STATS 551 - Article Summary 1

In “Induction and Deduction in Bayesian Data Analysis”, the author Andrew Gelman believes that deduction including model checking and falsification are at the center of the Bayesian modeling process, which contradicts the common idea that Bayesian inference is associated with inductive reasoning.

First, the author defines “the standard view of the philosophy of statistics” and indicates its bad influence on statistical practice. According to the view, statisticians are divided into two groups, each with a clear configuration of practice and philosophy. This wrong idea has led many falsificationists and others who are interested in objective scientific knowledge to shun Bayesian methods, as well this idea has led many Bayesians to shun falsification.

Second, the author states this view does not describe what statisticians do in practice. The view implies Bayesian models can never be directly falsified by a significance test. However, knowing ahead of time that assumptions are false, the author abandons a model when a new model has better performance. Because the posterior probability of a model depends crucially on its prior distribution, we should use predictive checks to compare models to data and use the information to motivate model improvements.

Third, Gelman gives two reasons why the consensus view of Bayesian inductions is popular. One is that at a practical level Bayesian methods work without p-value, the other is that bad modeling resulted in a motivation for the subjective inductive philosophy. Thus frequentists concluded that Bayesians were unwilling to see their models falsified, while they have unfortunately not kept up with developments on Bayesian model checking. In fact, neither subjective nor objective Bayesianism are possible, in that it represents personal degrees of belief and observation.

Fourth, he explains the relationship between falsification and Bayesian data analysis. The author tends to think of maximum likelihood and other analysis procedures as approximations to Bayesian posterior summaries or posterior predictive checks. Gelman illustrates by two simple examples of Bayesian falsification. In the theoretical example, he checked the fit of a model by comparing data to a fitted posterior distribution. In the applied example, simulation of replicated data from the fitted model yields a posterior predictive distribution for these test statistics.

Fifth, the well-known statement, “all models are wrong but some are useful”, leads an applied Bayesian two different directions: Bayes factors or posterior predictive checks. The Bayes factor approach abandons hypothesis testing entirely. In contrast, posterior predictive checks embrace rejection but with the goal of understanding what aspects of the data are not fit well by the model.

Sixth, the author reiterates that the goal of this paper is to break the link between Bayesian modeling (good) and subjectivity (bad). Bayesian inference need not be subjective nor must it be inductive in the sense of resulting in posterior probabilities of models being true. He encourages people to use falsification and thinks it can make statisticians willing to check our model fit. Although two kinds of incoherence exist in Bayesian data analysis, there is no available coherent alternative. At the end, he hopes that practicing Bayesians will recognize that falsification and model checking are consistent with a larger Bayesian approach.

Before reading this article, I did not know statisticians had such opinion about Bayesian analysis and deduction. From my perspective, it is true that we can use Bayesian methods to do statistical prediction, but that does not mean prediction is the only goal. For example, when the lecturer talked about conjugate prior distribution on class, I had an idea that in order to verify the rightness of the prior distribution cross validation could be used to check the model. In a word, I support the author’s view before looking through his work.

Furthermore, what really interests me is the opponent ideas make sense in some scenarios. Even the author admitted that he might make a mistake about his philosophy. Actually, although the so called standard view of the philosophy of statistics seem to have some drawbacks, I still think induction is the most appealing part of Bayesian analysis. Moreover, it is exact induction that makes Bayesian methods obtain more information than frequentist methods. The only problem is how you understand this standard view. I regard the point of view as direction rather than restriction. In a word, the use of induction and deduction should not be limited by statisticians’ philosophy, and any reasonable approach has a chance to lead to valuable outcomes.