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In “Biostatistics and Bayes”, the author Norman Breslow indicates that empirical use of Bayesian methods in Bioequivalence, sequential clinical trials, longitudinal data, model uncertainty, multiple comparisons, risk assessment, etc. He believes Bayesian methods offer a natural setting for the synthesis of expert opinion in deciding policy matters. And both frequentist and Bayes' methods have a place in biostatistical practice.

First, Breslow introduces the background of Bayesian statistics and the role of Bayesian statistics in biomedical applications. Then he talks about some research paper and important work by other statisticians.

Second, the author explains Bayes' theorem in the context of the diagnostic tests used in screening program. Bayes' theorem is used in therapeutic medicine to evaluate patient prognosis and thus contribute to clinical decisions. He uses Cornfield's (1951) demonstration to illustrates how relative risk of a rare disease is estimable from a case-control study using Bayes' theorem.

Third, he talks about problems of multiplicity. Multiple inferences abound in biostatistics. As for Longitudinal Data Analysis, the analysis of serial or repeated measurements on individuals has a long tradition in biometry. Such data may be collected for the purpose of constructing curves or predicting future events. The work of Dempster, Rubin and Tsutakawa (1981), Laird and Ware emphasize the connection between REML and Bayesian estimation. Hui and Berger's (1983) study of bone loss in postmenopausal women is a nice illustration of EB in practice with longitudinal data. As for small area estimation and mapping cancer rates, several research teams have applied EB techniques in order to estimate and map cancer mortality rates according to geographic area. Furthermore, in another application, Thomas et al. (1985) tried to make sense of data from a large case-control study designed to discover occupational carcinogens. More structure is assumed by Meng and Dempster (1987) in a toxicological analysis of tumors occurring at 17 separate sites for Sprague-Dawley rats in one treatment group, one concurrent control group and six historical control groups. At last of this part, the author says that The key concept that allows progress to be made in all these examples is that of "exchangeability".

Fourth, there is an example about species to species extrapolation in cancer risk assessment. A vexing problem in cancer risk assessment is a relative abundance of data on multiple animal species exposed to multiple environmental agents, but a paucity of such data on humans. The relevance of the animal data for assessing human risk has been a subject of considerable debate. DuMouchel and Harris (1983) ambitiously addressed this issue from a Bayesian perspective that made rather strong assumptions about the relatedness of the human and animal studies.

Fifth, the author states that bioequivalence is a perfectly natural concept for the Bayesians. Given appropriately diffuse prior distributions on parameters specifying the outcome distributions in treatment and control groups, they simply compute the posterior probability that the parameter of interest falls in the indifference zone and declare the two treatments "equivalent" if it is sufficiently large.

Sixth, sequential clinical trials. Clinical trials that are carried out with a fixed, large sample

size generally provide the most convincing evidence of therapeutic efficacy. However, adherence to a predetermined sample size may prove untenable when differences between regimens start to appear earlier than anticipated at the outset of the trial. Bayesian statisticians have much greater flexibility in dealing with sequential clinical trials because their posterior and predictive distributions depend only on the likelihood of the observed data and not on the stopping rule. Bayesian approach offers a considerable advantage in the context of sequential clinical trials by keeping the scientific inferences based on the observed data.

Seventh, assessing model uncertainty. The Bayesian paradigm provides a natural structure

for the synthesis of expert opinion. Model uncertainty is expressed by the experts in the form of a prior distribution on a discrete set of models that are chosen to span a reasonably comprehensive model space. Additional specification of priors for the parameters in

each models are required, but in many cases these could be assumed diffuse.

Eighth, Breslow concludes that Bayes' or empirical Bayes' procedures are useful for many practical problems. Bayesian methods have a more limited attraction when the goal is scientific description or explanation. In a word, it seems clear that Bayesian and frequentist approaches each will have a role to play in biostatistical applications in the years to come.

From my perspective, Bayesian analysis uses a different point of view to compute values compared with frequentists. In this paper, the author gives many examples of Bayesian analysis. From his examples I know Bayesian analysis is very useful in biostatistics. Maybe that is because prediction is the most important issue when talking about biology or medical problems. Now many machine learning methods use Bayesian thinking to solve problems, for example, naïve Bayesian classification is a simple case. So I believe Bayesian analysis can be used in many other fields.