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Book Review

A text on advanced categorical data analysis that includes helpful information for statistical dunces

van der Ark, A. L., Croon, M. A., & Sijtsma K. (Eds.). (2005). *New developments in categorical data analysis for the social and behavioural sciences*. Mahwah, NJ: Lawrence Erlbaum Associates. ISBN hardback: 0-8058-4728-6

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I received this book for review purposes in 2005 and did indeed intend to review it, to the point of carrying it about with me. I held back for a while, for the most part because the book is so unashamedly technical in its approach to categorical data analysis. The twelve chapters cover an extensive range of topics that include statistical models for categorical variables, misclassification phenomena, factor analysis with categorical indicators, Bayesian computational methods, comparisons of estimation methods, logistic methods, missing data imputation, item response theory models, and multilevel model assessment. Much of this passed well above my head. I scanned the text and passed on none the wiser.

On reflection, I found that the book includes information that seems helpful even to statistical dunces such as me. For instance, it includes a brief review of types of latent variables as a prelude to discussing factor analysis with categorical variables. Parametric factor analysis makes the simplifying assumption that a latent variable such as academic self-concept (e.g., Perception of Ability Scale for students [PASS]: Chapman & Boersma, 1986) can be estimated with the aid of ordinal indicators such as Likert scale response categories (ref. Likert, 1932; e.g., *Level of agreement*) or even via responses to dichotomous response categories (e.g., *No* vs. *Yes*). It is further assumed that such latent variables have parametric measurement properties (i.e., continuous and interval or equal interval levels of measurement). For instance, the PASS offers precisely two response categories (*No, Yes*) to the item, *"I always understand everything I read."* Nonetheless, the tacit assumption is that these categorical responses relate to a parametric continuum of thoughts and feelings that can be summarised as academic self-concept. An unbiased view might include not only the possibility that the external expressions of latent variables could be either parametric (continuous) or nonparametric (categorical), but also that the latent variables themselves could be categorical. It is entirely feasible, for instance, that the discrete or continuous responses to items expressing facets of academic self-concept might be expressing a categorical latent variable (i.e., Academic self-concept that is either low or high).

The book under review uses this discussion of types of latent variables as an entry point to an exposition of new classes of latent class analysis. However, even the statistical dunce might be influenced by its review of types of latent variables to consider nonparametric factor analytic alternatives to the hoary path of parametric exploratory factor analysis, especially when the latter is manifestly inappropriate. To this end, the SPSS package of analytic procedures offers nonparametric factor analysis options such as *Correspondence analysis, Optimal Scaling,* that perhaps could be used more often (e.g., Funnell, Bryer, & Grimbeek, 2004).

In a similar vein, the chapter on misclassification discusses changes in the number of participants selecting, say, *No* versus *Yes* response categories, in terms of the fallacy of regression to the mean. As the averagely statistically numerate reader would be aware, regression to the mean concerns the fallacy of misidentifying random changes as systematic. For instance, when the score for a subset of poor readers improves, one hails the reading program. However, these shifts in reading proficiency might well relate to some random variability in performance across time rather than the beneficent effects of the reading program. The book uses the phenomenon of regression to the mean to propose an analogous explanation for changes in categorical responses, termed the misclassification fallacy. Where a majority already select one option, one way to explain further shifts towards that modal response is in terms of the misclassification fallacy. One might conclude that the reclassification process resulted from an element of inbuilt randomness even when it appears otherwise. For instance, most participants might agree in relation to the PASS assessment of academic self-concept that they understand everything they read, and then, on retest, some of those who initially disagreed might agree that they also understand everything they read. The researcher could attribute this shift to significant programmatic events or alternatively identify it as an example of the misclassification fallacy.

A further example of the misclassification fallacy occurs in the case of a nurse tasked with deciding whether or not patients recovering from head injury have become functionally capable of driving a motor vehicle. The nurse might decide that most, but not all, patients are now competent to drive. In re-assessing the remaining fraction at a later date, this nurse might judge some of the remainder also fit to drive a motor vehicle. A clinical explanation is that those reclassified from the unfit group have recovered significantly in the interim. An alternative explanation, based on the misclassification fallacy, is to conclude that the initial process includes an element of inbuilt randomness. That is, when asked to make judgments repeatedly, we are ultimately likely to agree, for instance, that almost all human beings, whether or not head injured, are fit to drive (Whether this is a good judgment is another matter entirely).

The notion of reframing regression to the mean in terms of the misclassification fallacy gives rise to the irreverent thought that perhaps this fallacy is also active within the realm of economic thought. More specifically, Pareto's

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Principle, an economic notion based on the observation by Pareto in 1906, and later popularised by Dr. Joseph Juran (ref. Koch, 1998) postulated famously that 20% of the people own 80% of the wealth. Based on this notion, one explanation for the current observation that increasingly small groups are truly wealthy is that this phenomenon is not an example of significantly adverse redistributive economic change but rather the outworking of an inherently random tendency to classify increasingly larger proportions of the population as falling within the modal category of *"lacking wealth."*

Finally, perhaps the most relevant way to view this book is as part of a collection of recent texts that either warn about the dangers inherent in assuming that nonparametric data is parametric, or point to nonparametric alternatives. To that end, the take-home message in this book is consistent with Lee's (1998) cogent demonstration that the current approach to measuring attitude is riddled with inconsistencies. Lee focused on the mutability of cognitive measurements and their latent variables, and proffered the solution of reverting to behavioural models of human behaviour. While I am not enamoured with the behaviourist vision, the statistical analogue to Lee's explication is that, at some point, it might be statistically wise to consider using nonparametric measures and nonparametric latent variables (see also Grimbeek, 1999; Michell, 1999). Finally, Bond and Fox (2001), in showing the application of the Rasch model to qualitative data sets such as those based on Likert scale measurement, have provided yet another avenue of escape from the conventional assumption that the universe of measures and latent variables is parametric (see also Grimbeek, 2001).

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