# **Analysis of Mixed Data: Methods & Applications**

Edited by

Alexander R. de Leon Keumhee Carrière Chough

To my family — A. R. L.

To Nari and Hanna — K. C. C.

### Preface

Multivariate data of mixed types occur frequently in many fields of science and social science. The analysis of such data has created new challenges that have made it necessary to develop new statistical techniques and methodologies. Statisticians, working in collaboration with biologists, economists, epidemiologists, social scientists, and many others, have met these challenges with many remarkable advances over the past two decades. These include, among others, applications of mixed models to mixed outcomes in clustered and longitudinal studies, advances in dependence modeling of mixed data via copula and graphical models, extensions of Bayesian methods to mixed data settings, and adaptations of entropy- and divergence-based association measures to mixed outcomes.

Despite the attention researchers have given to mixed data analysis in recent years, there has been no single book that focused purely on this important topic. A close scrutiny of the literature reveals the following textbooks and monographs that contain discussions, albeit mostly brief, of mixed data analysis:

- H. Goldstein (2011). Multilevel Statistical Models. 4th ed.. Wiley & Sons, Inc.
- D. M. Berridge and R. Crouchley (2011). *Multivariate Generalized Linear Mixed Models in R*. Chapman & Hall/CRC.
- L. Wu (2010). Mixed Effects Models for Complex Data. Chapman & Hall/CRC.
- C. E. McCulloch, S. R. Searle, and J. M. Neuhaus (2008). *Generalized, Linear, and Mixed Models*. 2nd ed., Wiley & Sons, Inc.
- M. J. Daniels and J. W. Hogan (2008). *Missing Data in Longitudinal Studies: Strategies for Bayesian Modeling and Sensitivity Analysis.* Chapman & Hall/CRC.
- P. X.-K. Song (2007). Correlated Data Analysis: Modeling, Analytics, and Applications. Springer.
- G. Molenberghs and G. Verbeke (2005). Models for Discrete Longitudinal Data. Springer.
- A. Skrondal and S. Rabe-Hesketh (2004). *Generalized Latent Variable Modeling: Multilevel, Longitudinal, and Structural Equation Models.* Chapman & Hall/CRC.
- R. J. Little and D. B. Rubin (2002). *Statistical Analysis with Missing Data*. 2nd ed.. Wiley & Sons, Inc.
- J. L. Schafer (1997). Analysis of Incomplete Multivariate Data. Chapman & Hall.
- D. R. Cox and N. Wermuth (1996). *Multivariate Dependencies: Models, Analysis and Interpretations.* Chapman & Hall.
- G. A. F. Seber (1984). Multivariate Observations. Wiley & Sons, Inc.

In addition, the following edited volumes devote separate chapters to mixed data:

- G. Fitzmaurice, M. Davidian, G. Verbeke, and G. Molenberghs (Eds.) (2009). *Longitudinal Data Analysis*. Chapman & Hall/CRC.
- M. Aerts, H. Geys, G. Molenberghs, and L. M. Ryan (Eds.) (2002). *Topics in Modelling of Clustered Data*. Chapman & Hall/CRC.

However, since these books only provide snapshots of contemporary developments in mixed data analysis, there is thus a need for an authoritative book on mixed data analysis that traces important

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developments, systematizes terminology and methodologies, and gives an overview of applications. Our intention in producing this book is to show the depth and diversity of current research in the field, bringing together the work of as many researchers as possible, thus providing synthesis as well as development of directions for future research.

The twelve chapters in this book were written by leading researchers who have made important and sustained contributions to mixed data analysis, and who were selected with a view to covering as much ground as possible in this broad area. While each chapter is self-contained and can be read independently of the others, we have informally organized them into groups to facilitate smooth thematic transitions. With the technical nature of the subject and this being an edited volume with numerous chapter authors, we have endeavored to maintain a certain degree of clarity and harmony in the presentation style. We believe that we have achieved this goal for the following reasons:

- The book was carefully and thoroughly edited for smooth readability and seamless transitions between chapters. All the chapters follow a common structure, with an introduction and a concluding summary, and include illustrative examples, many drawn from real-life case studies in developmental toxicology, economics, medicine and health, marketing, and genetics.
- We have included ample cross-references between chapters to enable readers to connect the book's various topics and research strands and to facilitate self-study.
- We have, as much as possible, unified notations, table formats, and terminologies across chapters. In particular, we have adopted, whenever possible, a common set of notations for mathematical and statistical quantities, such as vectors and matrices (both random and fixed) as well as distributions.
- To facilitate easy referencing by readers, we have come up with a combined index as well as a single up-to-date bibliography for the entire book. The references collected at the end of the book provide the most comprehensive, most current, and most complete list of published material on mixed data analysis.
- As a unique feature of the book, we have included an introductory chapter that provides a "wide angle" overview and comprehensive survey of mixed data analysis. The chapter contains useful background material that should prepare readers for the rest of the book.

As with any similar collection, there are bound to be omissions of some topics. While we strived for a good balance between theory and applications, it is impossible to include all topics in a single volume. For example, mixed-data graphical models are not discussed, apart from a brief mention in Chapter 1. Nevertheless, the book's technical level along with the many examples and case studies should make the book appeal to a broad audience. We believe that it would be a valuable resource to methodologically interested as well as subject matter-motivated researchers. These include graduate students, applied statisticians, biostatisticians, and researchers in subject matter areas like medicine, health, genetics, and epidemiology, among many others. The book should be an excellent supplement to the textbooks and monographs enumerated above.

This book was completed with considerable help from several people. Our deepest thanks go to all the contributors, for their patience, enthusiasm, and expertise. Likewise, we are indebted to the following reviewers for their input and comments: Dipankar Bandyopadhyay (Division of Biostatistics, University of Minnesota, Minneapolis, MN), Kenneth A. Bollen (Department of Sociology, University of North Carolina, Chapel Hill, NC), Claudia Czado (Zentrum Mathematik, Technische Universität München, Munich, Germany), Ruzong Fan (Biostatistics and Bioinformatics Branch, National Institute of Child Health and Human Development, Bethesda, MD), Garrett Fitzmaurice (Department of Biostatistics, Harvard School of Public Health, Boston, MA), Helena Geys (Center for Statistics, Hasselt University, Diepenbeek, Belgium), Harry Joe (Department of Statistics, University of British Columbia, Vancouver, BC), Stefan Lang (Department of Statistics, University, New York, NY), Mingliang Li (Department of Economics, SUNY at Buffalo, Buffalo, NY), Irini Moustaki (Department of Statistics, London School of Economics, London, UK),

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> Alexander R. de Leon Calgary, Alberta Keumhee C. Chough Edmonton, Alberta

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### Editors

Alexander R. de Leon is Associate Professor in the Department of Mathematics and Statistics at the University of Calgary. Originally from the Philippines, he obtained his BSc and MSc, both in Statistics, from the School of Statistics of the University of the Philippines. After a research studentship at Tokyo University of Science, he completed his PhD in Statistics in 2002 at the University of Alberta. His research interests include methods for analyzing correlated data, multivariate models and distances for mixed discrete and continuous outcomes, pseudo- and composite likelihood methods, copula modeling, assessment of diagnostic tests, statistical quality control, and statistical problems in medicine, particularly in ophthalmology.

**Keumhee Carrière Chough** is Professor of Statistics in the Department of Mathematical and Statistical Sciences at the University of Alberta. After completing her BSc in Agriculture from Seoul National University, in Seoul, Korea, she earned her MSc from the University of Manitoba, and her PhD in Statistics from the University of Wisconsin-Madison in 1989. Since 1996, she has been with the Department of Mathematical and Statistical Sciences, University of Alberta, after stints as Assistant Professor at the University of Iowa (1990–1992) and University of Manitoba (1992–1996). She was also the Director of the Statistics Consulting Center at the University of Iowa (1990–1992). Her research interests include design and analysis for repeated measures data, missing data methods, high dimensional data analysis methods, multivariate methods, designs for clinical trials, item response data, variable selection methods, and survival analysis. As well, she specializes in such biostatistical methods as small area variation analysis techniques with applications to health care utilization. She has been a Health Scientist funded through the Alberta Heritage Foundation for Medical Research (1996–2011). She is a Fellow of the American Statistical Association, the Institute of Health Economics, and the Manitoba Centre for Health Policy.

# Contributors

| Qi An                   | Department of Mathematical Sciences<br>University of Memphis<br>Memphis, TN, USA  |
|-------------------------|---|
| François Bellavance     | Department of Management Sciences<br>HEC Montréal<br>Montréal, QC, Canada   |
| Peter M. Bentler        | Departments of Psychology and Statistics<br>University of California-Los Angeles<br>Los Angeles, CA, USA                |
| Dale Bowman             | Department of Mathematical Sciences<br>University of Memphis<br>Memphis, TN, USA  |
| Keumhee Carrière Chough | Department of Mathematical and Statistical Sciences<br>University of Alberta<br>Edmonton, AB, Canada                    |
| Michael J. Daniels      | Department of Statistics<br>University of Florida<br>Gainsville, FL, USA  |
| Alexander R. de Leon    | Department of Mathematics and Statistics<br>University of Calgary<br>Calgary, AB, Canada                                |
| Abdessamad Dine         | Department of Management Sciences<br>HEC Montréal<br>Montréal, QC, Canada   |
| Christel Faes           | Interuniversity Institute for Biostatistics and Statistical Bioinformatics<br>Hasselt University<br>Diepenbeek, Belgium |
| Jeremy T. Gaskins       | Department of Statistics<br>University of Florida<br>Gainsville, FL, USA  |
| E. Olusegun George      | Department of Mathematical Sciences<br>University of Memphis<br>Memphis, TN, USA  |

#### CONTRIBUTORS

| Ralitza Gueorguieva    | School of Public Health<br>Yale University<br>New Haven, CT, USA                                      |
|------------------------|---|
| Jaroslaw Harezlak      | Department of Biostatistics<br>Indiana University School of Medicine<br>Indianapolis, IN, USA         |
| Takahiro Hoshino       | Department of Economics and Business Administration<br>Nagoya University<br>Chikusa-ku, Nagoya, Japan |
| Jian Kang              | Department of Biostatistics and Bioinformatics<br>Emory University<br>Atlanta, GA, USA                |
| Minjung Kwak           | Office of Biostatistics Research<br>National Heart, Lung and Blood Institute<br>Bethesda, MD, USA     |
| Denis Larocque         | Department of Management Sciences<br>HEC Montréal<br>Montréal, QC, Canada                             |
| Armando Teixeira-Pinto | Department of Health Information and Decision Sciences<br>University of Porto<br>Porto, Portugal      |
| Regina Tüchler         | Department of Statistics<br>Austrian Federal Economic Chamber<br>Wien, Austria                        |
| Helga Wagner           | Department of Applied Statistics and Econometrics<br>Johannes Kepler University<br>Linz, Austria      |
| Niroshan Withanage     | Department of Mathematics and Statistics<br>University of Calgary<br>Calgary, AB, Canada              |
| Beilei Wu              | Department of Mathematics and Statistics<br>University of Calgary<br>Calgary, AB, Canada              |
| Colin O. Wu            | Office of Biostatistics Research<br>National Heart, Lung and Blood Institute<br>Bethesda, MD, USA     |
| Ying Yang              | Department of Mathematical Sciences<br>Tsinghua University<br>Beijing, P. R. China                    |

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| Gang Zheng      | Office of Biostatistics Research<br>National Heart, Lung and Blood Institute<br>Bethesda, MD, USA |
|-----------------|---|
| David M. Zimmer | Department of Economics<br>Western Kentucky University<br>Bowling Green, KY, USA                  |

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