

## Book review

# Exemplary Introduction to Bayesian Statistical Inference

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ISBN 978-0-470-14114-4, 2009 (xxiii+492pp., \$88<sup>1</sup>).

*Reviewed by* Ruud Wetzels, Eric-Jan Wagenmakers

The author of *Bayesian Modeling Using WinBUGS*, Dr. Ioannis Ntzoufras, is currently assistant professor in the Department of Statistics at the Athens University of Economics and Business, Greece. Over the last decade, Dr. Ntzoufras has made contributions to Bayesian model selection using MCMC, the choice of prior distributions for Bayesian variable selection, and the application of advanced Bayesian modeling techniques in actuarial science, sports, and medicine. Dr. Ntzoufras' website can be found at <http://www.stat-athens.aueb.gr/~jbn>.

The reviewers, Ruud Wetzels ([Wetzels.Ruud@gmail.com](mailto:Wetzels.Ruud@gmail.com)) and Eric-Jan Wagenmakers ([EJ.Wagenmakers@gmail.com](mailto:EJ.Wagenmakers@gmail.com)), both work at the University of Amsterdam. Their common research interests include Bayesian hypothesis testing and Bayesian variable selection in regression models.

Modern statistics is Bayesian statistics (Poirier, 2006), and this holds particularly true in the field of mathematical psychology. At the 2009 annual meeting of the Society for Mathematical Psychology, out of a total of 141 spoken presentations, 37 (i.e., slightly more than 25%) contained the words “Bayes” or “Bayesian” in title or abstract.<sup>2</sup>

To bolster our claim that Bayesian techniques are increasingly popular among mathematical psychologists, we also considered the proportion of articles published in *Journal of Mathematical Psychology* (JMP) that refer to “Bayes” or “Bayesian” anywhere in the text.

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<sup>1</sup>The Amazon price is \$88. At the time of writing, the Wiley price is \$110.

<sup>2</sup>The conference program is available at <http://www.mathpsych.org/conferences/2009/images/finalprogboek.pdf>.

Figure 1 suggests that this proportion has increased linearly over time, and that presently about one in every four JMP articles mentions “Bayes” or “Bayesian”.

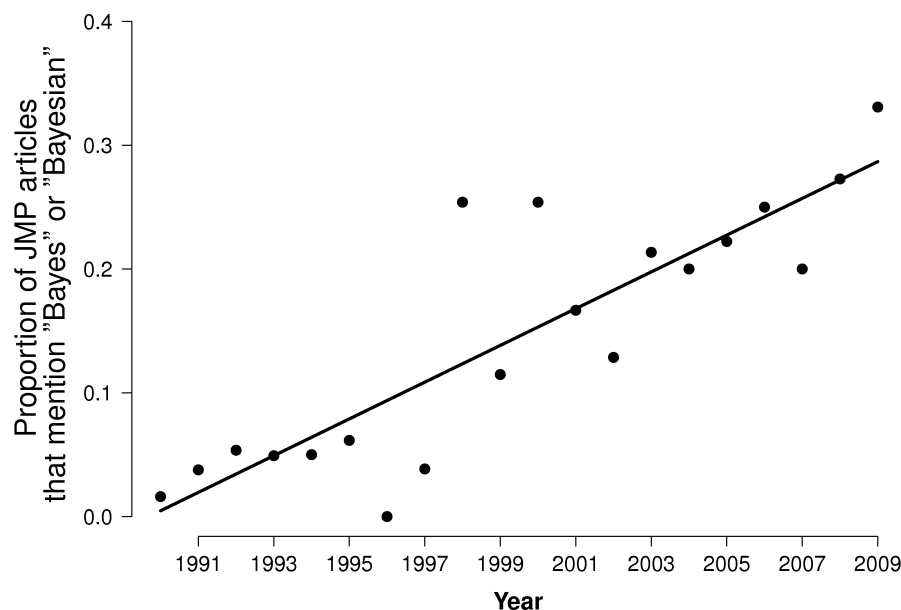


Figure 1. Proportion of articles in *Journal of Mathematical Psychology* that mention “Bayes” or “Bayesian” anywhere in the text. The straight line is a cubic smoothing spline.

The growing interest in Bayesian methods is arguably driven by two factors. The first factor is that mathematical psychologists are increasingly involved in developing and estimating cognitive models that respect the complexity inherent in real data. For example, mathematical psychologists have recently proposed models that capture individual similarities and differences by hierarchical group-level distributions (e.g., Morey, Pratte, & Rouder, 2008; Morey, Rouder, & Speckman, 2008; Navarro, Griffiths, Steyvers, & Lee, 2006; Wetzels, Vandekerckhove, Tuerlinckx, & Wagenmakers, in press), and models that account for variability in participants as well as in items (Morey, Pratte, & Rouder, 2008; Rouder, Lu, Morey, Sun, & Speckman, 2008). Within the Bayesian framework, such extensions of standard statistical modeling procedures are theoretically and computationally straightforward.

A second factor is the ascent of Markov Chain Monte Carlo (MCMC), the current-day workhorse of Bayesian inference. Before the area of MCMC, Bayesian models were only as good as their analytical solutions, and this limited both their scope and their practical appeal. Presently, the combination of MCMC algorithms and the availability of cheap computing power has freed the Bayesian paradigm from the absolute necessity of analytical solutions, and it is now said that Bayesian models are limited only by the user’s imagination.

Nevertheless, the application-specific construction of MCMC sampling routines still requires substantial expertise and effort, potentially restricting the use of Bayesian methods to a small group of mathematical statisticians. Enter WinBUGS (Bayesian inference Using Gibbs Sampling; Lunn, Thomas, Best, & Spiegelhalter, 2000; Lunn, Spiegelhalter, Thomas,

& Best, 2009), a flexible and user-friendly software package for MCMC-based Bayesian modeling.<sup>3</sup> With the help of the WinBUGS package, MCMC-based Bayesian modeling has become feasible even for researchers unable or unwilling to program application-specific MCMC sampling routines of their own.

The WinBUGS program comes with an array of predefined functions (e.g., `sqrt` for square root and `sin` for sine) and distributions (e.g., `dbin` for the binomial and `dnorm` for the normal) that allow users to combine these elementary building blocks into complex probabilistic models. Lunn et al. (2009) note that WinBUGS has over 30,000 registered users, 8000 of which are part of an active online community. Figure 2 shows the yearly number of Google Scholar hits for “WinBUGS”, confirming its rising popularity.

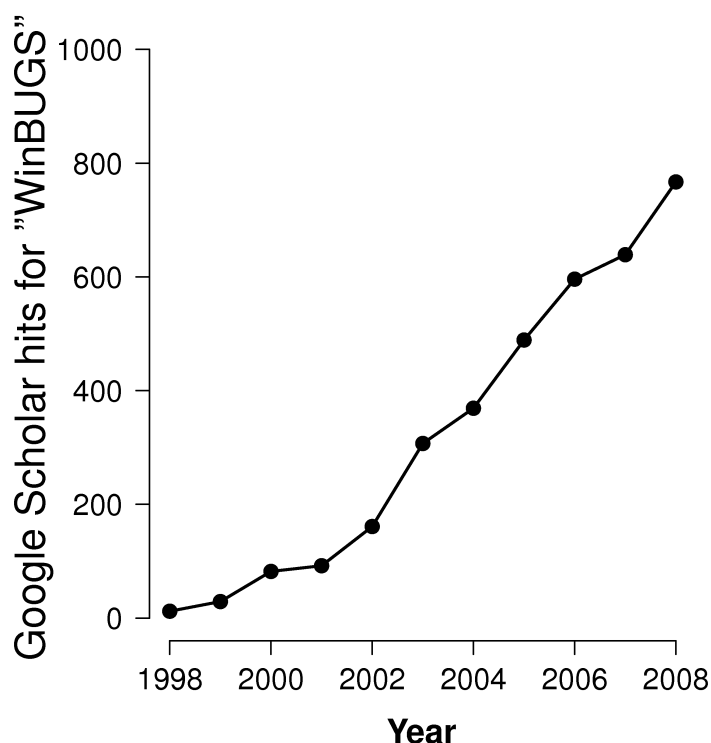


Figure 2. A Google Scholar perspective on the increasing popularity of Bayesian inference using WinBUGS.

Despite its popularity, however, few books have focused on how to use WinBUGS to implement standard statistical models (notable exceptions are discussed below). This is why we feel that the book under review here, *Bayesian Modeling Using WinBUGS* (BMW; Ntzoufras, 2009), is particularly useful for the statistical practitioner. The book is clearly written, covers a wide range of important statistical models, and—most importantly—illuminates theory with concrete examples implemented in WinBUGS. As stated on the book’s back cover,

“*Bayesian Modeling Using WinBUGS* provides an easily accessible introduc-

<sup>3</sup>WinBUGS is freely available at <http://www.mrc-bsu.cam.ac.uk/bugs/welcome.shtml>.

tion to the use of WinBUGS programming techniques in a variety of Bayesian modeling settings. The author provides an accessible treatment of the topic, offering readers a smooth introduction to the principles of Bayesian modeling with detailed guidance on the practical implementation of key principles.”

We agree with the publisher, and we unreservedly recommend the book for anyone who is interested in Bayesian inference using WinBUGS. A more detailed evaluation follows a description of the book’s content.

## Content

BMW is a “hands-on” introduction to the principles of Bayesian modeling using WinBUGS” (Ntzoufras, 2009, back cover). The book strikes an admirable balance between theoretical and practical aspects of Bayesian inference. BMW can be subdivided in three main parts:

### *Part 1: Introduction to Bayesian Inference and the WinBUGS software*

Part one comprises the first four chapters and presents a general introduction to both Bayesian statistics and the WinBUGS software. In chapter one, the author introduces the basic rules of probability and illustrates these rules with several statistical models. A few relatively straightforward example data sets are analyzed without recourse to WinBUGS.

In chapter two, the author briefly describes various popular MCMC samplers. The description is formal yet clarified by pseudocode and R code.<sup>4</sup> Using the author’s code, readers can implement their own samplers to better understand how MCMC samplers operate. Such understanding provides some insight to what happens “behind the scenes” when model parameters are estimated in WinBUGS.

In chapters three and four the author introduces the WinBUGS software. The author explains key WinBUGS syntax, shows how to implement a few simple models in WinBUGS, and provides WinBUGS code throughout. The author uses a large amount of screenshots to guide the reader through the basic options that WinBUGS affords. These screenshots allow the reader to understand the software even without access to a computer. Figure 3 provides an example illustration (from our own, but similar to the screenshots in BMW).

### *Part 2: Bayesian (generalized) linear models using WinBUGS*

Part two comprises chapters five to eight. Here the author introduces common statistical models and shows how these can be implemented in WinBUGS. Chapter five deals with various normal models (i.e, regression and ANOVA). Chapter six continues chapter five, but focuses on ANCOVA and the use of dummy variables to incorporate categorical covariates in regression.

Chapters seven and eight deal with generalized linear models (GLM). The author first explains the basic principles and then moves on to illustrate these with Poisson regression models, binomial response models, and models for survival analysis. These chapters include many examples, complete with data, WinBUGS scripts, and the resulting conclusions.

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<sup>4</sup>R is a popular and freely available package for statistical computing, see <http://www.r-project.org/>.

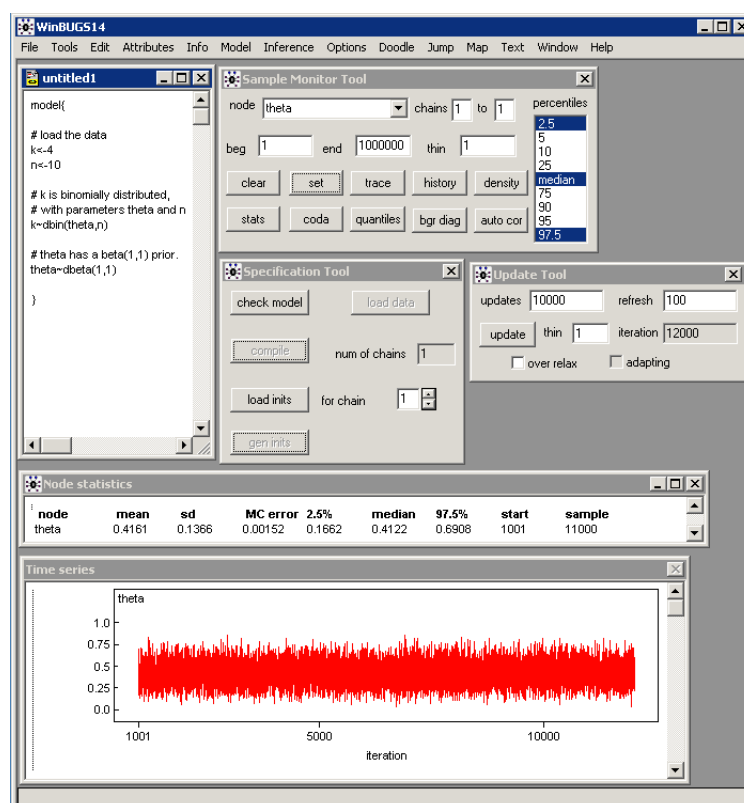


Figure 3. A WinBUGS screenshot that shows the model file (top left panel), various WinBUGS tools (three top right panels), and a single MCMC chain for a model parameter of interest (bottom panel).

### Part 3: Advanced topics

Part three comprises the remaining chapters, nine to eleven, which cover more advanced topics. Chapter nine deals with hierarchical modeling, chapter ten discusses posterior predictives and model checking, and chapter eleven focuses on Bayes factor model selection with an emphasis on variable selection in regression models. Throughout, the theory is illustrated with data and WinBUGS code. Examples include Kobe Bryant's field goal success rate, odds ratios of lung cancer for smokers versus nonsmokers, the outcomes of schizotypal personality questionnaire, the number of goals scored by teams participating in the 2000 water polo World Cup, the frequency of goals scored and conceded in home games of Manchester United, etc.

### Impression

*Bayesian Modeling Using WinBUGS* is a valuable resource for any researcher who uses WinBUGS or would like to. BMW has several appealing features, in particular:

1. BMW strikes an appropriate balance between statistical theory and statistical practice.

2. BMW explains the WinBUGS program with screenshots, making it almost impossible for readers to get lost.
3. BMW contains a wealth of interesting examples, WinBUGS code, and graphical representations of the resulting inference.
4. BMW starts with simple statistical models and then gradually ramps up the complexity. After working through the entire book the reader will come away with a solid understanding not just of Bayesian inference, but of statistical inference in general.
5. BMW provides WinBUGS scripts and data for all examples.<sup>5</sup>
6. BMW provides many helpful and up-to-date references in case a particular method or argument cannot be explored in full detail.
7. BMW complements the current literature. For example, BMW covers topics such as Bayesian model selection and variable selection, topics not discussed in otherwise excellent books such as *Bayesian data analysis* by Gelman, Carlin, Stern, and Rubin (2004) and *Data analysis using regression and multilevel/hierarchical models* by Gelman and Hill (2007). Also, the tutorial-style character of BMW contrasts with the more encyclopedic approach of *Applied Bayesian modelling* by Congdon (2003).
8. BMW can serve as a course book for advanced undergraduate or graduate students. The author has provided exercises that follow each chapter. For students without much background in statistics, the first two chapters may need to be supplemented by in-class instruction.

BMW also has some minor drawbacks. For mathematical psychologists, the most obvious drawback is that BMW does not discuss Bayesian inference for cognitive models.<sup>6</sup> Instead, BMW focuses on models in the GLM family. However, mathematical psychologist who have read BMW should be able to use WinBUGS for their own purposes with only minor adjustments. Besides, the GLM family is highly relevant not just for statisticians, but also for psychologists. We also noted that the first edition of BMW contains several typographical errors. However, the author's website keeps track of any such errors, and these are corrected in subsequent printings. Finally, it appears that the answers to the book's exercises are missing—we assume this is on purpose. Nevertheless, it would be good for lecturers to be able to obtain the answers, for instance through the publisher.

We conclude that *Bayesian Modeling Using WinBUGS* is an excellent tutorial-style textbook on practical Bayesian inference. It is through these kinds of textbooks that modern statistics—Bayesian statistics—can vie for a place in the curriculum of psychology students. Such a change in curriculum would benefit both the students and the field.

## References

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<sup>5</sup>Available from the author's website, [http://stat-athens.aueb.gr/~jbn/winbugs\\_book/](http://stat-athens.aueb.gr/~jbn/winbugs_book/).

<sup>6</sup>A WinBUGS-based course book for students in psychology and cognitive science can be found at <http://users.fmg.uva.nl/ewagenmakers/BayesCourse/BayesBook.html>.

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