Understanding Bayesian Statistics: Frequently Asked Questions and Recommended Resources

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This document is a guide for readers who wish to understand or employ Bayesian statistical approaches, particularly within the context of Federal research and decision-making. Each section begins with a frequently asked question, followed by a brief answer, and links to related resources for further reading and learning. Click the blue title in each citation to follow the link to each resource.

1. "WHAT ARE THE LIMITATIONS OF *p*-VALUES?"

Traditional frequentist methods—specifically, probability (*p*) values—are widely used in social science research and evaluation to guide decisions on program and policy changes. However, *p*-values have some inherent limitations that may lead to misuse, or misinterpretation, or misinformed decisions. Listed below are several articles that address the limitations of traditional frequentist methods. The resources include a seminal article published in 1978 as well as more recent statements on the issue, including from the American Statistical Association. These articles help explain why stakeholders may want to consider alternative statistical methodologies, such as Bayesian approaches.

Carver, R. P. (1978). The case against statistical testing. *Harvard Educational Review, 48*, 378–399. DOI: 10.17763/haer.48.3.t490261645281841

Gelman, A. (2017). The failure of null hypothesis significance testing when studying incremental changes, and what to do about it. *Personality and Social Psychology Bulletin, 44*, 16-23. DOI: 10.1177/0146167217729162

Gelman, A., & Loken, E. (2014). The statistical crisis in science. *American Scientist, 102*, 460–465. DOI: 10.1511/2014.111.460

Wasserstein, R. L., & Lazar, N. A. (2016). The ASA's statement on *p*-values: Context, process, and purpose. *The American Statistician, 70*, 129–133. DOI: 10.1080/0031305.2016.1154108

2. "WHAT ARE BAYESIAN STATISTICS?"

Bayesian methods are emerging as the primary alternative approach to traditional frequentist methods. In the Bayesian framework, unknown parameters are treated as uncertain and described by probability distributions. This is in contrast to the frequentist framework, which assumes there is one "true" parameter value (e.g., one true regression coefficient). Bayesian methods present results in probabilistic terms, (e.g., "There is a 90-percent chance the program reduced costs") to determine the importance of a finding, rather than using a strict cutoff value as in frequentist methods (e.g., $p < .05$). The resources below provide a nontechnical introduction to Bayesian methods and concepts.

Etz, A., Gronau, Q. F., Dablander, F., Edelsbrunner, P. A., & Baribault, B. (2017) How to become a Bayesian in eight easy steps: An annotated reading list. *Psychonomic Bulletin & Review.* DOI: 10.3758/s13423-017-1317-5

van de Schoot, R., Kaplan, D., Denissen, J., Asendorpf, J. B., Neyer, F. J., & van Aken, M. A. G. (2014). A gentle introduction to Bayesian analysis: Applications to developmental research. *Child Development, 85*, 842–860. DOI: 10.1111/cdev.12169

3. "HOW DO BAYESIAN AND FREQUENTIST METHODS DIFFER, AND WHAT ARE SOME ADVANTAGES OF THE BAYESIAN APPROACH?"

Unlike traditional frequentist methods, Bayesian methods enable researchers to incorporate information from prior studies into their analyses and to make probabilistic statements. These methods help address some of the common issues related to frequentist data analysis, including defining results according to significance testing alone, low power, and overemphasis on single studies. In addition, Bayesian methods address different questions. Frequentist methods answer the question "If the unobserved true effect is zero, how likely is it to obtain a result as extreme as the one observed?" This is rarely the question that a policymaker actually wants to answer. Bayesian methods, on the other hand, answer the question "What is the probability that the impact of X is at least Y," where Y is the impact meaningful to the policymaker. The resources below highlight key differences between the two methods by comparing analyses performed using both frequentist and Bayesian approaches.

Dienes, Z. (2011). Bayesian versus orthodox statistics: Which side are you on? *Perspectives on Psychological Science, 6*, 274–290. DOI: 10.1177/1745691611406920

Lindley, D. V. (1993). The analysis of experimental data: The appreciation of tea and wine. *Teaching Statistics, 15*, 22–25. DOI: 10.1111/j.1467-9639.1993.tb00252.x

Paddock, S. M. (2014). Statistical benchmarks for health care provider performance assessment: A comparison of standard approaches to a hierarchical Bayesian histogram-based method. *Health Services Research, 49*, 1056–1073. DOI: 10.1111/1475-6773.12149

Rouder, J. N., Speckman, P. L., Sun, D., Morey, R. D., & Iverson, G. (2009). Bayesian t tests for accepting and rejecting the null hypothesis. *Psychonomic Bulletin & Review, 16*, 225–237. DOI: 10.3758/PBR.16.2.225

Wagenmakers, E.-J., Morey, R. D., & Lee, M. D. (2016). Bayesian benefits for the pragmatic researcher. *Current Directions in Psychological Science, 25*, 169–176. DOI: 10.1177/0963721416643289

Wagner, K., & Gill, J. (2005). Bayesian inference in public administration research: Substantive differences from somewhat different assumptions. *Journal of Public Administration, 28*, 5–35. DOI: 10.1081/PAD-200044556

4. "WHAT IS THE BAYESIAN MODELING APPROACH, AND HOW DOES IT CHANGE INFERENCE AND PREDICTION?"

A key advantage of Bayesian methods is that they account for model uncertainty. They also enable researchers to combine estimates from study data with already existing relevant outside information (a prior probability distribution) to derive a posterior distribution, which reflects one's updated knowledge balancing prior knowledge with the observed data. The prior probability distribution can reflect all information available to date on a model parameter. However, the methods required to combine study data with the prior probability distribution are technical and complex. The resources below discuss issues relevant to Bayesian models, including how to understand and determine priors in Bayesian analysis. Some articles are technical and well suited for readers with prior understanding of Bayesian methods; these are marked with an asterisk (*).

*Clyde, M., & George, E. I. (2004). Model uncertainty. *Statistical Science, 19*, 81–94. DOI: 10.1214/088342304000000035

*Draper, D. (1995). Assessment and propagation of model uncertainty. *Journal of the Royal Statistical Society. Series B (Methodological), 57*, 45–97.

Gelman, A., Simpson, D., & Betancourt, M. (2017). The prior can often only be understood in the context of the likelihood. *Entropy, 19*, 555. DOI: 10.3390/e19100555

*Hoeting, J. A., Madigan, D., Raftery, A., & Volinsky, C. T. (1999). Bayesian model averaging: A tutorial. *Statistical Science, 14*, 382–417.

Kruschke, J. K. (2015). Introduction: Credibility, models, and parameters. Chapter 2, *Doing Bayesian data analysis*, 2nd ed. Waltham, MA: Academic Press/Elsevier Inc.

*Vandekerckhove, J., Matzke, D., & Wagenmakers, E.-J. (2015). Model comparison and the principle of parsimony. In J. Busemeyer, J. Townsend, Z. J. Wang, A. Eidels, J. Vandekerckhove, D. Matzke, and E.-J. Wagenmakers (Eds.), *Oxford Handbook of Computational and Mathematical Psychology*, pp. 300–317. Oxford: Oxford University Press.

For Further Study of Bayesian Methods…

Online Courses. The following two free courses provide an introduction to Bayesian methods for individuals with some statistical training.

Coursera. (2017). *Bayesian statistics: From concept to data analysis*. University of California, Santa Cruz.

Draper, D. (2013). *Bayesian modeling, inference, prediction and decision-making*. Department of Applied Mathematics and Statistics, University of California, Santa Cruz.

Blogs. The blogs below provide an approachable introduction to Bayesian methods.

Analytics Vidhya. (2016). *Bayesian statistics explained to beginners in simple English*.

Boone, K. (2016). *Bayesians statistics for dummies*.

Gelman, A. (2018). *Statistical modeling, causal inference, and social science*.

Kurt, W. (2016). *Count Bayesie*.

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