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Bayesian Reliability.

Michael S. HAMADA, Alyson G. WILSON, C. Shane REESE, and Harry F. MARTZ. New York: Springer, 2008, xvi+436 pp., \$89.95 (H), ISBN 978-0-387-77948-5.

As the introduction of this book states “the acceptance and application of Bayesian methods in virtually all branches of science and engineering have significantly increased over the past few decades.” This book is an effort to describe methods for analyzing reliability data from a modern Bayesian perspective. Martz and Waller (1982) presented a Bayesian perspective on reliability, but their analysis predated the use of simulation-based computational methods and relied extensively on the use of conjugate priors. This book is written to provide a reference collection of modern Bayesian methods in reliability. Since all of the chapters include exercises, it could be used as the basis for an undergraduate or graduate course in reliability.

Chapter 1 provides a gentle introduction to reliability concepts, exponential distributions, and common types of reliability data. Chapter 2 presents a capsule introduction to Bayesian thinking for discrete and continuous observations, including discussions of prior and posterior distributions, prediction, marginal densities, and Bayes factors. From this basic background of Bayesian modeling, Chapter 3 takes an “advanced” look at Bayes by introducing Markov chain Monte Carlo (MCMC) methods and Bayesian hierarchical models. Metropolis-Hastings and Gibbs sampler algorithms are described and hierarchical models are introduced in the setting where one wishes to simultaneously estimate the probabilities of successful launches for several vehicles. A Bayesian version of Pearson’s statistic is introduced as a general purpose method of assessing the goodness of fit of a model.

Many of the standard sampling distributions for reliability data are introduced in Chapter 4 including binomial and Poisson distributions for count data, and exponential, Weibull and lognormal distributions for failure times. This chapter includes discussions of censored data, hierarchical modeling, and Bayesian model selection diagnostics. The component data distributions are extended to models for describing the reliability of systems in Chapter 5. The chapter includes descriptions of series and parallel systems, fault trees, and Bayesian networks. Chapter 6 considers the reliability of multiple-time-use systems that are repaired when they fail. There are descriptions of renewal processes of failure time data, homogeneous and nonhomogeneous Poisson processes, and criteria for evaluating repairable system reliability. Hierarchical models are introduced as a natural way of representing multiple-unit systems.

Chapter 7 describes the use of regression models when the reliability data distribution depends on covariates. This chapter includes illustrations of logistic models for binomial data, Poisson log-linear models for count data, and lognormal and Weibull models for survival data. In addition, there are sections on accelerated life testing and the analysis of reliability data from designed experiments. Chapter 8 describes the use of degradation data to assess reliability, and Chapter 9 is devoted to planning for reliability data collection, including how to allocate resources among money, time, and number of experimental units. The book concludes in Chapter 10 by describing plans for assuring that a reliability measure exceeds a specific requirement with a given confidence. These plans are illustrated for testing with binomial, Poisson, and Weibull data.

The recent Bayesian reliability text by Singpurwalla (2006) gives a different perspective of the subject. Singpurwalla’s book gives a much broader, mathematical description of the reliability sampling models and prior distributions including nonparametric methods, but contains few examples and computational aspects. This book is complementary to Singpurwalla (2006) in that it provides a more concrete view of reliability with worked out examples.

This book appears to be an attractive vehicle for learning Bayesian modeling for reliability data. It does not require any background in Bayesian thinking from the reader—all that is required is a basic knowledge of probability and applied statistics. The authors describe a variety of reliability models using many real-life datasets. There is a special emphasis on the use of hierarchical models to analyze groups of reliability data and Bayesian goodness of fit measures are applied in many contexts. Although the authors say existing packages such as WinBUGS and R are used for implementing the MCMC calculations, the book does not describe the R or WinBUGS code for the examples. Perhaps the authors could add some illustrations of the Bayesian calculations on the book’s website. Also, the book is limited to discussing parametric models; nonparametric

methods such as the proportional hazards model are not covered. With these small caveats, I recommend this book to any reader who wishes to learn about the practical application of Bayesian thinking in reliability.

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REFERENCES

Martz, H., and Waller, R. (1982), *Bayesian Reliability Analysis*, New York: John Wiley.
Singpurwalla, N. (2006), *Reliability and Risk: A Bayesian Perspective*, New York: John Wiley.

Correspondence Analysis in Practice (2nd ed.).

Michael GREENACRE. Boca Raton, FL: Chapman & Hall/CRC, 2007, xiii+280 pp., \$83.95 (H), ISBN 1-58488-616-1.

Principal component analysis (PCA) is a well-known technique for exploring the structure of associations among a set of metric-scaled variables, whereas correspondence analysis (CA) explores the structure of associations among a set of contingency tables. Both methods produce underlying dimensions, which can be interpreted as latent variables. Since CA is applied to categorical data and because almost all survey research data are categorical, this method has a strong advantage over PCA. Input to (simple) CA can be any data table with nonnegative values, such as single contingency tables, stacked tables, Burt tables, or indicator matrices. In the latter two cases the method is known as multiple correspondence analysis (MCA). Although several principal investigators developed CA/MCA independently from each other, Greenacre focuses on the French tradition with its geometric emphasis (Benzécri et al. 1973), following the philosophy of his Ph.D. advisor Jean-Paul Benzécri that “the model should follow the data, not the inverse.”

The first English manuscripts on CA were by Greenacre (1984) and Lebart et al. (1984); since then, the number of methodological articles has steadily grown and the technique has increasingly been applied to different contexts and disciplines. While Greenacre’s first book is quite technical, the first edition of his *Correspondence Analysis in Practice*, which appeared nine years later (Greenacre 1993), is application oriented. This second edition of this practice-oriented introduction is completely revised; it is an up-to-date version, with a large number of marginal notes, informative figures and tables, and also end-of-chapter summaries. It is a nontechnical presentation of the method, with most of the mathematical aspects appearing in a theoretical appendix.

The book has 25 chapters, each chapter exactly eight pages, because Greenacre “wanted each chapter to represent a fixed amount to reach or teach” (p. xi). The first 12 chapters give a detailed introduction to simple CA, i.e., the analysis of single cross-tables, showing all the geometric properties that were popularized in the French tradition of this method. The next three chapters show the relations and connections to biplots, regression analysis, and clustering. After discussing important aspects of CA using easy-to-understand examples, the input data become increasingly complex in the following chapters: from multiway tables via stacked tables to Burt tables and indicator matrices. With respect to indicator matrices and Burt tables, Greenacre turns the attention to the association within a set of variables, which is MCA. The last chapters refer to recent developments of the method such as joint CA and subset CA, and to special applications such as squared tables. The geometric properties of the method as well as its extensions are very well illustrated with a large number of examples, mainly from the social and environmental sciences.

Apart from completely revising the original chapters and providing new examples, the book—compared with the 1993 edition—contains five new chapters: Transition and Regression Relationships, Stacked Tables, Subset Correspondence Analysis, Analysis of Squared Tables, and Canonical Correspondence Analysis. Finally, the appendix, Theory of Correspondence Analysis, has been largely extended, and there is a new chapter, Computation of Correspondence Analysis, where the author documents his CA package for R, including the commands for most of the analyses in the book. The R codes can be downloaded from www.carme-n.org, where carme-n stands for “Correspondence Analysis and Related Methods Network;” the website also provides the datasets used in the book and an errata list. In conclusion, I would like to note that the book also appears in Spanish (Greenacre 2008).

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