Measurement, Regression, and Calibration, by Philip J. BROWN, Oxford, U.K.: Clarendon Press (Oxford Statistical Science Series 12), 1993, ix + 201 pp., $45.

This well-written research monograph deals with regression problems that are not commonly covered in statistical methodology courses but that often arise in applications. Among such topics are the following:

1. How to estimate parameters of regression models with the primary goal of predicting future values of the response Y.
2. How to determine what value(s) of the vector X of explanatory (carrier) variables could have given rise to observed value(s) of the response (the "calibration" or "inverse regression" problem).

It is well known that the classical least squares estimator of the regression parameters does not generally give an optimal (or often even satisfactory) answer to topic 1, nor does inverting the fitted regression equation for Y so as to solve for X in terms of the observed Y provide the best answer to topic 2. These assertions are true even when standard normal distributional assumptions are valid. Consequently, much of Brown's monograph reviews alternative approaches that have been suggested in the literature to solve these two problems. Although the exposition is theoretical in nature, several interesting data sets introduced in Chapter 1 are used to provide motivation for, and illustration of, the procedures discussed.

Technometrics readers will find much of interest and use in Brown's monograph, not the least of which are expositions of the author's own very considerable contributions to the topics under discussion. Brown is very good at presenting apparently different approaches in a unifying framework that both brings out common features and clarifies differences. Examples are his discussion in Chapters 2, 3, and 5 of competing calibration approaches and his review in Chapter 4 of what he calls "regularized multiple regression" point estimators (cross-validation methods, ridge regression and other shrinkage methods, principal-component regression, partial least squares, continuum regression).

Brown's own preferred approaches to inference appear to be those based on profile likelihood and hierarchical Bayesian analyses. These approaches have the advantage of yielding credible regions for quantities of interest, as well as point estimators. (Whether such credible regions make adequate confidence and/or prediction regions seems to be a still unexplored question.) In Chapters 5 through 7, Brown's profile likelihood and Bayesian solutions to multiple calibration and modeling problems arising in spectroscopy are presented. Brown's construction (Chap. 6) of prior distributions that are coherent with the fact that the vector of observed spectral amplitudes is a discrete realization of a stochastic process over the spectral frequencies is persuasive. Some approaches to selecting spectral frequencies for calibration purposes are presented in Chapter 7. Brown also gives a Bayesian alternative to kriging for spatial processes (Chap. 6).

I do disagree with the importance Brown attaches throughout the monograph to the distinction between controlled calibration and natural calibration (i.e., fixed or random predictors). Actually both kinds of calibration model share the assumption that the conditional distribution of the response Y is the same in both training sample and future calibration contexts. Thus, when the regression of Y on X is linear and the conditional distribution of Y given X is normal, the slopes and conditional covariance matrix need to be determined. Sufficient statistics from the data for these parameters are their least squares estimators, regardless of whether the predictors are fixed or random. (If the X's are random, their values in the training sample are ancillary statistics.) The important distribution of X is that which governs the values ξ of the predictor in future calibration contexts; this distribution need not be identical to the distribution (if any) of X in the training sample. A more basic distinction, therefore, between types of calibration problems is between those in which the values of X observed in the training sample provide information about the distribution of future ξ values and those in which the training sample does not provide such information. Brown's Bayesian discussions show that he recognizes this distinction. My problem with his presentation is that the controlled/natural dichotomy that he emphasizes, although perhaps useful in motivating the predict-X-from-Y calibration estimator advocated by Krutchkoff (1967), obscures the more basic distinction noted here.

Although Brown briefly mentions the relationship of the multivariate calibration problem to errors-in-variables regression models, he misses the opportunity to use known facts about errors-in-variables inference to obtain useful insights about inference in the calibration problem. For example, the results of Gleser and Hwang (1987) showed that it is impossible to construct finite-diameter (with probability 1) calibration regions of nonzero confidence. Thus, the undesirable properties noted for the Fieller–Creasy-type calibration region are unavoidable if one desires the nonzero confidence property of this region. Again, large-sample results for inference in calibration problems can often be obtained from the rich literature on small-error-variance asymptotics in the errors-in-variance literature. Finally, it is not unusual for measurements of predictors obtained by calibration methods to be used in regression problems and (erroneously) treated as if they were exact; this can lead to serious bias, particularly if the model is later used with directly measured predictors (Buonaccorsi 1988). It is for these reasons that I previously noted the relationship between calibration and errors-in-variables regression models (Gleser 1991).

A final criticism that I have is that Chapter 8 is too sketchy to do justice to its subject (pattern recognition) and is only marginally related to the material presented in earlier chapters. The space taken by this chapter might have more usefully been devoted to giving greater detail about implementation of the inferential procedures presented in Chapters 2–7, including critical discussion of available computer software to supplement the advice about computation that Brown does present. (Note: An appendix to the monograph provides a computer algorithm written in S for doing partial least squares.)

Despite the preceding criticisms, Brown's monograph is a welcome contribution. Working statisticians, particularly chemometricians, will find it useful for summarizing and clarifying the choices of models and procedures available to them for inference problems that they often encounter and for which there are few alternative references. Academic statisticians will want to use this monograph as supplementary reading for graduate-level courses in regression and as a quick entry for finding open questions requiring research. I enjoyed reading this book and recommend it heartily.

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Kernel Smoothing, by M. P. WAND and M. C. JONES, London: Chapman & Hall, 1995, xii + 212 pp., 25 (pounds sterling).

This book provides a nice overview of kernel-smoothing ideas, methods, and open questions with a smooth, intuitive style. The reader should not expect, however, a comprehensive treatment of all aspects of kernels. To the authors' credit, they admit up front that the choice of topics is "personal" and point those interested toward the plethora of other books covering this subject. This book is meant as an introduction, but it does require some comfort level with calculus and linear algebra.

Following a short introductory chapter, the authors devote three chapters to density estimation, one to regression, and a closing chapter to whetting the appetite about other related topics. The book aims to provide the reader with sufficient understanding of the principles behind the mathematical machinery of kernel methods to make judgments about their proper use. Graphics liberally spread through the text illustrate the construction and properties of kernel estimates. In particular, the importance of curvature and boundaries is stressed in several places.

In a sense, this book fills a void, maintaining mathematical rigor while providing a more heuristic approach to the various compromises that are involved in kernel methods. The trade-offs between a clean parametric form of a density or regression function must be balanced with letting the data suggest the best shape. Suspending belief about the "true" form of a curve, however, adds uncertainty in estimating the shape. These issues are made precise in plain language in the first chapter. Later chapters reinterpret the questions raised in more mathematical terms, with immediate interpretation in words and graphs as appropriate.

Chapters 2–4 provide an up-to-date accounting of kernel density estimation, as would be expected from authors who have made important contributions in this area in recent years. Notation is introduced in a natural way as they build ideas. The chapter on bandwidth selection brings together many recent concepts that have not appeared in book form to date. Unfortunately, as Wand and Jones aptly point out, there is much we still do not know in this arena. Multivariate density estimation is briefly addressed, alluding to the "curse of dimensionality" while focusing largely on two dimensions.

The chapter on regression (5) considers "local polynomial kernel estimators," which have become quite popular. This appears to be the first treatment of this important area in book form, showing its advantages over other more traditional kernel methods in terms of large-sample properties and boundary behavior. Recent theoretical work on mean squared error (MSE) and bandwidth selection are smoothly incorporated, showing the connection with related work on density estimation. The reader primarily interested in nonparametric regression, however, would want to supplement this book with others, such as those of Green and Silverman (1994) or Wahba (1990), as encouraged by the authors.

The final chapter in a sense teases the reader, with only a few pages about each topic. In particular, censored data are lightly addressed even though there is considerable literature in this area. Space-time data, which could be viewed as a special type of multivariate data, seems to be ignored.

There is a curious feature in the examples used throughout the book. Most of the data sets appear to contain a few hundred observations, which places them toward the lower threshold of what is possible with kernel methods. Although this is laudable in some sense, it raises the question of how kernel methods function when the data set is huge, with millions, billions, or trillions of measurements. Data on this scale are being collected in areas of engineering and environmental and biomedical sciences. These problems cannot usually be considered as having the same degree of curvature throughout, and boundaries between regions may or may not be distinct. How well does kernel smoothing work here? Although the authors do not address this area directly, their insights can help the reader build intuition and a mathematical framework to further investigate important issues in kernel smoothing.

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Methods of Multivariate Analysis, by Alvin C. RENCHER, New York: John Wiley, 1995, xvi + 627 + disk, $39.95.

This is an excellent book for students and practitioners with minimal background in statistics who want to grasp multivariate techniques. The author points out in the preface that clarity of exposition was his major goal. The book meets this goal quite admirably. Two features of the book that must be pointed out in this regard are the following. First, the author introduces the definitions of several multivariate concepts first for the sample, then for the population, and illustrates them with a numerical example. This order of presentation is extremely helpful to a beginner. Second, before introducing the various multivariate procedures—for example, the tests—the corresponding univariate results are briefly presented. The univariate expressions are written in a way so as to make the multivariate generalizations very clear. Even though mathematical derivations are kept to a minimum, the author nicely motivates, justifies, and illustrates the various procedures. Consequently, the reader of this book will acquire a fairly good grasp of multivariate techniques.

The book covers the standard topics in multivariate analysis—the multivariate normal distribution, tests concerning means and covariance matrices in multivariate normal populations, multivariate analysis of variance (MANOVA), classification and discrimination, multivariate regression, canonical correlations, principal components, and factor analysis. Most of the preceding topics are treated in great detail and with clarity, even though the mathematical derivations are essentially omitted. With examples, the author has convincingly pointed out why univariate procedures are not enough in many applications and multivariate techniques are called for (e.g., see Ex. 5.2.2, p. 129). Roughly four pages (pp. 65–68) are devoted to the definition of the sample and population covariance matrices and to illustrating their computation, once again defining the sample covariance matrix first, then the population covariance matrix, and demonstrating the computation of the sample covariance matrix with an example. The same thoroughness and clarity is evident throughout the book—for example, in describing the computations for the MANOVA procedure (Sec. 6.1.2), in explaining the features of Wilks Λ (Sec. 6.1.3), and in interpreting the results from canonical correlation analysis (Sec. 11.5), principal-component analysis (Sec. 12.8), and factor analysis (Secs. 13.5.4 and 13.6). Important topics like repeated measures and growth curves and the problem of subset selection in multivariate regression are included and illustrated with examples. In the chapter on classification, apart from the standard classification rules, other procedures—for example, nonparametric—are also described. The chapter on factor analysis contains a detailed critique on the topic along with an example in which the procedure does not work. Several illustrative examples, based on actual data, are provided throughout the text and also in the exercises at the end of each chapter. There is an accompanying diskette that contains the data sets and SAS command files for the different examples.

I did notice a few typos and omissions. In Chapter 3, the terms "unbiased estimate" and "unbiased estimator" are used interchangeably (pp. 50, 53, 64, 68). In expression (4.32), the $\mathbf{x}$ should be $\mathbf{y}$. At the end of Section 6.6 dealing with multivariate mixed models, the author states that the Satterthwaite approximation is not available in the multivariate case. This is indeed available; see Tan and Gupta (1983), Nel and Van der Merwe (1986), and Khuri, Mathew, and Nel (1994). Moreover, on page 330, Rencher (1995) should be Rencher (1996)! I would also have liked to see a chapter on discrete multivariate methods (there is a brief discussion of classification procedures for multinomial data).

Several books are available on multivariate analysis; see Sen (1986) for a panoramic appraisal of 16 books on the topic. A practitioner who wants to carry out multivariate techniques in applied work and to interpret the results must have this book. The book is excellent for an introductory course in multivariate analysis for students with minimal background in mathematics and statistics. On the back cover, it is mentioned that this book is "the ideal user-friendly introduction to multivariate techniques." I fully agree.

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