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Causal Inference for Statistics, Social, and Biomedical Sciences: An Introduction. Guido W. Imbens and Donald B. Rubin. New York: Cambridge University Press, 2015, xix + 625 pp., $60.00 (H), ISBN: 978-0-52-188588-1.

Guido Imbens and Donald Rubin have written an authoritative textbook on causal inference that is expected to have a lasting impact on social and biomedical scientists as well as statisticians. Researchers have been waiting for the publication of this book, which is a welcome addition to the growing list of textbooks and monographs on causality. Causal inference plays an essential role in empirical studies that test scientific theories because scholars are concerned about causal relationships rather than associations. Similarly, policy makers, who are evaluating the efficacy of public policy programs, and marketing researchers, who are assessing the effects of advertisements, must build an effective *causal* model rather than a good *predictive* model. In the age of "big data," this distinction between causality and association is becoming more important than ever. The book should be of interest to many researchers and practitioners in a variety of fields.

Although the study of causality goes back to Neyman and Fisher in the 1920s, for a long time only limited progress was made in statistics regarding this important topic. A critical turning point may have been the publication of an article by Holland (1986), which highlighted the utilities of the potential outcomes framework developed by Neyman and Rubin. Since then, statisticians and methodologists from various disciplines have made numerous contributions to improve causal inference in both experimental and observational studies. Over the last three decades, causal inference transformed itself from an obscure topic to a major research theme in statistics. Imbens and Rubin played a significant role in this development and their perspective from numerous leading publications are now elegantly summarized in this book.

The most important feature of the book is that it is written exclusively from the potential outcomes perspective. After an accessible and informative discussion of the potential outcomes framework in Part I, the authors apply this approach to randomized experiments and then extend it to observational studies. The discussion is thorough with an effort to build everything from the first principles. In particular, the detailed derivation of variances under the Neyman's framework and posterior distributions under the Bayesian approach are insightful. Explicit efforts to connect the Neyman's approach to the model-based approach are also useful. This book should serve as the primary text for anyone who wishes to study the potential outcomes approach.

The focus on the potential outcomes approach also means that other alternative approaches, such as directed acyclic graphs (DAGs) and structural equation models (SEMs), are omitted from this book. In the end, it is impossible for any single book to cover every topic within this growing field of causal inference. Given that the authors of this book are the major developers and proponents of the potential outcomes framework, the scientific community benefits most from the book that elucidates their advocated approach. For the approach based on the DAGs and SEMs, researchers can consult the authoritative book by Pearl (2009).

One limitation of the book is that it does not cover a number of important topics. The authors spend the first 11 chapters discussing the potential outcomes framework and classical randomized experiments in detail. As a result, the book does not discuss such topics as cluster randomized experiments, interference between units, longitudinal data, mediation analysis, nonbinary treatments, regression discontinuity designs, and difference-in-differences designs. Applied researchers should consult other work to learn about these additional topics for causal inference that are relevant in many fields.

The authors write that their target audience is "researchers in applied fields." In my view, this book is best suited for applied researchers who have a solid understanding of basic probability and statistics. Those seeking a nontechnical introduction to statistics may have a hard time following the detailed mathematical derivation presented in the book. These researchers may find other textbooks such as Morgan and Winship (2007) and Angrist and Pischke (2009) more accessible. In addition, while the book includes many real-world applications, it does not provide tips on how to implement the methods. Online materials including the computer code for the results presented in the book would be a useful supplement to the text.

The authors' focus on the fundamental causal inference problems is apparent in their treatment of causal inference with observational studies. For example, Chapter 13 discusses the estimation of propensity scores through an iterative process of covariate balance checking and model respecification. Although several methods have been recently proposed to estimate the propensity score by directly optimizing covariate balance, these methods are not introduced. Similarly, Chapter 15 only discusses classic matching methods while newer matching methods are not included (see also Chapters 17 and 18). It may be that a separate book is required for a comprehensive treatment of methods for observational studies.

The materials in Part IV (Chapters 17–20) provide a succinct introduction to the series of recent articles on matching methods written by the authors. While applied researchers often compute the uncertainty estimates conditional on the matched sample, the authors show how to incorporate the uncertainty regarding the process of matching given a particular matching method. In practice, however, as illustrated in Chapters 13–15, applied researchers must choose among different matching methods and/or alternative propensity score models. Future research should address the issue of how to quantify additional uncertainty arising from the selection of matching methods.

In conclusion, the authors should be congratulated for the publication of this impressive volume. The book provides a unified introduction to the potential outcomes approach with the focus on the basic causal inference problems that arise in randomized experiments and observational studies. The book is most useful for researchers in statistics, social, and biomedical sciences who have a solid background in probability and statistics and are looking for a rigorous, but not overly technical, introduction to causal inference. While the book does not cover some important topics that may be of interest (and yet the book is more than 600 page long!), it provides readers with the foundation to explore the exciting and growing methodological research on causal inference.

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Data Analysis and Approximate Models: Model Choice, Location-Scale, Analysis of Variance, Nonparametric Regression and Image Analysis.

Laurie Davies. Boca Raton, FL: Chapman & Hall/CRC Press, 2014, xvi + 304 pp., $104.95 (H), ISBN: 978-1-48-221586-1.

Laurie Davies's *Data Analysis and Approximate Models* presents an alternative approach to statistical analysis that explicitly treats probability models as approximations. The approach is neither frequentist nor Bayesian: the data are taken as given, there are no true but unknown parameters, and there is no assumption of a true model.

The basic idea is that "a model is an adequate approximation to a dataset if 'typical' data generated under the model 'look like' the real data. The words 'look like' mean that certain features of the data are of importance and must be exhibited by 'typical' sets generated under the model... The word 'typical' is operationalized by specifying a percentage such that this percentage of samples generated under the model exhibit the features defining 'look like' " (p. xiv). The difficulty lies in specifying which features define "look like." Davies notes that selection of such features will depend on the purpose for analyzing the data and eschews the notion that this process be dictated by purely statistical concepts. In practice, selection of these features could prove tricky, and will likely require careful consideration.

After formalizing the concepts of approximation, Davies discusses approximation in the context of discrete data, the location and scale problem, and nonparametric regression. The book offers critiques of standard statistical methods throughout, with the final chapter targeting the likelihood principle, stopping rules, asymptotics, maximum likelihood, and model selection. Davies's work, though likely contentious, is both thoughtful and novel. I would primarily recommend the book to those interested in the foundations of statistics. Applied researchers with a strong grounding in probability theory may also be interested in exploring the methods.

All opinions and conclusions expressed in this review are those of the reviewer and do not necessarily reflect the views of the Federal Deposit Insurance Corporation.

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Data Analysis With Competing Risks and Intermediate States.

Ronald B. Geskus. Boca Raton, FL: Chapman & Hall/CRC Press, 2015, xxix + 247 pp., $79.95 (H), ISBN: 978-1-46-657035-1.

Competing risks studies are increasingly common in the era of data science and big biomedical data. These studies essentially involve dependent or informative censoring mechanisms. One example of competing risks is in breast cancer where a patient can have progression of the cancer after receiving treatment, or the patient may die without progression. It continues to be debated in the research community whether treatment benefits should focus on prolonged time to progression or time to death. Some breast cancer patients may also experience progression before death, and progression in this case is an intermediate state between the initial state of diagnosis or beginning of treatment and the final state of death. There are many other examples of competing risks, not only in medical science but also in engineering and the social sciences.

The book targets readers such as epidemiologists and medical statisticians. In contrast to the previously published *Competing Risks and Multistate Models with R*, by Beyersmann, Allignol, and Schumacher (2012), this book is less heavy on counting process notation and theory (often used in survival analysis) and instead emphasizes practical examples (using R) and interpretations.

Some of the terminology in the book deviates from that used in classical survival analysis and epidemiology practice in the U.S. Putting these relatively minor differences aside, the book reads relatively smoothly. The first chapter "Basic Concepts" is quite extensive, covering concepts such as censoring complete data (the usual noninformative right-censoring in survival data can bring substantial complications to the otherwise "censoring complete data"). This chapter also introduces left truncation, focusing on conditional inference with no discussion of the unconditional approach that has recently appeared in the survival analysis literature. To my knowledge, little work has been done using unconditional inference for competing risks.

Chapters 2 and 3 consider nonparametric estimation in the one-sample setting, that is, without any regressors or predictors.