utilization of conditional independence and proportionality more accessible to applied researchers.

Finally, Chapter 8 provides useful approaches for testing pieces of a simulator and revisits the issue of formal model comparison. Here an importance sampling estimator, the candidate's formula, and reciprocal importance sampling are discussed. Example 8.2.3 applies the candidate's formula to a normal mixture linear model. The suggested approximations based on the MCMC output hint at the fact that label switching may be a concern in this case. Then prior and posterior predictive analyses are introduced using examples.

The book concludes with an important discussion of how to deal with the fact that different clients may have different priors. Two solutions are offered. First, the complete MCMC output, including likelihood and prior evaluations, could be transferred to enable importance sampling by the client. Second, the investigator could report density ratio robustness bounds. However, both approaches do not seem to scale easily to more complicated hierarchical models.

I enjoyed reading Contemporary Bayesian Econometrics and Statistics and think it would make a great textbook for a Bayesian course at the graduate level in finance, business, marketing, and the social sciences. I note that Geweke is working on a solution manual to the exercises in the text. The book is also a great reference for the growing number of people who have been using MCMC methods without a firm grounding in the theory of Bayesian inference.

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Multivariate Bayesian Statistics: Models for Source Separation and Signal Unmixing.

Daniel B. ROWE. Boca Raton, FL: Chapman & Hall/CRC Press, 2002. ISBN 1-58488-318-9. xx + 328 pp. $99.95.

This book develops, clearly and in full detail, a Bayesian approach to a multivariate inverse problem called blind source separation. This problem has important applications in diverse areas of science and engineering, including image processing, remote sensing (hyperspectral imaging), acoustics, radar and sonar reconstruction, economics and finance, and biomedical imaging [electroencephalography, magnetoencephalography, and functional magnetic resonance imaging (fMRI)]. Most of these applications involve large or high-dimensional datasets.

The motivating example in the book is the famous cocktail party problem. The conversations of guests at a party are recorded by microphones scattered about the room, amidst background noise and other known signals. The problem is to reconstruct what each guest said. In mathematical terms, the basic version of the problem begins with m distinct sources producing temporal signals represented by a vector of time series $\mathbf{s}(t) = (s_1(t), \ldots, s_m(t))$. The source signals are not observed directly (thus the word "blind"), and in general, m is unknown. We do observe the output, $\mathbf{x}(t) = (x_1(t), \ldots, x_n(t))$, of n sensors, each of which records a noisy mixture of the source signals; thus we can write

$$\mathbf{x}(t) = A(\mathbf{s}, t) + \epsilon(t). \tag{1}$$

An essential feature of the problem is that the mixing function A is unknown. In the cocktail party problem, for instance, the sound received by a microphone depends on the positions in the room of the various speakers and on the acoustic configuration of the room. For many realistic systems, A will be nonlinear, will mix signals produced at different times (consider delays and echoes), and can vary over time. But a natural starting point is to take A to be linear, temporally homogeneous, and instantaneous in the sense that it mixes source signals only at a specific time, in which case we can write

$$\mathbf{x}(t) = A\mathbf{s}(t) + \epsilon(t). \tag{2}$$

In form, it seems that we have a linear model, but with a critical difference. Both $\mathbf{s}$ and A are unknown and of interest, $\mathbf{s}$ for recovering the sources and A for understanding the system. Because of the way in which they combine in the model, these quantities are not identifiable without further structural assumptions.

Although the book does not discuss it, an extensive literature in signal processing has built up around this problem. Most of the published approaches achieve estimability of A and $\mathbf{s}$ by imposing hard constraints on the source signals (e.g., independence, number, sparsity), mixing matrix (e.g., time invariance, rank, orthogonality), or noise process. Solutions are obtained through iterative optimization of a statistical or information-theoretic criterion function in a classical framework. Independent components analysis (introduced by Heurault and Jutten 1986 and developed vigorously since) is a prominent example in which one constructs a linear transform W such that the columns of $\mathbf{y} = W\mathbf{x}$ are as independent as possible as measured by the mutual information between $\mathbf{y}$ and $\mathbf{x}$. [In practice, this is approximated with a related criterion such as *Infomax* (Bell and Sejnowski 1995).] There are two different views of source separation that manifest in this literature: an inference problem of finding the unknown A and $\mathbf{s}$ and a representation problem of decomposing $\mathbf{x}$ into components with some useful properties. Many of the signal-processing methods solve the latter problem but still apply when the assumptions of the inferential problem hold.

In contrast, Rowe's book focuses directly on a Bayesian approach to the inferential problem. One advantage of the Bayesian approach in this context is greater flexibility in the constraints imposed on the model. Across increasingly complex versions of the source-separation problem, the book presents several basic models with standard priors (conjugate and a generalized form) and for each offers various approaches to inference from Bayes estimators based on posterior means or modes to approximate posterior expectations via Gibbs sampling. The emphasis is on models that are straightforward to understand and compute. Throughout the book, the derivations are detailed and complete, with few steps skipped, making it easy for the reader to follow the mathematics. The notation is consistent and generally well chosen. The material is clearly presented, although the treatment is light on discussion and conceptual interpretation.

Although developing Bayesian models for the source separation problem is the book's ultimate focus, *Multivariate Bayesian Statistics* builds to this from an introductory discussion of Bayesian methods. After motivating the source separation problem with the cocktail party metaphor, the first third of the book (Chaps. 2–7) covers the basics of statistical distributions (Chap. 2), Bayesian inference (Chaps. 3 and 6), prior distributions (Chaps. 4 and 5), and linear regression (Chap. 7). Several methods of assigning prior distributions are discussed briefly with an emphasis on conjugate priors and a simple generalization thereof, because these get heavy use later in the book. Chapter 5, on hyperparameters, emphasizes using the form of the posterior with conjugate priors to motivate hyperparameter assignment from previous data. Chapter 6, on inferential methods, covers posterior means and modes as estimators, direct integration to derive posterior distributions, iterated conditional modes, and Gibbs sampling. The description of Gibbs sampling is clear, but no introductory references are given to lead the reader to a more complete treatment, nor is any mention made of other Markov chain Monte Carlo techniques. Finally, as a prelude to the models covered later in the book, the derivation of Bayesian regression estimators and posteriors is given in complete detail in Chapter 7.

Overall, this introductory material is clearly and concisely written but necessarily terse given space limitations. Throughout the book, derivations are complete. Nonetheless, for a reader not familiar with these ideas, the presentation may be sufficient to follow the remainder of the book but not be sufficient to build a conceptual understanding of the material. The handful of exercises at the end of each chapter throughout this part tend to be basic and mechanical, rarely going beyond standard cases, yet perhaps useful as a check on comprehension. Guidance or annotated references to introductory sources for this material would be a useful addition to the text.

As a prelude to the source separation problem, the next part of the book (Chaps. 8 and 9) offers detailed derivations of various Bayes estimators for multivariate regression and factor analysis. The structure of these chapters is the same: a description of the notation and likelihood, the derivation of posteriors or estimators under conjugate priors, a similar derivation under generalized conjugate priors, and a small data example. The derivations are complete and easy to follow, and the exercises lead the reader to derive special cases. One way in which these chapters could be used would be to ask students to derive various posterior quantities under these models *before* reading the text, then letting the text serve as an extended set of hints and solutions.

Chapters 10 and 11 follow much the same template with the source separation problem, first with all source signals unknown and second with a mixture of known and unknown source signals. Chapters 13 and 14 extend the models to incorporate phenomena that are present in many realistic systems, such as delays, time-dependent mixing, and correlation among the source vectors. In these chapters, the models' likelihoods and priors are the same as those earlier in the book. This has the advantage of concreteness and allows detailed derivations, although other models and priors may be of interest. What is left unaddressed is a comparison between the Bayesian approach and the iterative approaches mentioned earlier. It should be possible to construct realistic situations that demonstrate the advantages of the Bayesian models. This would also be a useful framework within which to evaluate the sensitivity of the results to the model assumptions.

The use of source separation algorithms, particularly independent components analysis, has recently become a popular approach for analyzing fMRI data. These data offer a rich testbed for these methods, because there is substantial prior information about the response function being modeled and because there is interesting spatial structure to account for. Chapter 12 gives a case study applying the Bayesian methods developed earlier in the book to simulated and real fMRI experiments. The results are promising. The book's description of fMRI experiments will be clear to a nonspecialist. The models here can simultaneously account for the main sources of variation in the temporal data, including trends and physiological covariates that are usually "removed" during preprocessing. The extended models of Chapters 13 and 14 would be appropriate here to account for additional features in the signal, but these would be straightforward to implement. An advantage of this approach is that it provides a data-adaptive method for estimating response functions; commonly used methods either restrict to a simpler parametric model or use a separate regressor at each time point. Careful choice of a general prior for the source signals might further improve the fit.

Taken as a whole, the material in this book is technically detailed but narrow in scope, focusing on basic models and Bayesian methods. The writing is clear but does not elaborate on concepts and variations. Given the book's style and strengths, it would be appropriate for several audiences. For practitioners in an application area (e.g., fMRI) who want to study or implement methods for the source separation problem, this would serve as a useful reference because it presents all necessary technical detail. For statistics graduate students in a class on multivariate analysis or inverse problems, this could serve as a supplementary text, although it would need to be accompanied by material on other methods for the problem. In this case, most of the introductory material through Chapter 7 could be skipped. A similar recommendation holds for a short course on source separation problems. *Multivariate Bayesian Statistics* fits into a relatively small niche but serves its purpose well.

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Financial Modelling With Jump Processes.

Rama CONT and Peter TANKOV. Boca Raton, FL: Chapman & Hall/CRC, 2004. ISBN 1-58488-413-4. xvi + 535 pp. $79.95.

Before the work of Markowitz (1952), finance was more of an art than a science. Before the work of Black and Scholes (1973) and Merton (1973), financial practitioners did not have to worry about Brownian motion or Itô calculus. Since the work of Harrison and Pliska (1981), martingales have become recognized as natural tools in this area. As the limited ability of the standard Black–Scholes model to reflect financial reality has become ever clearer over the years, the pressure has been on to broaden the class of stochastic processes used in financial modeling to achieve a better fit to real markets and real data. As always, one is caught between the conflicting demands of simplicity (of concepts or of implementation) and of goodness of fit, or range of phenomenon that one can model adequately.

The thesis of this book is that *jumps* are needed in a model. The first chapter, "Financial Modelling Beyond Brownian Motion," is an eloquent and (to me) convincing argument for the necessity of jumps. At 16 pages, reading this would be a very good investment of time for anyone with access to this book.

The prototype of jump processes is the Poisson process, ubiquitous in the modeling of actuarial and insurance problems. These two processes—Brownian motion and the Poisson process—stand at opposite ends of a spectrum of processes forming an important class: *Lévy processes*, or stochastic processes with stationary and independent increments. These have a well-developed theory, and the class is flexible for modeling purposes. This book is essentially a monograph treatment of the burgeoning field of "Lévy finance," written with the practitioner as well as the student in mind.

The level of mathematical completeness, or of the prerequisites expected of the reader, is the first choice that the authors had to make. To make the book as accessible as reasonably possible to practitioners, the authors have (very sensibly) chosen to make no attempt to prove everything. Rather, they aim to "explain everything," writing what they need into the record, proving what they can, and giving detailed references to the literature (they cite 395 references) otherwise. Chapters end with a summary and further reading.

Part I (Chaps. 2–5) covers on mathematical tools. Here what is needed on measure theory, probability, and stochastic processes is summarized. Lévy processes are introduced. There is a whole chapter (Chap. 4) on building new Lévy models from old ones. Multidimensional models (dependence and copulas) are treated in Chapter 5.

Part II (Chaps. 6 and 7) covers simulation and estimation. Chapter 6, on simulating Lévy processes, includes approximation by compound Poisson processes and infinite-series representations. Chapter 7, on modeling financial time series with Lévy processes, includes the stylized facts of financial data, tail behavior (particularly heavy tails), time aggregation and scaling, and volatility clustering. I particularly liked Figure 7.6, a Venn diagram depicting the relationship between Lévy, Gaussian, and self-similar processes.

Part III (Chaps. 8–13), which studies option pricing in jump models, is the longest, and for the practitioner, the most important part. "Part IIIA" (Chaps. 8 and 9) covers theory, stochastic calculus with jumps (Chap. 8), and change of measure (Chap. 9). Girsanov's theorem, on change to an equivalent measure, is the core of *risk-neutral valuation* for complete markets (such as the Black–Scholes model, where one can hedge risk completely). It plays an important, though less dominant role, in *incomplete markets*, such as Lévy models typically give. "Part IIIB," on applications, begins (Chap. 10) with pricing and hedging in incomplete markets. It continues (Chap. 11) with risk-neutral modeling with exponential Lévy processes (the extensions to the Lévy case of the exponential Brownian motions of the Black–Scholes case). Chapter 12, on integro-differential equations and numerical methods, covers the extension of the (parabolic) partial differential equations (PDEs) of the Black–Scholes theory to the partial integro-differential equations (PIDEs) in the Lévy theory (the new term, the integral term, directly reflects the new feature, the jumps). Topics covered include pseudodifferential operators and their links with Markov processes, viscosity solutions, and the fast Fourier transform (FFT). Chapter 13, on inverse problems and model calibration, is the part of the book that a quantitative analyst or financial engineer perhaps will refer to most frequently.

Part IV (Chaps. 14 and 15) goes beyond Lévy processes. Chapter 14 looks at time-inhomogeneous jump processes (with additive processes in place of Lévy processes). Chapter 15 is on stochastic volatility (SV) models with jumps. It covers in particular the work of Barndorff-Nielsen and Shephard (2001) on non-Gaussian Ornstein–Uhlenbeck processes (which depends on the theory of self-decomposability), and the work of Carr, Geman, Madan, and Yor (2003) on time-changed Lévy processes.

One of the features of this book that I like most is the illuminating asides, often (but not always) in the summary or further reading sections at the ends of chapters. To quote just one (from 10.3.4, p. 330), "… pricing by utility maximization is more similar to a portfolio allocation problem than to arbitrage pricing models." (It would take us too far afield to explore this properly here; suffice it to say that the need to feed utility or the investor's attitude to risk into the picture goes hand-in-glove with the incompleteness that comes with the jumps.) Another nice feature is the short biographies at chapter ends (Poisson, Lévy, Bachelier, Meyer).

I loved this book (so too did Peter Carr, in the publisher's blurb). It will be required reading for students (mine, at least) entering Lévy finance. My judgment is that it will be useful both within academia, particularly to people in stochastics, econometrics, and other fields wanting to develop an interest in finance, and to practitioners. True, they will need a good mathematical background and a degree of persistence, but in view of the demands of the increasingly complex financial world we live in, they need these anyway.

JASA. Sep 1, 2006, 101(475):1306-1306.