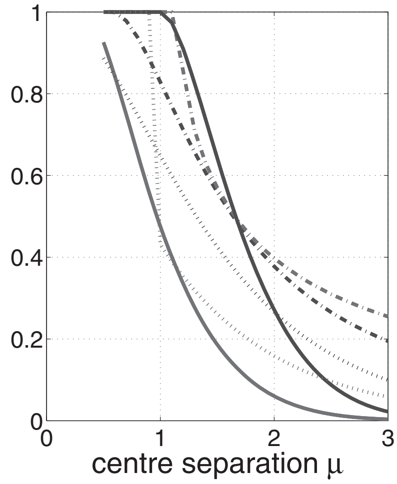

Fig. 12. Separation measures for two clusters in one dimension, $k=2$, $\pi_1=\pi_2=0.5$, $a_{1,2}=\pm\mu$ *versus* (half) the centre separation μ ($f_{\text{dip}}=f(0)/\max_x(f)$ and $p_{\text{u}}=\Pr\{0.5-\delta\leqslant P(1|x)\leqslant 0.5+\delta\}$ for $\delta=0.38$): · – · –, Cauchy f_{dip}; · – · –, Cauchy p_{u}; ——, normal, f_{dip}; ——, normal p_{u}; ·······, Laplace f_{dip}; ·······, Laplace p_{u}

standard deviation of f) and bimodality. I add label confidence $P(h|x)$. Fig. 12 displays the last two criteria for three standard cluster distributions: Cauchy, normal and Laplace. Since the standard deviation grows almost linearly with the separation, it is not shown. Bimodality is measured by f_{dip} which is the height of the 'valley' relative to the peaks; p_{u} is the population proportion that is 'unsure' of its assignment. For a normal ϕ, $\mu=1$ is the largest μ for which a mixture of two normal distributions is unimodal, and $P(h=1|x=\mu=1)=0.88$, which is nicely close to a confidence of 0.9; therefore $0.5+\delta=0.88$ is chosen.

From Fig. 12 we can derive separation in multiple dimensions as well, with the added assumption that $\phi_{1,2}$ are identical in all dimensions except the first. Then all criteria depend on the unidimensional marginal along the first dimension.

Daniel Müllensiefen and Naoko Skiada (*Goldsmiths University of London*)
Hennig and Liao's paper undoubtedly represents a significant contribution in as much as they demonstrate how to derive guidelines for cluster analysis from *a priori* data considerations ('the cluster philosophy') as well as provide new empirical insights into the constituents of social stratification. As they point out, social stratification as a concept has been of immense practical value in the past, ranging from a predictor of health outcomes (Adler *et al.* (1994), Link and Phelan (1995) and National Center for Health Statistics (2011), page 4) to a factor influencing academic achievements (Coley, 2002; National Center for Education Statistics, 2008), intelligence (Tucker-Drob *et al.*, 2010; Turkheimer, 2003), and psychological and social behaviour in general (McLeod and Kessler, 1990), However, in most psychological contexts, social stratification has been conceptualized and implemented as an ordered variable, enabling correlation and regression applications or structural equation models. This implementation of social stratification as an ordered concept has been inherent in the idea of social class since its inception in the early 19th century (Kuper, 2004). However, a clustering treatment of variables relating to social strata results necessarily in the derivation of a categorical variable that is less practical for many psychological applications. In addition, we note that almost all variables from the 2007 US Survey of Consumer Finances data set bear a natural notion of 'low' and 'high' or 'less' and 'more' and, as such, the derivation of an aggregate variable that pertains to a sense or order seems a viable option. In terms of the approaches that have been suggested for deriving a scaled variable from a mixed-type variable data set we consider mixed-type factor analysis (Pages, 2004) that combines multiple correspondence analysis for categorical variables and principal component analysis for ordered variables in a single procedure. Similar to considerations given by Hennig and Liao, variables of different types are scaled and weighted with the aim of providing comparable contributions to the overall variance in the data. Alternatively, we also consider the LINEALS procedure and the underlying concept of bilinearization that were suggested by DeLeeuw (1988a, b) which can be used

to preprocess categorical variables with the aim of combining them with scale-type variables in structural equation modelling framework (DeLeeuw and Mair, 2009) to identify a latent common factor 'social class' eventually. Discovering agreement and disagreement between the clustering solution provided by Hennig and Liao and the scaled solutions suggested here would allow interesting insights into the relationship between the two conceptual perspectives of social stratification.

Oliver Nakoinz (*Christian-Albrechts-Universität zu Kiel*)
This paper touches on three important issues. The first is the analysis of social classes which concerns an interdisciplinary audience. The second issue is the handling of mixed scales which is momentous for many fields of analysis.

The most important part of this paper is concerned with cluster philosophy. The ideas behind the 'cluster philosophy' can be expanded to other methods. The basic idea is that the choice of methods and the exact parameters of these methods should be based on objective, theory and data. The demand to justify the choice of methods considering objective, theory and data is quite rare. This philosophy is barely found in practice but we should definitely support it. This philosophy ties together far more indigenous connections of theory and application and thus produces a considerable increase in the scientific significance and meaning of the results of quantitative analysis in research projects. Furthermore this philosophy implies the abandonment of a common view, which is the idea that different methods can validate each other. This certainly is not so. Different methods have a different function which answers different objectives. In general different methods must have different results which do not contradict but complement each other.

Coming back to cluster analysis we find a hot spot of methodological perplexity for users with moderate statistical skills from several disciplines. Hence we should welcome a decision tree for choosing the cluster method (an attempt was made for example in Nakoinz (2010)) or rather a handbook as a guide in practical research projects. This handbook would have to consider theories and objectives as well as statistical knowledge to give good guidance. Even such a guide would allow a wide range of individual decisions. For example one could discuss the choice of the k-medoid method in this paper. The authors claim that k-medoids are the right method because this method does not require mean values of nominal and ordinal variables. Instead of discussing data one could discuss theory and ask whether the cluster representative must be real elements or rather can be ideal types which need not correspond to real objects and need not have realistic values.

Finally I thank the authors for this valuable paper which can be presumed to have considerable influence on the practice of data analysis in empirical research projects in many disciplines.

Rebecca Nugent (*Carnegie Mellon University, Pittsburgh*) **and Abby Flynt** (*Bucknell University, Lewisburg*)
We enjoyed reading this paper and thank the authors for highlighting one of the common, but perhaps less discussed, philosophical problems in cluster analysis. In some ways, it is akin to 'Which came first?: the chicken or the egg?'. Should the clustering approach dictate the type of clusters? Or should the desired type of clusters dictate the approach?

We would argue that both sides have merit; however, from a practical standpoint, we would advocate a balance between the two. For this socio-economic stratification problem, Hennig and Liao do a thorough job determining the appropriate variable forms, weights, etc., all using a large amount of substantive expert knowledge. What would we do with less knowledge, or perhaps none at all? How do we define these transformations, weights and dissimilarities to ensure that we find stable, contextually meaningful clusters? This analysis strongly supports working closely on interdisciplinary teams with both statisticians and subject matter experts (which obviously has benefits). However, in practice, we wonder whether it is always feasible. Many methodologists are interested in developing clustering tools with specific statistical properties for use with a broad array of applications; many applied practitioners are simply looking for which software package to run on their data. Although we advocate conversations between the two groups, we have concerns about moving too far towards making decisions that guarantee the presence of preconceived types of clusters without leaving room for discovery of the unknown.

For this particular analysis, several transformations are very specific (e.g. $q=\frac{1}{2}$ for nominal variables) and weights are chosen 'according to substantial requirements'. There is little discussion about the sensitivity of the results to these choices. Could we reproduce essentially these same clusters by using slightly perturbed weights or parameter values? For categorical variables, what if some of these categories were empty or did not exist? How would this affect our solution? Are the clusters obtained still stable and meaningful?