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Comment on Article by Gelman

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What fun! Andrew Gelman has given voice to many of the objections a Hypothetical Anti-Bayesian (HAB) might have. Leaving aside HAB's general grumpiness about the world passing him by, there are substantive points here worth responding to. As will not be a surprise, my viewpoint is Subjective Bayesian. Furthermore, the views I voice are actually what I think.

Subjective Probability

"Why **should** I believe your subjective prior?" I don't think you "should." It is my responsibility as an author to explain why I chose the likelihood and prior that I did. If you find my reasons compelling, you may decide that your prior and likelihood would be sufficiently close to mine that it is worth your while to read my papers. If not, perhaps not.

The idea that a statistical analysis is, or ought to be regarded as, "objective" is an attempt to bamboozle readers into suppressing their disbeliefs. Even if there were consensus on an analysis, that just makes it many people's opinions, not the "truth." As human beings, we are not endowed with the ability to identify objective truth. Thus to treat priors and likelihoods as subjective statements of belief is merely to admit what is manifestly the case.

The statement "as scientists, we should be concerned with objective knowledge" is an aspiration that no scientist can honestly meet. What we can objectively establish is that if this is your prior, that your likelihood and these your data then the resulting posterior is the following. If two Bayesians get different posteriors in that setting, at least one has made a provable error.

Randomization

If it were the case that Bayesianism and randomization were incompatible, this might be a serious issue. However, that's just not true (see (1) for elaboration on this point).

I agree that the design of experiments is a fruitful subject to study. I also think that Bayesians have a lot to offer in this study, since there is a lot of informal opinion that goes into design as currently practiced. I hope more Bayesians will take up the challenge of understanding from a Bayesian perspective the rich heritage of design.

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Empirical Bayes

This is a hybrid of Bayesian and classical methods. It involves maximum likelihood estimation at the highest level of the hierarchy, and then doing Bayesian calculations at lower levels of the hierarchy, conditioning on the maximum likelihood estimates. Because the maximum likelihood estimates are assumed to be the parameter values, empirical Bayes estimates of variances are too low, *i.e.* they do not reflect the total uncertainty of the inferences (see (6)). The assumption of exchangeability in these models is just the same as the assumption of (conditional) independence in classical models, so it is not a point of distinction between the approaches. In general, empirical Bayes is not regarded as a Bayesian method (Deeley and Lindley (3)).

Elicitation

There is a fair literature on elicitation at this point, the most recent contributions being the book by (7), the Garthwaite et al. review in *JASA* (2005), and the SHELF materials http://www.tonyohagan.co.uk/shelf/. The challenge of elicitation is to put questions to a subject matter expert in terms he or she can understand, (*i.e.* in his or her language), but with the property that the answers can be understood in probabilistic language. Like any aspect of a model (likelihood and prior), it is not expected or essential that the result be exact, but rather that it captures the main, important features of the expert's opinion. Thus the statement "it's not clear how to assess subjective knowledge" neglects this growing literature.

The use of conjugate priors is also mentioned. Since every prior is a mixture of conjugate priors (when these exist), Dallal and Hall (2), Diaconis and Ylvisaker (4), a single conjugate form may not be a bad place to start. Often a single conjugate is sufficient to capture the essence of what an expert is trying to convey.

Rather than being a burden, elicitation is, I find, an important part of understanding a model. After an elicitation one understands the parameterization of the model, and hence is in a position to appreciate the posterior when it comes.

Sensitivity Analysis

A critical part of understanding a probability model is to appreciate which assumptions are being relied upon most heavily and which are robust to reasonable deviations. Semi-parametric and non-parametric models do not escape from this; they rely very heavily on independence assumptions, and less heavily on a parametric form. This can be useful in some applications, but not so good in others.

There is no escape from the necessity of making assumptions to do statistical inference, I think. The benefit of the subjective Bayesian viewpoint is to make those assumptions explicit and public, so they can be appreciated and criticized.

Classical Methods

HAB has admiration for p-values, confidence intervals and unbiased estimation. All of these violate the likelihood principle, of course, in that they all rely on supposed probabilities of events that did not occur. They are based on the use of a procedure in a hypothetical infinite sequences of uses under the same circumstances. Thus classical inference relies on the idea that a single instance can be taken as typical of a hypothetical infinite population. I leave it to those who find this an attractive proposition to explain why.

Bayesian Use and Misuse

The growth in use and popularity of Bayesian methods has stunned many of us who were involved in exploring their implications decades ago. The result, of course, is that there are users of these methods who do not understand the philosophical basis of the methods they are using, and hence may misinterpret or badly use the results. (The same is true of classical methods like factor analysis and principal components). No doubt helping people to use Bayesian methods more appropriately is an important task of our time.

References

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