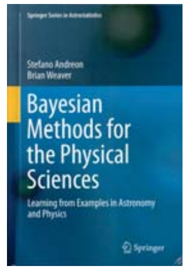
Bayesian Methods for the Physical Sciences



Learning from Examples in Astronomy and Physics

Stefano Andreon and Brian Weaver

Springer, 2015. $109.00 (238 pp.). ISBN 978-3-319-15286-8

Most of today's experimental physicists require computational data-analysis methods that can handle an enormous volume of data and still deliver the most precise results possible given the experimental design. That necessity has led to recent textbooks that attempt to go beyond the standard pathway of "learn what you need, as you need it, from the folklore of the discipline" and that cover probabilistic reasoning, an increasingly important subject. Done right, such a textbook could be used in a Computational Data Analysis for Physicists course to be taught alongside courses on electromagnetism, quantum mechanics, and general relativity.

One of the latest additions to that genre is *Bayesian Methods for the Physical Sciences: Learning from Examples in Astronomy and Physics* by Stefano Andreon and Brian Weaver. Others included in the growing category are *Statistics, Data Mining, and Machine Learning in Astronomy: A Practical Python Guide for the Analysis of Survey Data* (Princeton University Press, 2014) by Željko Ivezić, Andrew Connolly, Jacob VanderPlas, and Alexander Gray; *Data Analysis: A Bayesian Tutorial* (2nd edition, Oxford University Press, 2006) by Devinderjit Sivia and John Skilling; and *Information Theory, Inference, and Learning Algorithms* (Cambridge University Press, 2003) by the late David MacKay. I don't think any of those books is a perfect companion for the proposed course, but I do think that Andreon and Weaver—a statistically sophisticated astronomer and a statistician working in engineering and physics, respectively—have written a book that could be a valuable component in the new Computational Data Analysis course.

In the Bayesian approach, the rules of probability are applied to beliefs about parameters. In contrast, in the frequentist approach, the rules are applied exclusively to the generation of the data. One advantage of Bayesian reasoning, which comes at the cost of having to make additional assumptions, is the ability to perform integrals over parameters and determine their expectation values. The most significant consequence is the ability to do integrals to remove nuisance parameters. Of primary importance to both approaches is the so-called likelihood function: For a Bayesian, the function helps update beliefs; for the frequentist, it is used to construct optimal estimators.

Bayesian Methods for the Physical Sciences begins with basic probability calculus and introduces complex models and concepts as it goes along. The book has the great virtue of relating methodology to the objectives of the experimenter, and it explicitly discusses situations where that key step can be and has been done incorrectly. Most of the content is presented through real-world examples that could easily be adopted or adapted to new tasks.

My biggest complaints about the book concern what's missing. Beyond the introductory chapters, the authors rarely mention the likelihood function explicitly. Even in chapter 8, which covers a large range of important considerations in building sophisticated data models, the function appears only implicitly. I would love to have seen a clearer link between the technically subjective assumptions by the data analyst and the mathematical operations in the likelihood function.

Also missing are lessons on diagnosing when a data analysis is going off the rails and on locating and fixing the bugs. Diagnosis and testing are notoriously hard to teach, but it would be nice to see an attempt, since they are among the core skills of the data scientist. Among a few other minor complaints is the omission of an index, which would help readers locate the initial use and definition of obscure terminology.

Perhaps the best feature about *Bayesian Methods for the Physical Sciences*—and it is an extremely important one—is its use of real-world data sets and contemporary research questions (albeit heavily weighted toward astrophysics and astronomy). The use of realistic illustrative problems instead of toy models is refreshing. In describing the models and performing calculations, the book makes heavy use of the JAGS (Just another Gibbs Sampler) statistical package and so effectively provides a strong endorsement of JAGS. Tying the book to a single package has its disadvantages, but the big advantage is that the models are unambiguous and the results reproducible—and therefore adoptable and reusable.

That a textbook on computational data analysis contains reproducible code and real data sets is something we should require for all textbooks in this new—and critical—component of the physics curriculum.

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Why String Theory?

Joseph Conlon

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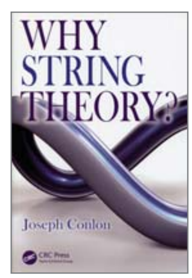
String theory is among the most ambitious and elaborate theoretical frameworks ever conceived. Even the theory's most skeptical critics would not deny its mathematical elegance. But skeptics do question its relevance to our physical world. In his delightful little book *Why String Theory?*, theoretical physicist Joseph Conlon takes up that question. In laying out his arguments, he also ventures onto a road less taken by touching on the sociology of string theory, and not just its scientific merits.



Conlon's book begins with a whirlwind tour of the great advances in physics prior to string theory. The theoretical jigsaw puzzle mapped out by the giants in physics remained, near the end of the 20th century, an unfinished one with several large and crucial pieces missing. Those gaps in our understanding of nature called for a critical rethinking of