbook instead of a reference book, students would find the inclusion of more worked examples and exercises helpful. But the book already is more than 500 pages long, and this suggestion possibly would increase its size significantly, with a possible threat of hampering the flow of development.

Using his unique presentation style, the author introduces some concepts in the first part of the book, and then recalls them later with more discussion. Some of these are quite interesting. For example, on page 11 the author reminds the reader that a vector space can be composed of objects other than vectors, and he discusses it again in Section 3.2 (p. 48). On page 29, he introduces Fourier coefficients in equation 2.37 and comes back to it again in Section 3 (eqs. 3.83 and 3.210). He even introduces some advanced concepts, such as flats and affine spaces, at the beginning of the book (Sec. 2). The author constantly draws the link between the "matrix theory" and "statistical application"; for example, at the end of Section 2, he devotes a section to variances and covariances of vectors. He gives nice geometric perspectives whenever possible. I particularly like Figure 8.6 (p. 296), which nicely displays the equivalence between generalized variance and the volume of the parallelotope determined by the columns or rows of a variance–covariance matrix $S$, and the fact that when the columns or rows of $S$ are more orthogonal to one another, the volume of the parallelotope is greater.

The author provides nice supplementary information about the methods he presents. Informing the reader that the common vector multiplication is Cayley multiplication (p. 59); the common multiplicity is algebraic multiplicity, which differs from geometric multiplicity (p. 113); and the usual norm is the Frobenius norm (p. 131) is useful. As another example, the author states that "the Jacobi method is one of the oldest algorithms for computing eigenvalues, and has recently become important again, because it lends itself to easy implementation on parallel processors" (p. 249).

I really enjoyed reading some of the comments, which are worth mentioning here: "Remember that for purposes of computations, 'zero' generally means 'near zero,' that is, to within some set tolerance" (p. 254), and "it is relevant to note that the system is singular because most standard software packages will refuse to solve singular systems whether or not they are consistent" (p. 242). I also enjoyed reading the section on "Writing Mathematics and Writing Programs" on pp. 446–447. In Section 12.2, the author judiciously suggests that the symbol "_" should never be used for assignment in R (p. 467). In fact, the current version of R will give an error to `x _ 3`, which should be written as `x = 3` or `x <- 3`.

In Section 12.1, the author discusses computational efficiency, including how the performance of a computer program is affected by the execution of loops. He illustrates the difference between the two following loops and why the extra programming is worthwhile:

```
do i = 1, n           versus  do i = 1, n, 7
  sx(i) = sin(x(i))             sx(i) = sin(x(i))
end do                          sx(i+1) = sin(x(i+1))
                                sx(i+2) = sin(x(i+2))
                                sx(i+3) = sin(x(i+3))
                                sx(i+4) = sin(x(i+4))
                                sx(i+5) = sin(x(i+5))
                                sx(i+6) = sin(x(i+6))
                              end do,
                              plus a short loop for any
                              additional elements
                              in x beyond 7⌊n/7⌋.
```

Overall, I really enjoyed reading *Matrix Algebra: Theory, Computations, and Applications in Statistics*, and I would recommend it as a nice reference to anyone interested in linear models, particularly its numerical aspects.

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## Missing Data in Clinical Studies.

Geert MOLENBERGHS and Michael G. KENWARD. Hoboken, NJ: Wiley, 2007. ISBN 978-0-470-84981-1. xx + 504 pp. $110.00.

Clinical studies often involve complex designs that require specialized statistical techniques. The high prevalence of missing values in these studies adds to their complexity and perhaps is a barrier to the validity and objectivity of the corresponding statistical inference when no principled action is taken. *Missing Data in Clinical Studies* meets an important need for a comprehensive collection of methods for clinical studies with missing data. This book builds on the key concepts and techniques offered in the seminal books on missing data (e.g., Little and Rubin 1987, 2002; Rubin 1987; Schafer 1997). Its key contributions to the literature are (1) its focus on clinical studies with longitudinal data where missing data are present as a result of attrition or dropout, (2) the use of missing-data techniques from parametric and semiparametric schools of thought, (3) the extensive discussion and exposition of sensitivity analyses, and (4) the use of real data examples. The book builds nicely on and extends the work with semiparametric roots by Rotnitzky and Robins (1995, 1997) and Tsiatis (2006), as well as traditional survey books that focus on nonresponse, such as that by Sarndal and Lundstrom (2005). Although the book is titled *Missing Data in Clinical Studies*, the methods can be applied to nonclinical data with little difficulty. The authors make this point clear when they demonstrate the very important topic of sensitivity using a Slovenian public opinion survey. The organization of the book follows an exemplary approach to teaching difficult but very useful concepts and methods for missing values in clinical studies.

This book has numerous strengths. It is carefully and thoughtfully written and obviously reflects the authors' deep understanding of difficult concepts in missing data. Along with a comprehensive discussion and collection of methods on missing data in clinical studies, it contains a significant amount of material on implementing these methods using SAS. My personal favorite parts of the book are the graphical displays, illustrations of concepts using real data examples, realistic sensitivity analyses for nonignorable missingness mechanisms, and the discussion of uncongeniality [e.g., combining generalized estimating equations (GEE) and multiple imputation (MI)].

For readers to fully benefit from this book, they should have a fairly good understanding of the basic concepts in missing-data theory and mixed-effects models (e.g., marginal vs. random-effects models). The previous texts on missing data (e.g., Little and Rubin 2002; Schafer 1997) would be perfect complements to this text, as well as texts on the analysis of longitudinal data (e.g., Hedeker and Gibbons 2006; Fitzmaurice, Laird, and Ware 2004; Verbeke and Molenberghs 2000). Some additional knowledge on computing and programming would be helpful. I would definitely adopt parts of this book in my class on missing data. Representation of methodology in worked examples and reproducibility is a good substitute for exercises typically found in a course text and provides for a potentially better learning experience.

The book comprises five sections with a total of 26 chapters. The first three chapters establish the commonly used missing-data language and notation and introduce the data examples. These examples play a significant role in demonstrating the advanced methods presented in the second part of the book. Next, the authors present relatively more complex concepts, such as missing-data mechanisms and ignorability, and discuss some commonly used analytical models corresponding to these mechanisms, such as pattern-mixture models operating under nonignorable or missing not at random (MNAR) mechanisms. Overall, these three chapters are easy to read and do a good job in establishing a solid foundation. Simple illustrations (even hypothetical ones) of missing-data mechanisms in the data examples would have been a great complement.

The second part of the book presents and critiques unprincipled, easily implemented methods for missing data, and it provides the necessary background for a discussion of principled methods. Some of the unprincipled methods discussed include case deletion and last observation carried forward (LOCF). As the authors note, these methods can lead to highly biased results, especially in such complex settings as longitudinal designs, which are commonly seen in clinical studies. This section could have benefited from a discussion of single imputation beyond LOCF as a "procedural" method for handling missing values in clinical trials. The authors transition to a discussion of principled methods by introducing likelihood methods. Interesting data examples finish the book's second part with a major demonstration of trajectories estimated under different missing-data mechanisms. However, LOCF is a bit misplaced in the plots with missing at random (MAR) and missing completely at random (MCAR), which refer to missing-data mechanisms rather than to imputation procedures.

Starting in the third part, the book takes a turn toward more modern methods for handling missing data under a given missingness mechanism. The focus here is on methods that operate under MAR and ignorability. Some of the material on inference by multiple imputation as well as the EM algorithm can be found in earlier texts on missing data, and it would have been nice if the authors had modified the material so that the reader could focus on the use of these concepts in the clinical studies context. For example, what would be the imputation model in a longitudinal study with missing values due to dropout and partially collected data? Given the increasing popularity of MI, a discussion of the impact of the design features (e.g., multilevel, unequally spaced measurement times) on the imputation model would be desirable. The authors do provide a useful discussion on such compatibility issues in the context of congeniality (Meng 1994) of imputation models with an analyst's model. Chapter 14 provides valuable information on how to implement all of the techniques of Section III in SAS. The reader should exercise caution in using SAS PROC MI in time dependent measurements, because it is not designed to handle longitudinal data. Other choices, such as the R package (Schafer and Yucel 2002) or MLwiN (Rasbash, Steel, Browne, and Prosser 2006) might be more appropriate for producing multiple imputations in longitudinal and/or clustered applications. A major strength of this section is the discussion of MAR and MCAR, which ties these techniques to modern estimation techniques, such as weighted estimating equations and direct likelihood inference.

The book's fourth and fifth sections present material that perhaps is most relevant in clinical studies: methods for MNAR (or nonignorable) and sensitivity analyses. Chapters 15–18 illustrate models operating under MNAR. Owing to the nature of the context, the level of presentation here is a bit more technical. The authors' wise use of data examples promote the comprehension of these concepts, models, and estimation techniques. The inclusion of SAS code leading to results in these examples would have been useful. Chapters 19–24 present strategies for conducting sensitivity analyses. A potentially great danger is quickly eliminated by the authors in the beginning by noting that MNAR often relies on unverifiable assumptions and that the proposed tests also rely on alternative model holding, which can be assessed only using observed data. The reader should note that most of these analyses are valid for the realized data only and, as the authors indicate, they rely on the posited but unverifiable models and thus they do not necessarily hold an inferential meaning in a traditional sense.

The final section presents case studies that focus mostly on methods assuming the MNAR mechanism. This section is very beneficial, with earlier concepts and techniques (such as sensitivity) put into context through examples. Chapter 25 discusses analyses using MAR, MCAR, and MNAR. The chapter gives the impression that fair comparisons can be made across these mechanisms. An informed reader will understand the implications of making such comparisons;