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Commentary

The Potential of Growth Mixture Modelling

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INTRODUCTION

The authors give a description of growth mixture modelling (GMM) and related techniques as applied to antisocial behaviour. It is laudable that the paper helps make such techniques become known to a broader audience given that many research questions about development naturally call for such techniques. The following comments intend to elaborate more fully on the potential of GMM.

NOT GMM VERSUS LCGA, BUT BOTH IN A GENERAL LATENT VARIABLE FRAMEWORK

The authors bring up the important issue of choice of model within the general framework of mixture modelling, especially the choice between latent class growth analysis (LCGA) techniques developed by Nagin and colleagues versus GMM developed by Muthen and colleagues. LCGA specifies that all individuals in a trajectory class behave the same, whereas GMM allows for within-class variation. Nagin's writings show reservations about the virtues of GMM (see Nagin, 2005; Nagin & Tremblay, 2005) and some of this is reflected in the current paper. Unfortunately, in my view, Nagin's writings on GMM contain many misconceptions. One is that the inclusion of within-class variation clouds the meaning of the resulting classes. Another is that LCGA is superior to GMM by avoiding normality assumptions on the growth factors, instead using an unrestricted, non-parametric representation with latent classes capturing the latent variable distribution. What is lost in Nagin's writing is that GMM and LCGA are closer in spirit than what first impressions might suggest. Furthermore, statistics can help choose the model that fits the data best. If the GMM model gives a considerably better log likelihood value for fewer (or at least not many more) parameters than the LCGA, GMM should clearly be chosen over LCGA. Having access to the general latent variable modelling framework of the

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Mplus program that was used by the authors, makes is possible to explore all of these alternative models under one roof.

Regarding the argument against within-class variation, it is curious to see that Nagin actually supports the idea of within-class variation in the Nagin and Tremblay (2005; pp. 892–895) Criminology discussion of 'Misconception 3: Trajectories of Group-Members Follow Group-Level Trajectory in Lock Step'. Key is the discussion around Figure 5, Panel B (p. 893). This identifies a typical developmental trajectory of 'High Desister', characterized by starting high at an early age, increasing, and then desisting. Interested readers will note that the three individual trajectories plotted around this typical development can be seen as different variations on the High Desister theme. Hence, this is an argument for using GMM—a mean curve plus variation around it. There is no clouding of the meaning of class (or group), but instead a more realistic representation of complex data.

Regarding the supposed LCGA advantage of a non-parametric representation of growth factors, what is overlooked is that GMM can also be used to specify a non-parametric representation of the growth factors, avoiding normality assumptions. Furthermore, Nagin's work has not explored the powerful combination of non-parametric and more fundamental classes. One can think of fundamental classes as the themes (an example being the above-mentioned High Desister class) and within-class variation as variation on these themes. The generality of the latent variable framework in Mplus is flexible enough that a researcher can specify which classes are merely non-parametric variations on a theme and which classes provide the theme. In this way, GMM presents a bridge between conventional multilevel modelling and LCGA. The authors of the current article have not explored this possibility. For an example of bridging the techniques, see Kreuter and Muthen (2006), analysing the Cambridge crime data. In line with this, it would have been valuable if the authors had done a thorough investigation of alternative models, comparing their likelihood values. This can be done along two strands for which the best models are then compared. First, do conventional growth modelling with normal growth factors (single-class analysis), followed by GMM with normal growth factors, followed by non-parametric GMM. Second, do latent class analysis, followed by LCGA.

CHOOSING A GOOD GMM

The authors use conventional mixture modelling tools such as BIC for choosing the number of classes. It should be noted that a better alternative is the use of a bootstrapped parametric likelihood ratio test (BLRT), made possible in Mplus Version 4. In a recent paper, Nylund, Asparouhov, and Muthen (2006) show in Monte Carlo simulation studies that BLRT consistently outperforms alternatives such as BIC.

The authors overlook a basic option for model choice. This relates to the reported convergence problem of the 3-class model. The model the authors use to decide on number of classes is overly flexible, allowing full across-class variation of growth factor variances and outcome residual variances, as well as across-class variation of regressions of growth factors on covariates. A better approach is to first work without covariates and hold variances equal across classes, using this model to take a first stab at number of classes. Then use the Mplus graphics to plot the individual variation around the estimated, class-specific mean curves to see which classes need class-specific variation. And then add covariates. Muthen

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(2004) argues for the need to bring in covariates in a final decision on number of classes, but this should mostly be seen as a warning that a researcher should not be surprised if the class formation changes when adding covariates.

ALTERNATIVE GMMS

Unfortunately, the authors do not provide histograms of their outcomes. This would probably have shown that the outcomes are very non-normal with strong floor effects. For such data, it may be more appropriate to use a mixture model version of two-part growth modelling (Olsen & Schafer, 2001). In two-part modelling, a more thorough job is done in terms of modelling the large number of individuals at the floor value. Two-part modelling splits the outcome into a binary part (acting out or not) and a continuous part (if acting out, how much). Typically, the log of the continuous part is considered to bring in a long tail. The two parts are analysed as parallel processes, where if the binary variable is off (no acting out), the continuous part is scored as missing. For an application to a preventive intervention, see Brown, Catalano, Fleming, Haggerty, and Abbot (2004). Mplus allows generalizations of two-part modelling to mixtures as well as multilevel data. Two-part growth mixture modelling may have given different results for these data because the non-normality of the outcomes is handled more thoroughly.

REFERENCES

Brown, E. C., Catalano, C. B., Fleming, C. B., Haggerty, K. P., & Abbot, R. D. (2004). Adolescent substance use outcomes in the Raising Healthy Children Project: A two-part latent growth curve analysis. *Journal of Consulting and Clinical Psychology*, in press.

Kreuter, F., & Muthen, B. (2006). Methodological challenges to an analysis of population-based criminal trajectory profiles. *Draft*.

Muthén, B. (2004). Latent variable analysis: Growth mixture modelling and related techniques for longitudinal data. In D. Kaplan (Ed.), *Handbook of quantitative methodology for the social sciences* (pp. 345–368). Newbury Park, CA: Sage Publications.

Nagin, D. S. (2005). *Group-based modelling of development*. Cambridge: Harvard University Press.

Nagin, D. S., & Tremblay, R. (2005). Developmental trajectory groups: Fact or a useful statistical fiction? *Criminology*, *43*(4), 873–903.

Nylund, K. L., Asparouhov. A., & Muthen, B. (2006). Deciding on the number of classes in latent class analysis and growth mixture modelling. A Monte Carlo study, submitted for publication.

Olsen, M. K, & Schafer, J. L. (2001). A two-part random effects model for semicontinuous longitudinal data. *Journal of the American Statistical Association*, *96*, 730–745.

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