Gogh's *Starry Night* has in it the genesis of the roll-up and pairing processes "occurring" in the gargantuan vortices of galactic black holes, or that a neurologist's explanation for the brain's cell structure is somehow related to the same roll-up and pairing of earthy mixing layers.

The book appears to have been submitted to the publisher as a camera-ready manuscript, as was the case with prior editions. As a result, numerous typographical and grammatical errors fell through the cracks. A few examples: "standed" in the preface (written correctly as "stands" in prior editions, but I presume the author wished to change the tense of the verb); equation (2.37) on p. 35 is incomplete; "reprensented" on p. 94; "whith" on p. 187; "irrealistic" on p. 240; "artefact" on p. 242; "submitted" and "above" on p. 455, which are probably meant to read "subjected" and "earlier"; and the order in the alphabetical list of references sometimes reverts to disorder. This all is unfortunate because Marcel Lesieur, whose mother tongue is French, has very good command of the English language. A zealous copy editor is a safety net for the best of us.

All in all, this is a good book that could with some effort become a great one. (A cursory reading of Jim Collins' *Good to Great* may help.) But since no critical review has been written for two decades, the author has had a reasonable excuse not to reach for the stars, or the galactic black holes. Perhaps this review will be in a small way a call to arms. For now, Pope's textbook is the better choice for classroom teaching for both first and second courses on turbulence. Lesieur's monograph is recommended for those who already know quite a bit about turbulence, for the theoretically inclined, and for those interested in particular in homogeneous turbulence and geophysical flows and their numerical simulation.

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Bayesian Methods: A Social and Behavioral Sciences Approach. Second Edition. *By Jeff Gill.* Chapman & Hall/CRC Press, Boca Raton, FL, 2007. $69.95. 752 pp. ISBN 978-1584-8856-2-7.

Bayesian statistics means different things to different people. To nonstatisticians, Bayes is about assigning probabilities to scientific hypotheses. For example, one summary of moderately-informed opinion says:

> Bayesian inference uses aspects of the scientific method, which involves collecting evidence that is meant to be consistent or inconsistent with a given hypothesis. As evidence accumulates, the degree of belief in a hypothesis ought to change.... [P]roponents of Bayesian inference say that it can be used to discriminate between conflicting hypotheses: hypotheses with very high support should be accepted as true and those with very low support should be rejected as false."
>
> —Wikipedia article on "Bayesian inference"

It may come as a surprise to many readers that this is not how I view Bayesian inference at all!

In my work, I treat Bayesian methods as souped-up least squares or maximum likelihood, a way to perform better inference within a model. For example, when modeling the rates at which New York City police stopped people of different ethnic groups [4], we did *not* attempt to compute the probability of the hypothesis that police stopped blacks, Hispanics, and whites at the same rate; rather, we estimated these different probabilities and assessed how they varied for different types of crimes and in different parts of the city. In estimating social networks using survey data [5], we did not estimate our degree of belief in the hypothesis that people formed social ties at random; instead, we fit a model in which people varied in their social networks, and compared our fitted model to predictions from the simpler model. And so on. I have worked on hundreds of applied research projects, but I don't know that I've ever accepted a hypothesis as true (as the Wikipedia quote above suggests is appropriate). Conversely, I would not reject a model just because it is "false"! False models help us learn about the world; that's what much of statistics is about (as in the famous quote of Box and Draper [1] that "all models are wrong, but some are useful"). Otherwise, I don't know what all that stuff in classical statistics about maximum likelihood from the Poisson distribution, etc., is for.

I'm not trying to argue that the Wikipedians' interpretation is wrong, just that their view focuses on what seems to me to be a small part of what Bayesian statistics is about. It also represents a view of the philosophy of science with which I disagree, but this review is not the place for such a discussion. What is relevant here—and, again, which I suspect will be a surprise to many readers who are not practicing applied statisticians—is that what is in Bayesian statistics textbooks is very different from what outsiders think is important about Bayesian inference or Bayesian data analysis.

This brings me to the second edition of Jeff Gill's book, which does an excellent job of presenting my view of Bayesian inference—as a method for fitting models and estimating parameters—in the language of scientific hypotheses.

The thing that makes this book excellent for the social sciences is not so much its examples (although these are real social science examples, which can be hard to find in statistics textbooks) but the tone, a sort of theoretically minded empiricism that is hard for me to characterize exactly but strikes me as a style of writing, and of thinking, that will resonate with the social science readership.

Compared to a more mainstream Bayesian data analysis book such as Carlin and Louis [2] or our own [3], Gill has more on history (addressing questions such as why Bayes has suddenly seemed to become more popular) and a lot on hypothesis testing, which is a big issue in social science, where a standard research paradigm is that falsifiable research hypotheses are set up and then put to the test.

One great feature of this book is its use of examples where real prior information is used. Not just convenient noninformative priors, but specific discussion of how prior information comes into the analysis. As a related point, summaries such as that on page 64 are particularly useful in comparing Bayesian and classical approaches to statistics. This kind of thing is great for a class: if students disagree, it can spark useful discussion.

The presentation of results is done largely in a standard social science manner; for example, the table on page 121 presents posterior intervals to three decimal places ([6.510:11.840], etc.), and the table on page 126 presents variable names in all-caps (EXTENT, DIVERSE, etc.). This isn't how I would do it, but it does approach more closely what is usually done in social science, which can be a virtue here.

Gill's book also has a fairly theoretical treatment of computational issues, actually more theoretical than our book [3], which might seem surprising (I'd think that, if anything, social scientists would be less likely to want to see heavy Markov chain theory), but it makes sense for a couple of reasons. First, Gill himself does research in statistical computation and can give readers the benefit of his insight. Second, social scientists, not being mathematicians themselves, do want to see the rigorous mathematical foundations of their methods. It's fine for me to just describe methods and sketch proofs in my book, because much of my audience is made up of statisticians who will know where to find the more detailed derivations if they need to, but Gill is connecting with social science students who might not want see this anywhere else.

Finally, given that Gill does talk about history, I would have liked to have seen a bit more discussion of the applied Bayesian work in the "dark ages" between Laplace/Gauss in the early 1800s and the use of the Gibbs sampler and related algorithms in the late 1980s. In particular, Henderson and others used these methods in animal breeding (and, for that matter, Fisher himself thought Bayesian methods were fine when they were used in actual multilevel settings where the "prior distribution" corresponded to an actual, observable distribution of entities, rather than a mere subjective statement of uncertainty); and Lindley and Smith, Dempster, Rubin, and their collaborators did sophisticated pre-Gibbs-sampler work, published

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in *JASA* and elsewhere, applying Bayesian methods to educational data. Also, in parallel, Box, Tiao, Stein, Efron, Morris, and others did parallel work on shrinkage estimation and robustness. These statisticians and scientists worked their butt off getting applied Bayesian methods to work *before* the new computational methods were around and, in doing so, motivated the development of those methods and actually developed some of them themselves. Writing that these methods, "while superior in theoretical foundation, led to mathematical forms that were intractable," is a bit unfair. Intractable is as intractable does, and the methods of Box, Rubin, Morris, etc., worked. The Gibbs sampler and so on took the methods to the next level (more people could use the methods with less training, and the experts could fit more sophisticated methods), but Bayesian statistics was more than a theoretical construct back in 1987.

In conclusion, Gill has written a thoughtful and thought-provoking book, focusing more on priors, motivation, model evaluation, and computation, and less on the nuts and bolts of constructing and fitting models. As such, it fits in very well with existing books that focus more on the models.

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Practical Algorithms for Image Analysis: Description, Examples, Programs, and Projects. Second Edition. *By L. O'Gorman, M. J. Sammon, and M. Seul.* Cambridge University Press, Cambridge, UK, 2008. $65.00. vi+349 pp., hardcover. ISBN 978-0-521-88411-2.

This book is a good introduction for a hands-on novice who likes to try out various imaging algorithms. It feels like a well-organized manual of essential imaging methods. As the title says, it is very "practical."

The contents includes a wide array of topics such as intensity histograms, color transformations, convolutions, edge detections, wavelet analysis, noise removal, shape analysis, line and spline fitting, the k-nearest-neighbor problem, and discrete Fourier transforms. However, these are all covered in a light and clear manner. A typical subsection, covering one algorithm, starts with a summary of applications and related topics. It follows with a few pages of description and ends with the program to achieve implement the algorithm. The best part of the description is the image examples from both before and after the algorithm is applied. The book also comes with a CD-ROM containing C source code, executables, and descriptions.

I believe this is a good reference for beginners who are interested in practical imaging algorithms, and is written like a cookbook for imaging techniques. It may not be suitable as a main textbook, but is a good practical reference for any introductory imaging classes. This book is not for advanced researchers interested in mathematical imaging techniques, such as calculus of variation, variational approaches, or partial differential equation-based methods, and it contains minimumal mathematics, but instead more practical applications and examples.

The book covers a wide range of essential topics, and this will be a good starting point for undergraduate students or others interested in experimenting with imaging techniques.

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