AbstractID: 9816 Title: Models in Medicine. II. Introduction to Resampling and Bayesian Models.

Resampling and Bayesian models are computer-intensive, data-driven, models of statistical inference. Resampling models are informed by Neyman-Pearson (N-P) inference: 1) a relative frequency theory of probability, 2) "*eschewal of a formal role for prior knowledge,*" and 3) *hypothesis testing* and *parameter estimation* implemented by the *tail areas* of a reference distribution. Classically, these are distributions of the *pivotal* statistics: t, F, χ^2, etc. In the Resampling models, Permutation and Bootstrap, the reference distributions required for N-P inference are constructed from the sample itself by repeatedly (say 100-10,000 times) resampling the sample data. In the Permutation model the reference distribution is the Permutation distribution of the sample constructed by resampling *without replacement.* Permutation tests of hypotheses provide *exact p-values*. In the Bootstrap model the reference distribution is constructed by the resampling *with replacement* from the *empirical distribution* of the sample. The Bootstrap model provides a powerful method for obtaining point and interval estimates of parameters of unknown or non-Normal probability distributions. The advantage of Resampling models over the classical N-P model of inference is that the investigator is not constrained to base inferences only on standard statistics, say, a difference of means, that can be assimilated to one of the pivotal statistics. Rather, the statistic can be *nonstandard*, say, an effect size, or a median. Moreover, data are not required to be independent identically distributed random samples from a Normal population. The Bayesian model of statistical inference differs fundamentally from the Neyman-Pearson model. First, the definitions of probability are quite different; in the Bayes model probability is a relation between an estimate or hypothesis and the evidence for it. *It is a measure of the degree of belief warranted by the evidence*. Second, in the Bayesian model, the unknown parameters, θ, are considered to be *random variables* with probability distributions: the *prior*, $p(\theta)$, and *posterior*, $p(\theta|x)$, density functions (pdfs). The prior pdf provides the means for formally incorporating prior knowledge on θ into statistical inferences. $p(\theta)$ is combined with the *likelihood* density function, $p(x|\theta)$, of the sample data, x, to give the posterior pdf.: $p(\theta|x) \propto p(x|\theta)p(\theta)$. $p(x|\theta)$ contains all of the information on θ contained in the sample. Thus, Bayesian inferences are conditional on the observed data, x, rather than the *unobserved data* that generates the tail areas of the pivotal statistics on the N-P model. Third, the Bayesian *predictive pdf,* $p(x^*|x)$, can make predictions of *future* data x^* conditioned on the likelihood of x^*, the prior, and the current data, x. Thus, there are two kinds of unobserved quantities for which Bayesian inferences can be made: *unobservable* parameters and potentially observable *future* observations. Fourth, all Bayesian inferences follow directly from the posterior pdf, $p(\theta|x)$, without need for separate theories of estimation and testing; e.g., no hypothesis testing in Bayesian inference. Various Monte Carlo sampling methods are used to construct both Resampling reference distributions and, increasingly, the Bayesian posterior pdfs. Medical applications of both models are described. **Educational Objectives:** Understanding of 1) The Resampling Models. 2) The Bayesian Model.