Sensitivity Analysis

Geert Molenberghs

I-BioStat, Universiteit Hasselt & Katholieke Universiteit Leuven, Belgium.

Statistical models often extend beyond the data available. First, in so-called coarse data, what is actually observed is less detailed than what might ideally be observed, owing to, for example, incompleteness, censoring, grouping, or a combination thereof. Second, in augmented data settings, the observed data are hypothetically but conveniently supplemented with such structures as random effects, latent variables, latent classes, frailties or component membership in mixture distributions. For convenience, the two settings taken together will be referred to here as *enriched data*.

Reasons for modeling enriched data encompass mathematical and computational convenience, advantages in interpretation, and substantive plausibility of such constructions. It is generally known that models for enriched data combine evidence coming from empirical data with unverifiable model components, resting entirely on assumptions. This has important consequences, broadly referred to as *sensitivity*. Generally, sensitivity is defined as the impact of empirically unverifiable model components on parameter estimation, precision estimation, and statistical inferences. It has to be juxtaposed with conventional model assessment tools, which are directed towards the agreement between the data on the one hand and empirically verifiable components of a model on the other.

This, in turn, has lead to the emergence of a very active area of research: *sensitivity analysis*. In view of the above, sensitivity analysis is understood as the assessment of unverifiable modeling assumptions on the ensuing conclusions. An overview is given in Molenberghs and Kenward (2007). Some sensitivity analysis tools are directed towards the impact of distributional and/or modeling assumptions, whereas others refer to the impact one or a few subjects can have on the conclusions. As such, there is an obvious connection with robust statistical methodology and outlier detection. Also, some authors have advocated the use of so-called semi-parametric methods where, rather than specifying the full likelihood, a limited number of moments only are formulated, and reducing the amount of assumptions that have to be made.

References

Little, R.J.A. and Rubin, D.B. (2002) *Statistical Analysis with Missing Data* (2nd ed.). New York: John Wiley & Sons.

Molenberghs, G., Beunckens, C., Sotto, C., and Kenward, M.G. (2008) Every missing not at random model has got a missing at random counterpart with equal fit. *Journal of the Royal Statistical Society, Series B*, **70**, 371–388.

Molenberghs, G. and Kenward, M.G. (2007) *Missing Data in Clinical Studies.* Chichester: John Wiley & Sons.

Verbeke, G. and Molenberghs, G. (2010) Arbitrariness of models for augmented and coarse data, with emphasis on incomplete-data and random-effects models. *Statistical Modelling*, **00**, 000–000.

Acknowledgment

Based on an article from Lovric, Miodrag (2011), International Encyclopedia of Statistical Science. Heidelberg: Springer Science +Business Media, LLC