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CORR Insights®: Prediction of Postoperative Clinical Recovery of Drop Foot Attributable to Lumbar Degenerative Diseases, via a Bayesian Network

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Where Are We Now?

Most medical and surgical statistics are performed using a frequentist approach, where the population value of the parameter of interest (for example, the mean difference in scores

between two treatments) is a fixed—though unknown—quantity. Results of the statistical analysis then are presented as point estimates, confidence intervals, or p values. The confidence interval represents a range of values within which we can be confident that the true value of the parameters belongs [7]. To test a specific null hypothesis such as the absence of a mean difference in scores, a p value is computed. This is the probability that a result equal to the one observed or less in favor of the null hypothesis would have occurred, were the null hypothesis to be true. This represents a sort of reverse reasoning, where we reject the null

hypothesis if the data observed were unlikely to have occurred under this hypothesis. There are, however, other ways to approach the question of uncertainty of data, and there are different ways to perform statistical analyses in this setting. Bayesian methods represent one such approach.

The Bayesian approach formally accounts for the uncertainty on the unknown quantities by using probability distributions [1, 2]. The analysis starts by determining a prior distribution representing our previous knowledge or beliefs on the parameter of interest. A Bayesian “prior probability” is analogous to the pre-test probability a clinician might develop based on a patient’s presenting symptoms and signs. The data analyzed are then used to modify the prior distribution into a posterior distribution that represents the current knowledge on the distribution of this parameter; likewise, a Bayesian “posterior” is analogous to a post-test probability a clinician might develop in response to the result of a diagnostic test about a

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patient's health. In this respect, used to analyze data, perform simulations, and check model assumptions, Bayesian reasoning is more familiar to clinicians than non-Bayesian (frequentist) statistics, since clinicians—whether they know it or not—engage in Bayesian reasoning every day in the office. In a way, Bayesian statistics also try to answer questions in the “correct” sense, by providing a plausible range of values for an unknown parameter or the probability of a given statement (eg, the revision rate for implant X is lower than that for implant Y) given the data observed, rather than a measure of how likely these data would have occurred under a specific theory (like a null hypothesis).

In addition, results provided by a Bayesian analysis arrive in terms of a plausible range of values (called a credibility interval); this probability statement actually corresponds to how most researchers and physicians misinterpret non-Bayesian confidence intervals and p values. Finally, Bayesian methods naturally handle the analysis of accumulating information in a study, without raising the question of multiple testing and p value correction, and are well-suited for combining different sources of data such as in meta-analysis.

Despite these apparent advantages over frequentist statistics (statistics that just use p values), we only rarely

see Bayesian statistics in medical journals. Why might this be? First, Bayesian theory has been taught less often than frequentist statistics, and so few statisticians have been properly trained to use it [1], though perhaps this is changing [8, 11]. Bayesian analyses also are more computationally demanding, though recent advances in computing speed have made it possible to run complex models without special equipment. Another challenge is the choice of prior distribution, and some cite this as an element of subjectivity in a process that should be objective. However, this, too, is an unfair criticism; first, there is a great deal of choice and subjectivity in frequentist statistical analyses. In addition, one can always choose a noninformative (“flat”) prior distribution that makes no assumptions about prior research or events as the point of departure for Bayesian analysis, although to fully benefit from the power of Bayesian statistics, it is advantageous to form a thoughtful prior distribution (again, analogous to a “pre-test probability”) when considering the results of an experiment, if the prior can be formed on robust earlier work. Last, because of our reliance on a prior distribution and the added flexibility of models, different analysts will end up with different results on the same data; however, I would contend this is equally true for

non-Bayesian analyses, at least as soon as the models or methods become even slightly complicated.

The present study by Takenaka and Aono used a Bayesian network model to develop and internally validate a prediction model for the recovery of drop foot resulting from degenerative lumbar diseases. Without going into the details, the use of a Bayesian approach in this context allowed a formal description of uncertainty and provided grounded tools to adapt the complexity of the model to the size of the data [6]. In addition, Bayesian networks supplement some shortcomings of other “modern” statistical learning approaches by producing models with an easily understandable structure.

Where Do We Need To Go?

The ubiquitous use of non-Bayesian statistical testing and p values has been recently challenged [10], and Bayesian methods undoubtedly deserve more attention in clinical research studies. For instance, as Bayesian methods naturally handle the updating of information as data accumulate, these models are particularly well suited for sequential analysis of clinical trials. They are also useful for complex analyses combining several sources of data, such as in network meta-analyses [4, 5].

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There certainly is a lack of adequate training of future statisticians in practical Bayesian statistics, and so, not surprisingly, few clinical researchers have been exposed to these approaches, either. This is a missed opportunity—and one worth correcting—because they could lead to more thoughtful—though more demanding—analyses. Trying to define the prior knowledge on a parameter should be an essential part of any study because data on the topic usually already exist. For example, before planning a new trial, it would be worth to have a broad view of which comparisons among treatment options for that condition have been performed, as well as perhaps an indirect estimation of the difference in outcome between the two treatments we wish to compare [3].

How Do We Get There?

To increase the use of Bayesian methods in clinical research studies, there is a need for adequate training of statisticians, which is beyond the scope of a single journal. However, there is also a need to break down the barriers

into using Bayesian approaches, and in that respect, the publication of thoroughly conducted and clearly reported and interpreted Bayesian analyses will help researchers become aware of the methods, and understand what they can offer. We also need additional guidance in the conduct and reporting of Bayesian analyses, although some work has already been done in that sense [9].

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