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## **Bayesian Essentials with R**

Jean Micheal Marin and Christian Robert  
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<https://www.ceremade.dauphine.fr/~xian/books.html>

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This book from the series “Springer texts in Statistics” is the thoroughly revised version of the book “Bayesian Core: A Practical Approach to Bayesian Computational Statistic” by the same authors (Marin and Robert 2007). Jean Michel Marin and Christian Robert have had years of experience in teaching courses based on the materials. Based on this experience they designed the book and now adapted their previous work to end up with “Bayesian Essentials with R”.

The focus on accompanying a course has left its marks on the book for the better. In particular, the authors included warnings of pitfalls likely experienced by applicants or previous course participants, but also explicitly refer to changes on chapters and arrangements compared to the previous book. For example the authors point towards having left out the detailed treatment of the reversible jump MCMC (Markov chain Monte Carlo) algorithm purposefully based on students feedback. The practical advice given is adequate for a first time experience, whereas interlinking working through this book with other textbooks by the authors is often referred to and recommendable for anyone wishing to delve more deeply into Bayesian analysis. For the reason of the years-long experience, this book became longer than its predecessor, even when leaving out parts due to the change of focus. However, “Bayesian Essentials with R” is not a quick reader, but instead a textbook through which the reader has to work thoroughly. This is due to the fact that the authors chose a more technical and theoretically well-founded approach than standard textbooks aiming for application of methods in R, as mentioned in the review of the previous book (Hilbe 2007).

The authors clearly set the goal of this book to provide a self-contained introduction into the key methods of Bayesian inference containing all basic explanations. Apart from a well-founded mathematical understanding of the methodology, the authors wish to support their readers with developing an intuitive understanding of practical issues, like model identifiability or computational pitfalls such as badly mixing Markov chains and label switching. Yet, the aim for the book to be self-contained is only partially fulfilled. The balance between a self-contained and a thoroughly well-grounded textbook is a hard one and met by the authors in almost all chapters. The graduate student or scientist interested in rooting the provided

models and backgrounds in theory is often referred to additional books by the author Christian Robert, specifically dealing with Bayesian theory, such as [Robert \(2001\)](#). Those readers with further interest in algorithmic properties and implementations are pointed towards [Robert and Casella \(2004\)](#). Other than this, the union of the book and the authors' specifically designed package **bayess** ([Robert and Marin 2013](#), available on CRAN) is self-contained in providing a plethora of input for learning and starting out with applying Bayesian analysis in different fields of application. Collecting the previously separately available code in an R package was an excellent way for improving the availability and applicability of the software.

However, running the package **bayess** in parallel with reading the book and working through the examples is not only a provided feature but also a necessity for understanding. The authors provide working code for all chapters, although some more theoretical subsections or complex algorithms have no detailed programmed solution at hand in the package. Including the corresponding R code right after the formulae allows in many cases for a better understanding not only of the implementation but of the formal structure itself, if properly thought through. However, some code for creating figures is less informative in itself and could be left out in order to increase readability and not disturb the text flow, given that the code of plots is available in the package demos.

Considering how much proficiency in R is required, an introduction or previous expertise is required. At first glance, writing an introduction to R might appear unnecessary given available materials and the many times the authors refer to other sources of information. But their brief introduction is not only straight-to-the-point but also informative even for readers with experience in working with R. The availability of all code within the demo of **bayess** allows readers to quickly adapt existing code without requiring full programming skills in R. The explanations and examples pointing towards traps and downfalls provided in this chapter are not only invaluable throughout the book, but also in general when handling R. The specific typesetting style for warnings of practical issues one might run into with a specific model type or algorithm is truly invaluable.

The authors elegantly introduce the most frequently applied methods of Bayesian inference stepwise. Within each chapter, not only a more advanced modelling approach, but also a new computational technique is introduced. Algorithms advance alongside their applications, starting out with Gibbs sampling for simple posterior inference, turning towards Metropolis-Hastings and importance sampling for linear and generalised linear models, finally leading to dimension switching and filtering algorithms for time series and state space models. This approach is an excellent didactic way of making the reader familiar with various techniques through different model settings without filling at least two separate chapters with computational methods only.

While the authors suggest to cover the book in a 13 to 15 weeks course with 3 hours of lectures per week, an unaccounted for number of hours of practice is likely required. Given the convenient structure of the book, it can easily be adapted to a shorter course length by leaving out some of the more advanced chapters. The actual core of the “Bayesian Essentials” are chapters 1 through 4 which contain Bayesian parameter estimation, hypothesis testing including Bayes factors, linear models and generalised linear models, in particular the logit and probit model. Alongside the models and methods, concepts like the exponential family of distributions, conjugate, informative and non-informative prior notions, ranging from Zellner’s G-prior to Jeffrey’s prior are discussed and compared. The sampling methods introduced alongside include the key components of MCMC sampling, the Gibbs sampler and

the Metropolis-Hastings sampler, as well importance sampling. This conceptual and computational ‘Bayesian core’ takes up a little less than half of the book. These four chapters are compulsory for an understanding of concepts, as well as any course. While they might appear basic, the authors’ interesting remarks pointing towards standard and less standard approaches along with warnings of pitfalls make them worth reading even for more experienced Bayesians.

Among the other chapters, one can still work through them separately based on personal preferences or required methods of a specific field, as these chapters are in great parts independent of one another. For a course it might be worthwhile to only cover a selection of these problems depending on the audience. Capture-recapture models are presented for their classical application in biology, while pointing towards more general applications such as survey and web data. The very generally applicable accept-reject sampler is discussed and implemented through the scenario dataset. Mixture models are a very general class of models which can be applied not only in various fields, but also for flexible goals reaching from clustering to semi-parametric density estimation. The chapter gives an excellent summary of the mixture of normals model setting along with its typical inference through data augmentation the notion of which is introduced in this way. Then, they discuss typical pitfalls of mixture modelling, such as the careful choice of priors, mixing and identifiability issues of the algorithms and models themselves, such as the label switching problem and the tempering methodology. The authors very briefly introduce the semi-parametric density estimation idea which is extremely nice and general without reverting to complex notions which make Bayesian semi-parametrics often hard to understand. In this chapter, several changes happened in the implementation part compared to the previous book. Reversible jump MCMC is only mentioned but not introduced in detail which is most likely helpful for first time readers. However, returning to the reversible jump notion in a later chapter appears not well motivated given the method was left out purposefully.

The final two chapters deal with temporal and spatial dependence structures in data, respectively. Time series data have a wide range of applications, financial analysis data and gene comparison data are presented as two representative examples. Along with the most common methods, autoregressive (AR) models, moving average (MA) models and ARIMA models, ARCH and stochastic volatility models are introduced for finance data. For the second example data set, hidden Markov models are presented. Image Analysis, the most frequent application of spatial analysis, titles the final chapter, presenting Markov random fields and the two most common models, the Ising and Potts model. Along with these, not only the original Metropolis-Hastings sampler, but also the notion of upcoming method of approximate Bayesian computation (ABC) is introduced and implemented. For these two final chapters, the authors often use a very technical notation and drop algorithmic handling more and more which makes these the hardest chapters to read and understand. For this reason, they are recommendable for specifically interested and mathematically advanced readers only, whereas the first chapters can also be presented to a more general audience.

A major feature of their software package **bayess** is that it reproduces the commonly known and easily available R output for linear models and generalised linear models regarding its structure. Here, the p-values are systematically replaced by Bayes factors while heuristics and straight-forward understanding of Bayesian testing are provided without requiring a chapter of its own. This is not only a didactical break-through for anyone teaching Bayesian statistics to students familiar with R and standard model summaries, but also a huge step in helping

scientists in applied fields understand outcomes of Bayesian approaches.

Another positive aspect is the introduction of one or more data sets per chapter which are not hand-tailored for certain problems, but might point out difficulties of the model specification or the inference alike. By building a story on the real data sets, the authors provide a recurrent theme which runs like a thread through the whole chapter and often links subsections. Interweaving this plot line with models and algorithms lightens up the serious content, while helping to understand and focus attention on an example. Often, only few lines of code are executed to support the theory immediately with a numerical application. In addition to the examples throughout the text, several theoretical and applied exercises are provided at the end of each chapter. More than once the authors point toward exercises which help to deepen the understanding of notions or demonstrate possible pitfalls.

A minor issue is that graphs are sometimes very small making it hard to determine features, such as separating lines of different colours for model assessment. Even though providing “quality plots” of MCMC simulation is a necessity for understanding basic concepts and recognising algorithmic misbehaviour, several graphs have become almost too small to recognise anything, where focusing only a subset of graphs would help with readability. As the **bayess** should be executed alongside reading, it would be recommendable to provide the full set of plots through the package and provide only relevant plots within the book.

Despite some critical words, the authors succeeded in improving upon their previous textbook. The authors provide a wide range of examples, models and methods demonstrating the variety of applications for Bayesian methods nowadays. This book provides a nice introductory textbook for courses of graduate and Ph.D. students with an intermediate to high mathematical skill level. But the volume also works as a very valuable reference for researchers with varying degrees of intimacy with R or Bayesian analysis, respectively. Interweaving the text with the package **bayess** and providing book demos along with generally applicable code examples, “Bayesian Essentials with R” is an excellent basis for applied Bayesian modelling for researchers and practitioners alike.

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