

ing the best approximating model to use (and, therefore, having to estimate this). Thus, if one uses a method such as AIC to select a parsimonious model, given the data, and estimates a conditional sampling variance, given the selected model. Then estimated precision will be too small because the variance component for model selection uncertainty is missing. Model selection uncertainty is the component of variance that reflects that model selection merely *estimates* which model is best, based on the single data set; a different model (in the fixed set of models considered) may be selected as best for a different replicate data set arising from the same experiment.

Failure to allow for model selection uncertainty often results in estimated sampling variances and covariances that are too low, and thus the achieved confidence interval coverage will be below the nominal value. Optimal methods for coping with model selection uncertainty are at the forefront of statistical research; better methods might be expected in the coming years, especially with the continued increases in computing power. Model selection uncertainty is problematic in making statistical inferences; if the goal is only data description, then perhaps selection uncertainty is a minor issue.

One must keep in mind that there is often considerable uncertainty in the selection of a particular model as the “best” approximating model. The observed data are conceptualized as random variables; their values would be different if another, independent sample were available. It is this “sampling variability” that results in uncertain statistical inference from the particular data set being analyzed. While we would like to make inferences that would be robust to other (hypothetical) data sets, our ability to do so is still quite limited, even with procedures such as AIC, with its cross-validation properties, and with independent and identically distributed sample data. Various computer-intensive resampling methods will further improve our assessment of the uncertainty of our inferences, but it remains important to understand that proper model selection is accompanied by a substantial amount of uncertainty. The bootstrap technique can effectively allow insights into model uncertainty; this and other similar issues are the subject of Chapter 5.

Perhaps we cannot totally overcome problems in estimating precision, following a data-dependent selection method such as AIC (e.g., see Dijkstra 1988, Ye 1998). This limitation certainly warrants exploration because model selection uncertainty is a quite difficult area of statistical inference. However, we must also consider the “cost” of *not* selecting a good parsimonious model for the analysis of a particular data set. That is, a model is just somehow “picked” independent of the data and used to approximate the data as a basis for inference. This procedure simply ignores both the uncertainty associated with model selection and the benefits of selection of a model that is parsimonious. This naive strategy certainly will incur substantial costs in terms of reliable inferences because model selection uncertainty is ignored (assumed to be zero). Alternatively, one might be tempted into an iterative, highly interactive strategy of data analysis (unadulterated data dredging). Again, there are substantial costs in terms of reliable inference using this approach. In particular, it seems



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