Basic Bayes

A Very Quick Overview of Some of The Features and Benefits of Bayesian Analysis

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1 Bayes

Figure 1: Thomas Bayes

2 Bayes Theorem

$$P(H|D) = \frac{P(D|H)P(H)}{P(D)}$$

3 In Words:

posterior $\propto$ likelihood $\times$ prior

4 Benefits

1. In Bayesian analysis, we are *not* assessing the plausibility of the data ($P(D|H)$), given the assumption of a null hypothesis H_0 : parameter value = 0. This feature of Bayesian analysis has a few key implications:

   - We are actually estimating–*the probability of a particular hypothesis given the data*–what we often *think* we are estimating in Frequentist analysis. Thus, after conducting a Bayesian analysis, we can simply say, "The probability of our hypothesis ($P(H|D)$) given the data is x," rather than engaging in complicated statements about "Were the null hypothesis to be true, we estimate that it is p likely that we would see data as extreme, or more extreme, than we actually observed."
   - Because we are directly estimating the probability of hypotheses, we can not only evaluate the probability of the null hypothesis (H_0), but also accept the null hypothesis (H_0), something that we are never supposed to be able to do in frequentist analysis. Being able to accept the null hypothesis may have implications for *equivalency testing* and *theory simplification* and may reduce publication bias, if we are not always looking for ways to reject H_0.

2. In Bayesian analysis, we are able to incorporate *prior information* ($P(H)$). Prior information may reflect particular beliefs about the likely value of a parameter, and have higher (vague prior) or lower (informative prior) levels of uncertainty. Prior information may come from a number of sources:

   - Prior history of a project.
   - Meta-analyses or systematic reviews of the question being considered.
   - Expert knowledge, or community beliefs or wisdom.

3. Because Bayesian estimation relies on *Markov Chain Monte Carlo (MCMC)* simulation methods, Bayesian methods may perform better when there are small samples. In multilevel modeling, Bayesian methods may perform better when there are small *level 1* and/or *level 2* samples. Adequate model performance will likely depend upon having good prior information.