To benefit from this book, a reader would need a solid background in statistical theory and distributions, as well a good handle on the mathematics. Although not required, it would also be helpful for the reader to have previous experience with classical regression and familiarity with S (or R) software to be able to use the S objects given at the end of each chapter. As such, the book seems appropriate for a graduate-level or advanced undergraduate statistics course in nonparametric regression. Most of the problems at the end of each chapter deal with the theoretical details or refinements of existing S objects to perform the analysis of data.

A practitioner with experience using S can use the S objects to perform basic nonparametric regression analyses. Many of the figures in the book can be recreated with the code provided at the end of each chapter, which is useful for someone just learning the basics. The comments and notes for the portions of code are helpful for users wishing to modify the code to suit their particular purposes. At times, the book has the feel of a collection of tools rather than a sequential narrative, which makes it easier for the user to utilize a particular tool, assuming that he or she knows which tool he wants to use.

I was surprised by the paucity of real data examples. Many of the examples are based on simulated datasets created to show a particular point, and the examples based on real data sets are usually meteorological or agricultural examples. To encourage a broader spectrum of application, I felt it would have been helpful to include a wider variety of examples. In addition, very few of the problems at the end of the chapters deal with analysis of real datasets. In fairness to Takezawa, many other related books (listed in the references) also lack real data examples.

A minor criticism of this book deals with the figures. None of them have legends, few of them have descriptive titles, and those with multiple panels do not have informative labels. All of the information about the figures are contained in the captions, requiring a little more effort to determine the point of the figure in question. In addition, the figures are rarely on the page on which they are discussed, requiring a lot of page flipping, and there are a number of pages with a large amount of white space and a single figure or two.

It should be noted that this book fills a niche in this area of statistical knowledge. Often nonparametric regression is covered only in conjunction with other regression techniques and smoothing methods, such as the books of Green and Silverman (1994), Fan and Gijbels (1996), Christensen (2001), and Härdle, Müler, Sperlich, and Wewatz (2004). It is nice to have a book with an exclusive focus on nonparametric regression. Gentler and less meaty introductions to nonparametric regression than the current volume are those by Eubank (1999), Fox (2000), and Härdle et al. (2004). Alternatives that contain a similar level of coverage to this book are the books by Härdle (1990) and Ruppert, Wand, and Carroll (2003), although neither of these books contain end-of-the-chapter problems.

In summary, *Introduction to Nonparametric Regression* provides an accessible theoretical treatment of nonparametric regression. However, because of its lack of real data examples, it falls a little short in providing software tools to make nonparametric regression more accessible to the practitioner, particularly for the reader not familiar with S or one looking for some "case studies" using nonparametric regression.

Willis A. JENSEN
W.L. Gore & Associates, Inc.

REFERENCES

Christensen, R. (2001), *Advanced Linear Modeling: Multivariate, Time Series, and Spatial Data; Nonparametric Regression and Response Surface Maximization*, New York: Springer-Verlag.
Eubank, R. (1999), *Nonparametric Regression and Spline Smoothing*, New York: Marcel Dekker.
Fan, J., and Gijbels, I. (1996), *Local Polynomial Modelling and Its Applications*, New York: Chapman & Hall.
Fox, J. (2000), *Nonparametric Simple Regression: Smoothing Scatterplots*, Thousand Oaks, CA: Sage.
Green, P. J., and Silverman, B. W. (1994), *Nonparametric Regression and Generalized Linear Models: A Roughness Penalty Approach*, New York: Chapman & Hall.
Härdle, W. (1990), *Applied Nonparametric Regression*, New York: Cambridge University Press.
Härdle, W., Müller, M., Sperlich, S., and Werwatz, A. (2004), *Nonparametric and Semiparametric Models*, New York: Springer-Verlag.
Ruppert, D., Wand, W. P., and Carroll, R. J. (2003), *Semiparametric Regression*, New York: Cambridge University Press.

Semiparametric Regression.

David RUPPERT, M. P. WAND, and R. J. CARROLL. New York: Cambridge University Press, 2003. ISBN 0-521-78516-2. xvi + 386 pp. $49.99 (P). E-book: $38.00.

The aim of this book is to present flexible nonlinear regression, or the so-called "nonparametric regression," as a fairly simple extension of parametric regression. The current literature on parametric and nonparametric regression exhibits profound differences in the level of mathematical and technical sophistication used in exposition. The authors attempt to bridge these differences from the perspective of mixed models. They treat nonparametric regression as an extension of linear modeling by combining fixed-effects parametric terms with random coefficient regression splines and provide a unified mixed model approach to smoothing. The book's title, emphasizes this strategic combination of parametric and nonparametric modeling. The integrated approach taken in the book has two main consequences. First, it facilitates a mathematically gentle transition from parametric regression to spline-based nonparametric regression. Second, it allows for existing inferential and computational tools that were originally developed for mixed models to easily transfer over to nonparametric regression. Those familiar with standard linear regression and mixed-effects models can easily grasp how to build flexible models by including spline basis functions as random components and controlling the amount of smoothing through the corresponding variance component estimation.

In terms of its target audience, the book distinguishes itself from other existing texts on nonparametric regression with splines. By taking a minimalistic approach to the use of elaborate statistical methodologies, the authors' introduction to nonparametric smoothing and its useful applications reaches out to graduate students with no advanced background in mathematics and to "statistically oriented scientists" with a working knowledge of regression. Throughout the book, methods are motivated mostly by numerous real-world applications, some of which were, in fact, born out of the authors' collaborative research projects. Illustrative figures promote an intuitive understanding of nonparametric modeling. Effective use of marginal notes and appendixes discussing technical complements and computational issues aids the novice. Each chapter ends with a summary of formulas, which might be handy for practitioners but feels like pampering to some advanced readers. The book would be an excellent textbook or reference for a graduate-level course on smoothing, and it would be most effective when preceded by a course in mixed-effects modeling or at least an adequate preliminary treatment of the topic.

Although appealing to statistically-oriented scientists, this book also should not fail to attract the attention of experts in the field, because it provides a fresh perspective on smoothing and addresses ongoing computational and theoretical issues. The text is quite comprehensive, and the chapters are carefully organized for a coherent development of the subject. Chapter 1 begins the book with data examples that motivate nonparametric smoothing. These examples are revisited in later chapters for analysis and discussion, as proper statistical tools are developed. Chapters 2–4 review parametric regression, penalized regression splines for smoothing, and mixed models. At the end of Chapter 4, penalized splines for nonparametric regression are represented as a mixed model. At this point, I expected a substantive discussion of the connection between the mixed-model representation of penalized splines and the well-known Bayesian interpretation of smoothing splines. Considering that the mixed-model approach to nonparametric regression is the main focus of the book, the absence of such a discussion is somewhat disappointing. Chapter 5 deals with automatic choices of various model parameters involved in penalized regression splines, including the smoothing parameter. In particular, the reader can see how the mixed model representation facilitates the selection of the smoothing parameter through the restricted maximum likelihood estimates of the variance components. Chapter 6 focuses on statistical inference for nonparametric regression models with close ties to inference for mixed models. Based on the mixed-model representation of smooth functions, Chapters 7–13 generalize a semiparametric model with a single predictor for a Gaussian response variable to situations with multiple predictors and a non-Gaussian response variable. Starting from a simple semiparametric model under which only a single predictor is modeled nonparametrically (and all of the other predictors are modeled linearly), Chapters 8 and 9 consider an elaboration of the model that allows additive nonparametric terms for several predictors through additive modeling. Chapters 12 and 13 present ways to incorporate an interaction between a continuous variable and a categorical variable or between two continuous variables through a smooth function. In addition, more general bivariate smoothing methods such as kriging and radial smoothing are discussed. For the treatment of a non-Gaussian response variable, Chapter 11 extends the generalized linear modeling technique to include nonparametric terms. With an emphasis on computations, Chapter 16 presents a fully Bayesian approach to smoothing and deals with Markov chain Monte Carlo-based Bayesian techniques for fitting semiparametric models. Finally, the last several chapters discuss further adjustments to the rich family of semiparametric models to handle heteroscedasticity, measurement error, and potential spatial nonhomogeneity in smoothness.

There are some typographical errors and a couple of figures that do not match the descriptions in the text. However, these are very minor glitches that should hardly hinder the reader's ability to follow the main ideas. Overall, the book, written with extreme clarity by authors well known for their excellence in research, successfully accomplishes its goal of "providing a foundation for understanding nonparametric modeling" (p. vii). I would not hesitate to say that among the existing texts on spline-based nonparametric smoothing, such as those by Green and Silverman (1994), Gu (2002), and Wahba (2001), and aside from books on local regression or kernel smoothing for nonparametric regression, *Semiparametric Regression* gives novices the most approachable introduction to penalized splines for smoothing yet available.

As mentioned in the Preface, the choice of a nonparametric method may be "a matter somewhat of individual taste and background." Perhaps, largely due to my own background, I think that the mixed-model approach to smoothing somewhat lacks the mathematical elegance of smoothing splines; for example, the roughness penalty measured by the curvature of a function in smoothing splines is mathematically more lucid than the ridge regression-type penalty in the mixed-model approach. Its interpretation as the bending energy of a draftsman's spline is still fascinating to me, and the historical link of splines to the approximation theory pioneered by Schoenberg is not to be missed. However, understanding smoothing splines requires substantially more mathematical knowledge than the mixed-modeling approach, and the numerical examples in the book show that there is not much difference between the two approaches in practice.

Certainly, I am not a minimalist. Having said that, however, this is a book that I would strongly recommend to practitioners who want to learn nonparametric regression techniques and apply them to their own problems without being burdened by advanced mathematical concepts such as a reproducing kernel Hilbert space.

Yoonkyung LEE
Ohio State University

REFERENCES

Green, P. J., and Silverman, B. W. (1994), *Nonparametric Regression and Generalized Linear Models*, London: Chapman & Hall.
Gu, C. (2002), *Smoothing Spline ANOVA Models*, New York: Springer-Verlag.
Wahba, G. (1990), *Spline Models for Observational Data*, Philadelphia: SIAM.

Quantile Regression.

Roger KOENKER. New York: Cambridge University Press, 2005. ISBN 0-521-84573-4. xv + 349 pp. $75.00 (H). ISBN 0-521-60827-9. $34.99 (P). Digital: $28.00.

This is apparently the first book devoted completely to quantile regression, although some textbooks or monographs already contain sections devoted to this subject (e.g., Hájek, Šidák, and Sen 1999). Although the idea of a sample quantile is very natural and old, this concept was successfully extended to the regression model only in 1978, when Koenker and Bassett introduced their τ-regression quantile as a solution of a certain minimization problem (Koenker and Bassett 1978). Because this concept showed itself to be a (long-expected) straightforward extension of sample quantiles, it was immediately accepted by the statistical community; thereafter, it became an important inference tool for statisticians and econometricians.

Roger Koenker has a profound knowledge of econometrics, linear and nonlinear programming, statistics and computational statistics, and a strong intuition, combined with a sense for practical problems. As a result, this excellent book combines all of these above aspects and covers a broad spectrum, from practical applications to the weak convergence of probability measures through examples on maximum daily temperatures to Choquet capacities. Koenker has the courage to start with nontraditional models and methods that enable one to attack more complex problems than conservative methods, which require on strict optimality. The result is a book providing, in the author's words, a "comprehensive introduction to quantile regression methods," serving to "stimulate others to explore and further develop these ideas in their own research"; I can confirm this.

Although written as an introduction to the field, *Quantile Regression* will be difficult reading for beginners in the area. One needs a fairly good knowledge of statistics, computational techniques, and probability, along with some imagination. I can confirm this after a systematic reading of the book with our doctoral students of statistics and probability in the regular semester seminar. The reader is exposed to a variety of ideas, methods and applications, and should refer to the cited literature for a more profound acquaintance of the subject.

The book comprises eight chapters, plus a short concluding Chapter 9 and an Appendix devoted to a brief tutorial introduction to quantile regression in the reals. The list of contents shows a wide variety of methods and applications of quantile regression, sometimes even surprising ones. After an introductory Chapter 1, Chapter 2 provides the fundamentals of quantile regression. The important Chapter 3, "Inference for Quantile Regression," touches on tests of linear hypotheses and subhypotheses of the Wald type, based on regression quantiles, and discusses tests based on regression rank scores, estimation of the covariance matrix based on regression quantiles, and goodness-of-fit tests with nuisance parameters using the Khmaladze martingale transformation. A strict mathematical statistician can ask for precise alternatives to the hypotheses and can question the omission of the classical Neyman–Pearson structure of the tests; however, as the author states in the concluding chapter, they should be willing "to peer occasionally outside the cathedral of mathematics and see the world in all its diversity."

Chapter 4, "Asymptotic Theory of Quantile Regression," is devoted to an exposition of the basic theory of asymptotic theory of the quantile regression process, also in the autoregressive time series (AR and ARCH setups). Further topics treated include penalty methods, sparsity and covariance estimation, and resampling schemes and the bootstrap. Extreme regression quantiles are also touched on. There are hints of proofs for some propositions and citations for the proofs of others.

In the important Chapter 5, "L-Statistics and Weighted Quantile Regression," the author concentrates on a regression/scale model, kernel smoothing for quantile regression and weighted quantile regression. Chapter 6, "Computational Aspects of Quantile Regression," helps the reader understand the structure of regression quantiles. It explains in detail their linear programming structure, the existence and optimality of the solution, and this structure's link to the simplex method. Considerable attention is devoted to the old/new interior point method for linear programming and especially for quantile regression; both exterior and interior methods are compared. The chapter also considers some aspects of the nonlinear quantile regression, the linear quantile regression supplemented with inequality constraints, weighted sums of objective functions, and the sparsity problem.

The main subject of Chapter 7, "Nonparametric Quantile Regression," is an estimation of the conditional quantile function based on bivariate observations that covers locally polynomial quantile regressions as a special case. Besides the kernel method, considerable attention is devoted to penalty methods for univariate smoothing and to extensions to bivariate smoothing, based on Koenker's and coauthors' recent results using the Voronoi tessellation, triangulation, and other tools of geometric statistics.

Chapter 8, with the mysterious title "Twilight Zone of Quantile Regression," mentions several other potential spheres of application of quantile regression, including quantile regression for survival data, discrete response models, quantile autoregression, copula functions and nonlinear quantile regression, high-breakdown alternatives to quantile regression, multivariate quantiles, penalty methods for longitudinal data, causal effects and structural models, and Choquet utility, risk and pessimistic portfolios.

This chapter alone offers so many possible subjects for further development that this book should definitely be on every statistician's and econometrician's shelf.

Jana JUREČKOVÁ
Charles University

REFERENCES

Hájek, J., Šidák, Z., and Sen, P. K. (1999), *Theory of Rank Tests* (2nd ed.), New York: Academic Press.
Koenker, R., and Bassett, Jr., G. (1978), "Regression Quantiles," *Econometrica*, 46, 33–50.