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Introduction to Special Section on Bayesian Data Analysis

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Psychologists are trained to think of research design and analysis as a procedure for rejecting null hypotheses. Is the difference between two groups nonzero? Is the correlation between two measures nonzero? Is the proportion of correct responses different than the chance (null) value of 0.5? This framing of research questions is driven largely by an institutionalized method of statistical inference, called *null hypothesis significance testing* (NHST). There are many deep problems with NHST (e.g., Kruschke, 2010; Loftus, 1996; Wagenmakers, 2007). Some of the problems are incurred by NHST's inability to tell us what we want to know. For instance, the p value of NHST tells us about the probability of possible data that we did not observe, instead of about the probabilities of hypotheses given the data we did observe. And some of the problems of NHST are more foundational. For instance, the p value is not even well defined, because its value depends on the covert intentions of the data collector, such as why data collection was stopped and what other tests were planned.

Bayesian data analysis offers an alternative approach that solves the problems of NHST and also provides richer, more informative inferences and more flexible application. Bayesian data analysis is now accessible to psychologists because of recent advances in computational algorithms, software, hardware, and textbooks. Indeed, whereas the 20th century was dominated by NHST, the 21st century is becoming Bayesian (as forecast by Lindley, 1975). As psychologists transition to Bayesian data analysis, they might retain the habit of inquiring after null values (instead of asking about magnitudes of effects and regions of uncertainty). How does Bayesian data analysis address questions about null values? This special section discusses answers to that question.

The article by Dienes (2011, this issue) shows how Bayesian inference is intuitively more coherent than NHST. The discussion focuses on fundamental research questions, such as "Should the reason for stopping collection of data affect the interpretation of the data?" and "Should the motivation for conducting a test (e.g., knowing or not knowing of a theory that predicts a difference) affect the interpretation of the test?" Answers to these questions from common practice and educated intuition align with normative Bayesian inference, not with NHST.

Dienes also explains one method for conducting a Bayesian hypothesis test. In this method, the null hypothesis is pitted against an alternative hypothesis in which a range of candidate values is given prior credibility. Bayesian inference indicates which hypothesis is more credible, given the data. The relative credibility of the two hypotheses is indicated by the so-called *Bayes factor*. Dienes explains how the Bayes factor can be influenced by the specific formulation of the alternative hypothesis, which should be an informed expression of the meaningful alternative theory being tested.

The article by Wetzels et al. (2011, this issue) shows how so-called default Bayes factors generally correlate well with conclusions from NHST in a survey of hundreds of published t tests. A default Bayes factor uses an alternative hypothesis established by generic mathematical properties, such as invariance under changes in scale, instead of by theoretical meaning. Whereas default Bayes factors correlate strongly with p values, the conventional thresholds for declaring significance are noticeably different. Bayes factors require stronger data for significance than NHST p values. Wetzels et al. also emphasize that Bayes factors can provide evidence in favor of the null hypothesis, unlike NHST which can only reject the null hypothesis.

The article by Kruschke (2011a, this issue) juxtaposes the Bayes-factor approach with a more common Bayesian approach called parameter estimation. In parameter estimation, the analyst asks the straight-forward question: What are the relative credibilities of all possible values? The Bayesian answer provides an explicit probability distribution that indicates not only the best value but also the relative veracity of all other values, including the null value. Kruschke explains how the two Bayesian methods ask different questions that may be applicable to different circumstances, but he argues that Bayesian parameter estimation is generally the more useful and informative method.

The method of parameter estimation is used in numerous major textbooks on Bayesian data analysis (e.g., Bolstad,

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2007; Carlin & Louis, 2009; Christensen, Johnson, Branscum, & Hanson, 2010; Gelman, Carlin, Stern, & Rubin, 2004; Gelman & Hill, 2007; Jackman, 2009; Kruschke, 2011b; Ntzoufras, 2009). Notably, the only author from these textbooks who dwells on the application of Bayes factors to null hypothesis testing is a psychologist (Kruschke, 2011b). For nonpsychologists, Bayesian null hypothesis testing is an ancillary issue, unmentioned or treated only as needed in specific applications. Thus, part of the bigger transition to Bayesian thinking will be to stop automatically framing every research question in terms of rejecting a null hypothesis.

In summary, the articles in this section explore the intuitiveness of Bayesian inference, the consistency of Bayesian conclusions with conclusions from NHST, and the richness of Bayesian inference when used in its full-fledged form of parameter estimation and hierarchical modeling. From the perspective of the authors in this section, psychologists must transition away from thinking of research in the problematic NHST framework and toward thinking of research in the Bayesian framework. The articles in this section provide a stepping stone in that transition, offering Bayesian approaches to assessing null values and acting as a gateway to the richness of Bayesian parameter estimation.

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Supplementary information can be found at http://www.indiana.edu/~kruschke/

Declaration of Conflicting Interests

The author declared that he had no conflicts of interest with respect to his authorship or the publication of this article.

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