be familiar with a computer algebra system like MAPLE, thus eliminating the learning step required to use a professional system. MAPLE—a general-purpose integrated environment for doing mathematics on a computer—is more flexible than a statistical software system. Unlimited precision allows the user to compute expressions like $\binom{365}{20}20!/365^{20}$ exactly as a rational number; there is no need to take precautions for possible overflow of intermediate results. MAPLE performs algebraic manipulations, and the authors make use of this feature in proofs and in computations of nonnumerical results. For instance, they compute the expectation of a random variable having the Poisson distribution by first defining the function

$$\texttt{g} := \texttt{k} \rightarrow \texttt{exp(-lambda)} \times \texttt{lambda\^{}k/k!};$$

and then

$$\texttt{E} := \texttt{sum(k} \times \texttt{g(k), k = 0...infinity)};$$

to get the result $E = \lambda$. This example might seem like "killing a fly with a sledgehammer," but students can become preoccupied with tedious work and be distracted from the underlying principles. Using MAPLE removes some of the tedium, thus allowing more emphasis to be placed on principles.

Principles can also be stressed too much. Chapter 2 has a very good introduction to the theory of measure and integration; however, in the MAPLE session at the end of the chapter, too much emphasis is put on numerical methods with left, right, and middle sums, the trapezoid rule, and Simpson's rule. The student might get a wrong impression of numerical methods for quadrature.

MAPLE offers packages for statistical computations. With MAPLE, it is easy to run probabalistic and statistical experiments and to visualize the results using the plot commands. Many functions are available to do simple simulations such as rolling a die, and more complicated simulations like Markov chains and Wiener processes. The authors of the book make use of the `stats` package and subpackages like `statsplot` and `combinat`. S. Cyganowski and P. Kloeden also developed the MAPLE `stochastic` package, which offers a number of functions for stochastic differential equations.

Almost every chapter contains paragraphs labeled "MAPLE Assistance." These (mostly short) MAPLE scripts simulate or illustrate the preceding theory. Simulations are often used to confirm the theoretical results. The scripts can all be downloaded from the authors' web pages. Each chapter also ends with a set of exercises, most of which do not require programming or the use of MAPLE.

The book can serve very well as a textbook for a modern course in computational statistics. It fits into the growing set of mathematical textbooks that use software systems for computer-aided mathematics. To date, more than 400 books have written about MAPLE or provide MAPLE supplements. Of these, nine deal with probability and statistics (see *www.maplesoft.com/publications/books/browseAll.shtml*). For MATLAB, the situation is similar; there are more than 500 books, including 20 books in statistics and probability (see *www.mathworks.com/ support/ books/index.jsp*). *From Elementary Probability to Stochastic Differential Equations with MAPLE* is the only one that deals with stochastic differential equations.

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Time Series Analysis by State-Space Methods.

J. DURBIN and S. J. KOOPMAN. New York: Oxford University Press, 2001. ISBN 0-19-852354-8. ix + 253 pp. $65.00 (H).

In this book, James Durbin and Siem Jan Koopman provide an interesting and fresh treatment of standard, linear Gaussian state-space methods as well as a thorough treatment of nonlinear, non-Gaussian methods by means of importance sampling. The text is presented in a largely self-contained manner that should appeal to students who are just becoming acquainted with the field and more experienced researchers alike. Students new to the field will benefit from the fact that the text presupposes only a basic knowledge of elementary statistics and matrix algebra, whereas more advanced students and researchers will benefit from the text's clear and concise presentation of both old and new results, which makes this book especially useful as a reference.

At every stage, the book strikes an excellent balance between providing a detailed and rigorous treatment of the material while presenting a broad array of empirical examples, ranging from financial economics to environmental science, that enhance the theoretical exposition. The book also contains two chapters (9 and 14) devoted to providing useful illustrations of the methods developed. Additionally, the book is well integrated with two modern computing tools for state-space analysis—SsfPack and STAMP 6.0—developed and supported by one or more of the authors. In many instances, the book directs the reader to the specific functions within SsfPack or STAMP that can be used for empirical implementation of the methods discussed. In this way, the book provides an invaluable reference for those students and applied researchers wanting a text that links the theoretical treatment of state-space models with their practical implementation. The authors also maintain a website (*www.ssfpack.com/dkbook*) containing the data used for illustrations in the text as well as links to related research and sites for STAMP and Ssfpack.

The book is organized in two parts. Part I deals with the linear Gaussian statespace model and covers the first two-thirds (Chaps. 1–9) of the text. The essential tools of forecasting, filtering, smoothing, and simulation of linear Gaussian systems are all treated in a concise, uncluttered manner. In particular, Chapters 2 and 3 cover the local level and other linear Gaussian models, Chapters 4 and 5 cover filtering and smoothing, and Chapters 6–9 cover computational aspects of the Kalman filter, including estimation and illustrations.

In addition to a thorough exposition of the main tools of forecasting, smoothing, and simulating state-space models, the book provides a number of practical suggestions and tools that will be of interest to applied researchers. Examples include discussions of handling missing observations (Sec. 4.8), the univariate treatment of multivariate observations (Sec. 6.4) and spline smoothing (Sec. 3.11). An entire chapter devoted to the computational aspects of the Kalman filter (Chap. 6) is also included. A particularly useful feature of the first part of the text is the treatment (in Chaps. 2 and 7) of diagnostic checking of model residuals for departures from the linear model's maintained assumptions. Apart from providing the reader with a useful set of diagnostics, the discussion foreshadows the necessity and relevance of the nonlinear and non-Gaussian techniques explored in Part II.

Estimation of standard linear models is handled from both the classical (Chap. 7) and Bayesian (Chap. 8) perspective. The classical treatment covers the standard prediction-error decomposition of the likelihood and then moves on to a detailed treatment of the likelihood when some elements of the initial state vector are treated as diffuse. The details on computation of the score vector, as well as on numerical maximization algorithms such as BFGS and the EM algorithm are discussed at length. The chapter on Bayesian methods of estimation is rather abbreviated and is more of an overview, providing a number of useful references. What is important about this chapter is that it introduces the reader to the idea of simulation through importance sampling, the central tool used in the development of the nonlinear, non-Gaussian methods of Part II.

Although many of the topics covered in Part I will be familiar to the initiated, there is a considerable amount of new material in this section of the text that derives from the authors' original research. One of the major new developments contained in the first part of the text is the development of the exact Kalman filter (Sec. 5.2) in the presence of a diffuse initial state vector as an alternative to (and alongside) the augmented Kalman filter of Rosenberg (1973) and de Jong (1988, 1991). The authors provide a derivation of the exact filter as the variance of the diffuse elements of the initial state vector tends to infinity. Aside from its natural motivation, one principal advantage of the new exact filter is reduced computational burden. In comparing the exact filter with the augmented filter, the authors demonstrate that across a variety of standard state-space models, the new filter reduces the number of filtering computations by between 50% and 60%. The text also shows how the diffuse treatment of the initial state vector can ease the computation of disturbance and simulation smoothing. The effects of treating the initial state vector as diffuse on the likelihood function and on maximum likelihood estimation are also explored. Interestingly, the authors show that, in many relevant circumstances, use of the exact initial Kalman filter also eases computation of maximum likelihood estimates relative to those computed using the augmented Kalman filter.

Unlike Part I, all of the material in Part II is new, on the frontier of nonlinear and non-Gaussian state-space research. Much of this material is a direct result of the authors' original research (most notably Durbin and Koopman 1997, 2000). Part II comprises five chapters (10–14) and accounts for the final one-third of the text. It opens with a chapter of illustrations and examples in which the standard linear assumptions of Part I are naturally untenable, and serves as a call to action for the more general nonlinear and non-Gaussian methods developed in subsequent chapters. This chapter and the subsequent ones pay special attention to cases in which observations are generated from a non-Gaussian member of the exponential family, and cases where the observable can be thought of as the sum of a Gaussian signal and a serially independent non-Gaussian noise component. Particular attention is paid to the stochastic volatility (SV) model in Chapter 10 and throughout Part II. In several instances, the SV model is used as an illustration of the nonlinear, non-Gaussian techniques as they are developed throughout the text. For this reason, the book is a valuable resource for those researchers interested in details about filtering, smoothing, and estimation of the SV model, as well as comparisons between the exact maximum likelihood estimator and approximate state-space methods for the SV model.

Chapter 11 deals with the method of importance sampling and construction of a linear approximating model for the general nonlinear, non-Gaussian model and constitutes, from a methodologic perspective, the most important chapter of Part II. This section of the text proposes approximating the general model by a linear Gaussian model that shares the same mode (for the state vector) as the nonlinear, non-Gaussian model. The approximate model is then used to construct the importance density (using the simulation smoother outlined in Chap. 4), which serves as the basis for constructing all objects of interest from the likelihood to functions of the state vector. The text provides a detailed discussion of the construction of the approximating model and provides a number of useful examples along the way. Also, aside from the proposed importance sampling technique, the text does discuss some alternative methods for non-Gaussian models that do not require importance sampling, such as models in which the innovations in the observation equation are generated from a finite mixture of normal distributions or a t distribution. In this way, the text provides some perspective for judging the efficacy and generality of the newly proposed methods.

The next two chapters of Part II are devoted to a discussion of estimation from both classical and Bayesian perspectives (Chaps. 12 and 13) in the general nonlinear, non-Gaussian case. Mimicking Part I, the section on classical analysis is more thorough and provides more practical guidelines and information than the section on Bayesian analysis. The discussion of classical analysis provides some useful suggestions for obtaining a quick initial parameter vector for use in the maximization routine, as well as some practical advice on how to choose the number of draws from the importance density. The book closes with a series of illustrations of nonlinear, non-Gaussian state-space models ranging in scope from an application of the SV model, to the daily pound/dollar exchange rate to the use of a Poisson density in modeling the number of van drivers killed in Great Britain. The examples clearly demonstrate the advantages of entertaining non-Gaussian alternatives in practical modeling situations and illustrate the potential of the methods outlined in the text.

On balance, this new text provides an excellent discussion and exposition of a broad class of state-space models. Part I provides a concise and thorough distillation of the standard state-space methods, like those considered by Harvey (1989), with a smattering of useful new results. Part II makes a new and significant contribution to the literature on nonlinear and non-Gaussian state-space systems and continues the recent trend in advances in non-Gaussian and nonlinear modeling methodologies (see, e.g., Kim and Nelson 1999). Perhaps one disappointing feature is the distribution between new and old material. Given the novelty and importance of the methods introduced in Part II, it seems reasonable to wonder whether most readers wouldn't benefit from an expanded Part II and a compressed Part I. In particular, Part II could possibly benefit from some direct comparisons with other existing methods for handling non-Gaussian and nonlinear state-space models. The authors rightly point out that methods based on importance sampling are likely to be faster, computationally inexpensive, and easier to implement than other existing (e.g., Markov Chain Monte Carlo) methods. Although it is not hard to imagine that the authors are correct, a concrete example illustrating these important points would be useful for those researchers contemplating experimenting with these newer and arguably faster and simpler methods.

The text might also benefit from a more thorough discussion of the benefits and shortcomings of the proposed importance sampling technique. Under which circumstances is it expected to perform best and worst? When a nonlinear model results in a multi-modal distribution for the state vector, which mode should be matched by the linear approximating model? Although *Time Series Analysis by State-Space Methods* goes a long way towards making the authors' approach to nonlinear, non-Gaussian models accessible to students and researchers, there are still some important stones yet to be turned over. Despite these qualifications, this impressive book belongs on the bookshelves of students and researchers interested in moving to the frontier of nonlinear and non-Gaussian state-space research.

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Bayesian Statistical Modelling.

Peter Congdon. Chichester, UK: Wiley, 2001. ISBN 0-471-49600-6. xi + 531 pp. $65.00 (H).

Applied Bayesian statisticians, researchers in applications areas in which Bayesian statistical analysis is standard, and statistics teachers have eagerly awaited a book that can serve as an introduction to the philosophy and methods of Bayesian statistics, as a guide to real-data analysis with the popular Bayesian software package WinBUGS (Spiegelhalter, Thomas, and Best 2000), and as a showcase of application areas in which Bayesian statistics are used. This superbly referenced book makes a very useful contribution in the latter two regards, but could prove confusing to a student or novice attempting to learn Bayesian concepts and procedures.

The author is a Research Professor in Statistical Geography in the Department of Geography, Queen Mary, University of London. His own research interests in health services research, health outcomes models, and medical geography are reflected in the abundance of examples related to health and social science.

Chapter 2, "Standard Distributions: Updating, Inference, and Prediction," introduces Bayesian prior specification, estimation, prediction, and hypothesis testing in the context of simple models, beginning with a normal likelihood with population mean unknown and population variance assumed known. Illustrating each model with an example based on a small dataset, the chapter proceeds through normal models with both mean and variance parameters unknown; comparison of means in two or more normal populations; t likelihoods; binomial, Poisson, and multinomial likelihoods for categorical data; and multivariate normal and multivariate t likelihoods.

The subsequent chapters present more advanced topics in Bayesian statistical modeling, which enable realistic modeling in many application areas. These include hierarchical modeling, models for temporally and spatially correlated data, linear and generalized linear regression, and survival analysis.

Data and WinBUGS code for the worked examples are available via ftp from *ftp://www.wiley.co.uk/pub/books/congdon*. Because the WinBUGS programs are not quoted in the book (except for occasional brief code fragments), the reader must download them to fully understand the examples and learn WinBUGS programming methods.

The examples contain many useful coding tricks in WinBUGS, including multivariate normal likelihood with some missing data (Example 2.18), use of the `equals` function in computing intervals to which values of latent variables