MULTILEVEL MODELLING NEWSLETTER

The Multilevel Models Project
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Vol. 8 No. 1 **April, 1996**

Workshop in Glasgow, Scotland: A second workshop on the use of multilevel modelling in Public Health and Health Services Research will be held at the University of Glasgow on 25-27 September 1996. This workshop will give participants the opportunity to analyse personal data sets using *MLn* as well as following worked examples introducing a variety of models applied in the health field. Course fees for academics and non-academics respectively are £360 and £610, inclusive of a (limited) working version of *MLn* and lunches and dinners. Further details are available from *Dr Alastair Leyland*, Public Health Research Unit, University of Glasgow, 1 Lilybank Gardens, Glasgow G12 8RZ. Tel: 0141 330 5091/5399 Fax: 0141 337 2776 E-mail: *a.leyland@udcf.gla.ac.uk*.

Workshop in The Netherlands: An introductory workshop on multilevel modelling will be organised by *iec ProGamma* in Tilburg on 3-5 June 1996. The workshop will be assisted by a team from the Multilevel Models Project. For further details contact *Sebina Heida*. Email: *s.heida@gamma.rug.nl* Tel: +31 (0)50 636900. Fax: +31 (0)50 636687.

Workshop in Norwich, England: A three day workshop on multilevel modelling will be held at the University of East Anglia from 18-20 October 1996. It will be assisted by a team from the Multilevel Models Project and will give participants the opportunity to use a preliminary version of *MLn* for Windows. For further information contact *Anne-Lise McDonald at Health Policy and Practice Unit, UEA, Norwich, NR4 7TJ*. *a.cox@uea.ac.uk*. Tel +44 (0)1603 593631.

Workshop in Houston, USA: A three day introductory workshop on multilevel modelling will be held at the School of Public Health, University of Texas from 13-15 November 1996. It will be assisted by the multilevel models project team and provide participants with an oppoitunity to use a preliminary version of *MLn* for Windows. Places are limited. For further information contact Prof. R. Harrist; sph005@utsph.sph.uth.tmc.edu.

Announcement: Due to the ending of the current Multilevel Models Project funding from the Economic and Social Research Council (ESRC) (UK), we have no financial support for the MM newsletter after this issue. It is nevertheless our intention to continue to produce the newsletter and also to continue other activities such as the monthly *MLn* clinic, and general support, while further funding is sought.

We are grateful for support from our readers received over the last seven years, and and to ESRC for their financial support.
(***The MMP team***)

Also In This Issue

aLCD analysis OF LARGE AND COMPLEX DATASETS

E·S·R·C ECONOMIC & SOCIAL RESEARCH COUNCIL

Some Recent References

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MLn Clinics in London 1996

Tuesday May 7
Tuesday June 4
Tuesday July 16
Tuesday September 3
Tuesday October 8
Tuesday November 5
Tuesday December 3
at
Multilevel Models Project
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Contact Min Yang for appointment
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Theory & Applications

Consistent estimators for multilevel generalised linear models using an iterated bootstrap

Harvey Goldstein, Institute of Education, University of London, UK

Introduction

Several papers have addressed the issue of the parameter biases which can occur when fitting multilevel models with non Normal responses. Breslow and Clayton (1993) discuss various fitting procedures including those based upon linearising transformations, maximum likelihood and Gibbs sampling. Direct maximum likelihood or restricted maximum likelihood, while feasible for simple models, becomes quickly intractable as the number of random effects increases: Gibbs sampling is an attractive alternative, but neither procedure necessarily provides unbiased estimates (Kuk, 1995). Approximate methods based upon linearising transformations and applying quasilikelihood estimation are attractive since they pose no serious computational problems and can be fitted using modifications to existing multilevel software packages.

Rodriguez and Goldman (1995) illustrate how severe underestimation can occur in a simple variance components model with binary responses, especially for the level 2 variance. They use a 'first order MQL' method (Goldstein, 1991). Goldstein (1995) and Goldstein and Rasbash (1995) develop improved linearising approximations and show that for models where there are adequate numbers of level 1 units per level 2 unit these give satisfactory results. Nevertheless, where the numbers of level 1 units per level 2 unit is small and for binary responses as in the Rodriguez-Goldman data sets, there is still some underestimation. In this paper we set out a procedure (Kuk, 1995) which yields asymptotically unbiased and consistent estimates for such models and which can be applied in general to any kind of non linear multilevel model.

Iterative bootstrap bias correction

We shall illustrate the procedure with a simple 2-level variance components model, as follows

$$\text{logit}(\pi_{ij}) = \beta_0 + \beta_1 x_{ij} + u_j$$
$$u_j \sim N(0, \sigma_u^2)$$
$$y_{ij} \sim Binomial(1, \pi_{ij})$$

Given a set of initial estimates, obtained using for example the first order MQL approximation,

$$\hat{\sigma}_u^{2(0)},\ \hat{\beta}_0^{(0)},\ \hat{\beta}_1^{(0)} \qquad (1)$$

we generate a set of bootstrap samples, from the model using the estimates (1) and averaging over these we obtain the set of bootstrap estimates

$$\tilde{\sigma}_u^{2(0)},\ \tilde{\beta}_0^{(0)},\ \tilde{\beta}_1^{(0)} \qquad (2)$$

We now obtain the bootstrap estimate of the bias by subtracting (1) from (2). These bias estimates are subtracted from the initial parameter estimates as a first adjustment to give new bias-corrected estimates

$$\hat{\sigma}_u^{2(1)},\ \hat{\beta}_0^{(1)},\ \hat{\beta}_1^{(1)} \qquad (3)$$

We generate a new set of bootstrap samples from the model based upon the estimates given by (3), subtract (3) from the new mean bootstrap parameter estimates and subtract from the initial estimates to obtain a new set of bias corrected estimates. When it converges, Kuk (1995) demonstrates that this procedure gives asymptotically consistent and unbiased parameter estimates.

In the present case the bootstrap samples have been generated parametrically by sampling from the distributions with the estimated parameters: in the present case from a Normal distribution for the level 2 residuals and a binomial distribution (with denominator one) for the level 1 residuals. The alternative would be to sample estimated residuals at levels 1 and 2, but while this is valid where all the distributions are Normal, it is not clear that this produces acceptable results in the present case. Further work on this would be useful.

With non linear models the bias is typically a function of the parameter values themselves, so that several iterations may be necessary. In the next section we show the results of a simulation study and suggest strategies for carrying out the computations.

Care needs to be taken with small variance estimates. To estimate the bias we need to allow negative estimates of variances, as is possible in *MLn*. If an initial estimate is zero, then clearly, resetting negative bootstrap sample means to zero implies that the bias estimate will never be negative, so the new updated estimate will remain at zero. Moreover, as confirmed by simulations, all the estimates will exhibit a downward bias if negative bootstrap means are reset to zero. We also note that where an unbiased variance estimate is close to zero, the bias is anyway small, so that full bias correction is less important and, for example, a second order PQL estimate may be adequate (see below).

A simulation

We simulate 100 replications of the model for a binary (0,1) response with all three parameters equal to 1., with 50 level 2 units and 2 level 1 units per level 2 unit. This is a rather extreme case where we would expect serious underestimation of parameters.

To decide how many bootstrap samples we need for each iteration of the procedure we keep a running mean such that when, at the *t*-th bootstrap sample, for the running means $\theta_t, \theta_{t-1}, \theta_{t-2}$

$$|\theta_t - \theta_{t-1}| < \varepsilon \text{ and } |\theta_{t-1} - \theta_{t-2}| < \varepsilon \qquad (4)$$

then we accept convergence. We have chosen the value of ε as 0.001 and set a minimum number of samples as 10. We note, in passing, that the device of maintaining a suitable running statistic to judge convergence is applicable for bootstrap sampling when attention is focused on other functions of parameters, for example the standard deviation or a percentile estimate. New parameters also need a criterion for judging convergence of the bootstrap bias corrected estimates. In an application convergence needs to be monitored closely, especially for small values of random parameters. We finally adopted the following criteria for the simulations

We compute the average of the current and previous two estimates, say $\bar{\theta}_t$ and the average of the three estimates prior to these, say $\bar{\theta}_{t-1}$, and judge convergence as follows

$$\begin{aligned} &|(\bar{\theta}_t - \bar{\theta}_{t-1}) / \bar{\theta}_t| < 0.02 \text{ if } \bar{\theta}_t \geq 0.25 \\ &|(\bar{\theta}_t - \bar{\theta}_{t-1})| < 0.005 \text{ if } \bar{\theta}_t < 0.25 \end{aligned} \qquad (5)$$

For small estimated values convergence is often slow and an absolute rather than relative criterion seems appropriate. The mean number of iterations required was 13.8 and the mean number of bootstrap samples per iteration was 80.5.

The basic results are given in Table 1. We have used the standard deviation rather than the variance for reporting means since the distribution of the latter is skew.

It is clear that the serious underestimation for all the parameters has been eliminated, and the final estimates are unbiased within the limits of sampling error. The initial second order PQL estimates using Iterative Generalised Least Squares (IGLS, which is Maximum likelihood in the multivariate Normal case) of the fixed parameters in fact show no bias, but with underestimation of the standard deviation. With Restricted Iterative Generalised Least Squares (RIGLS which is restricted maximum likelihood in the multivariate Normal case) the variance estimate is less biased, although there appears to be a slight overestimation of the slope parameter. Interstingly, the first order PQL (RIGLS) estimates are no better than the first order MQL (IGLS) estimates, which suggests that second order PQL estimates should be used where possible for exploratory purposes.

Table 1. Bootstrap simulation results with initial estimates (s.e.) for MQL, PQL

	1st order MQL, IGLS	1st order PQL, RIGLS	2nd order PQL, IGLS	2nd order PQL, RIGLS
σ_u				
Initial	0.49 (0.03)	0.49 (0.04)	0.84 (0.06)	0.93 (0.07)
Final	0.98 (0.06)			
β_0				
Initial	0.89 (0.03)	0.88 (0.03)	1.03 (0.04)	1.07 (0.04)
Final	1.05 (0.04)			
β_1				
Initial	0.91 (0.03)	0.88 (0.03)	1.02 (0.03)	1.10 (0.04)
Final	1.07 (0.04)			

It would of course be possible to start with the second order PQL estimates and use this estimation procedure for the bootstrapping. A difficulty with this is that each estimation takes rather longer and this will usually be an important consideration. Secondly, in some cases (5% in the present case) the second order procedure fails to converge whereas the first order one almost always does.

At convergence we can then generate a final sequence of bootstrap samples to provide estimates of precision, confidence intervals etc. The number of samples required for such purposes will generally be larger than used in the updating, but as pointed out above we can use a running statistic for judging convergence at any prespecified accuracy.

Figure 1 shows the relationship between the final and initial MQL estimates and illustrates how substantial adjustments can be made when the initial estimates are moderately large.

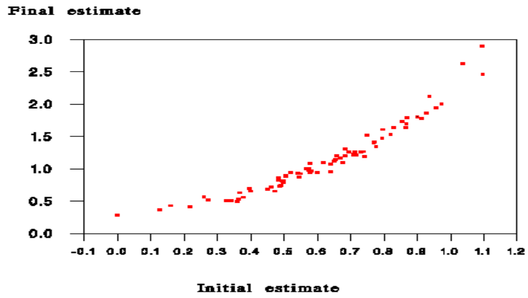

Figure 1. Final iterative bootstrap estimate of level 2 standard deviation by initial MQL first order estimate. The value for the initial estimate of zero is the mean over the 22 such values.

Conclusions

The procedure outlined is quite general, and can be applied to any non-linear multilevel model. As mentioned above, it will usually not be necessary where there are sufficient level 1 units per level 2 unit. In practice, where the number of such units is small, a useful strategy is to base model exploration on the second order (RIGLS) PQL estimates and then compute final bias corrected estimates using the first order MQL as here. In many cases the second order (RIGLS) PQL estimates will be perfectly adequate and further research into the conditions for this is needed. For very large data sets it is possible that a procedure based upon subsampling higher level units and then carrying out bias correction on smaller samples in order to estimate the relationship between parameter estimates, bias and sample size, may be useful, and this needs further exploration.

The criteria chosen for judging convergence and the number of bootstrap samples to use are somewhat arbitrary and the optimum criteria will generally depend on the data themselves and further work on this would be useful. For the bias corrected estimates the procedure may not always converge or convergence may be extremely slow. For MQL estimation neither of these problems has been encountered but they seem more likely to occur with PQL estimation and is a further reason for preferring the former to the latter.

A set of *MLn* macros has been written using the convergence criteria described above and where convergence parameters can be set by the user.

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Multilevel models for longitudinal growth norms

Huiqi Pan, Harvey Goldstein & Jon Rasbash
Institute of Education, University of London

The construction of longitudinal norms for growth has been pursued by a number of authors, for example Tanner et al (1970), Healy (1974), Cameron (1980), Berkey et al (1983) and Cole (1994). These have been limited to the study of yearly measurements on the distribution of a measurement at an (exact) age conditional on the same measurement one year previously.

Longitudinal data have a hierarchical structure, where level 2 is the individual and level 1 is the occasion. Royston (1995) uses a multilevel model for the calculation of conditional centiles for foetal size based on transforming both the measurement and age to force a linear relationship between them.

We have explored a general approach to creating longitudinal centiles using multilevel models. There are three stages involved:

Stage 1: Generating Normal scores

The LMS method of Cole and Green (1992) allows skew data to be converted to an approximate Normal distribution. z scores. We can also use a 2-level model to fit raw data and then transform these using Normal Score.

We have used both procedures to produce an limited set of data which have standard Normal distribution conditionally on age.

Stage 2: Fitting 2-level models to the Normalised scores

If we denote th *ij*-th score for the *j*-th subject by z_{ij}, we have the 2-level model:

$$z_{ij} = \sum_{l=0}^{p} \beta_l t_{ij}^l + \sum_{l=0}^{q} u_{lj} t_{ij}^l + e_{ij}$$

By virtue of the prior Normalisation with the usual assumption, the random coefficients are assumed to have a multivariate Normal distribution.

Stage 3: Establishing norms

Using the estimates of the fitted model, we can calculate any required function of the z_{ij} and estimate the population distribution for this (Goldstein, 1995). This function could be an acceleration, or the distribution of a measurement conditional an 2 previous measures. There is no requirement for a fixed set of ages and so any set of longitudinal data can be used.

This approach has been used for height and weight and for a 'bivariate' model for weight and height so that longitudinal weight-for-height norms can be constructed.

Pc software is currently being developed so that users can input data and explore various functions and resulting Norms graphically. For further details cantact *Pan Huiqi* at *teuephq@ioe.ac.uk.*

(*This work is supported by a grant from the Medical Research Council in UK.*)

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HLM 4 for Windows and DOS Extender Now Available

HLM 4 offers a number of advances over version 3 in convenience of use. It greatly broadens the range of hierarchical models that can be estimated. Key new features are:

Windows Interface. All models can be formulated in Windows. As you specify variables at each level, the relevant equations for each level are immediately constructed in a graphics box. These are saved and can be easily modified for subsequent analysis. Data are also easily read into HLM using Windows.

Interface with Widely Available Statistical Packages. HLM 4 can read data from a variety of statistical packages, including SPSS, SAS, SYSTAT, and STATA.

Hierarchical Generalized Linear Models. HLM 4 allows estimation of Bernouli and binomial models for binary data with logit link function and Poisson models for count data with constant or variable exposure with log link function.

Generalized Estimating Equations. HLM provides estimation of population-average models using Generalized Estimating Equations.

Fisher Scoring/EM Algorithm. HLM 4 now combines an EM algorithm with the Fisher scoring algorithm to produce a high standard of speed and reliable convergence for both two-level and three-level programs.

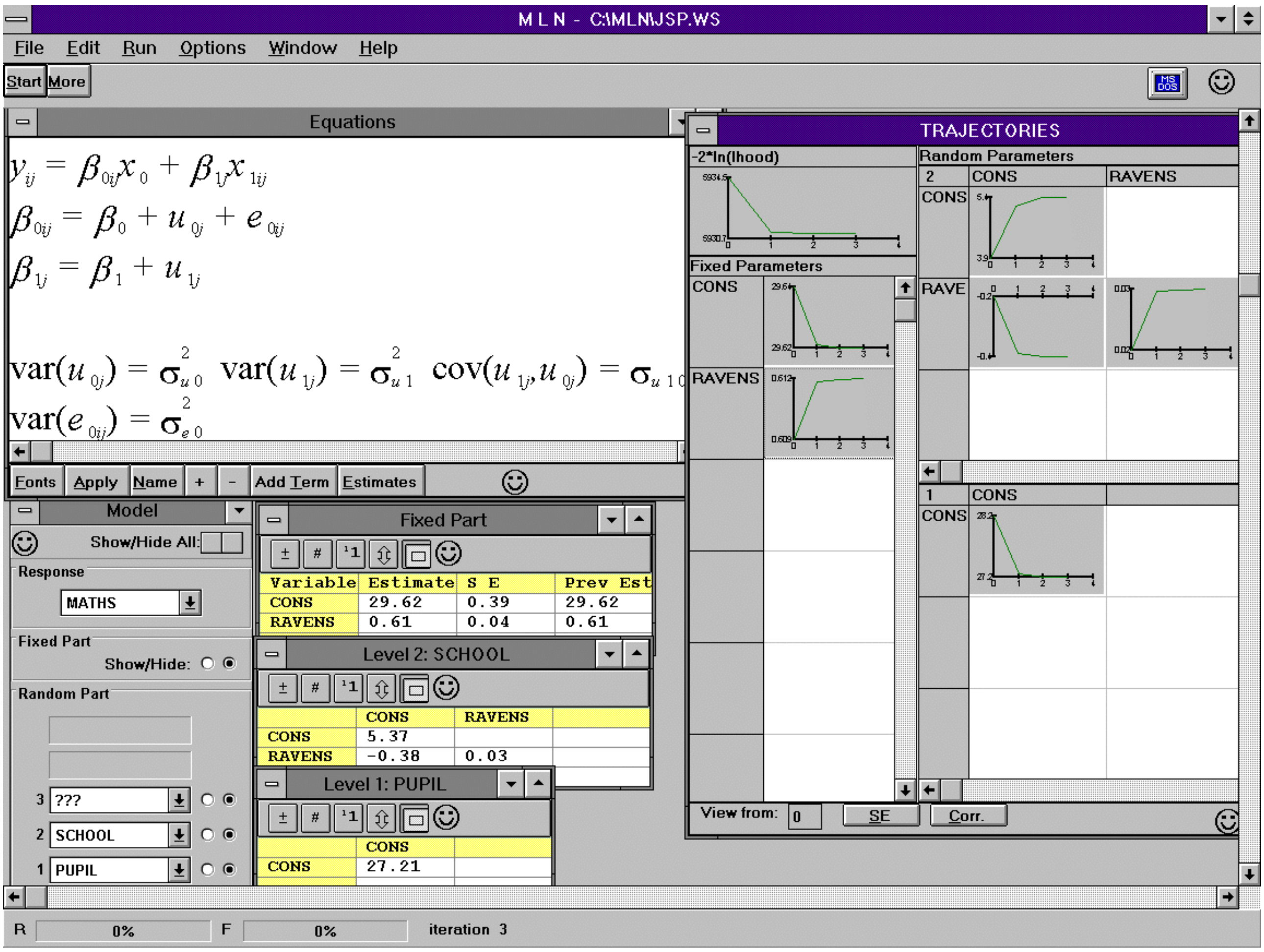
Automated Production of Command Files. Interactive runs automatically output command files which can be executed via batch or read into Windows. For more information contact:

Scientific Software International
1525 East 53rd Street, Suite 530
Chicago, Illinois 60615-4530, USA
Tel: (312) 684-4920, Fax: (312) 684-4979

A Snapshot of Windows *MLn* under development

We are currently developing a windows version of *MLn* which is due to be released in late Autumn of 1996. Some of the features to be included are

- The ability to specify, manipulate and explore the results of models using tabular screen objects (such as those in the bottom left of the diagram below) or alternatively using the model equations directly (the "Equations" window on the diagram below).
- View trajectories of parameter estimates while the model is being estimated.
- A scratchpad facility which can include equations, graphs, tables and text which can be printed out directly or imported into word processing packages via the clipboard.
- User configurable menus for *MLn* macros.
- Improved interactive Cartesian graphs for model exploration and diagnostics.



(This screen is taken from the current development version.) *Jon Rasbash*

Abstracts of Some on-Going Studies

Some techniques for assessing bivariate normality with applications to multilevel models (*Sangeeta Bhattacharya,University of Texas, SPH1309@utsph.sph.uth.tmc.edu*)

Much work has been done on the development of standard techniques to test if a given univariate data set comes from a population of known distribution, usually a normal distribution. However the problem becomes more complicated when we have multivariate data at hand. Although the assumption that the data come from a multivariate normal distribution is often made, satisfactory techniques for testing multivariate normality still have not been developed.

This paper attempts to check bivariate normality of an arbitrary bivariate sample. Three methods have been proposed and used to test the assumption that a given bivariate sample was drawn from a bivariate normal distribution. Direct analogies have been drawn from univariate residual analysis to develop the three approaches namely the Mahalanobis Plot, Ellipses and Sectors. The example data sets which include repeated measurements on blood pressure and jaw measurements help to illustrate the point that different tests may be needed to capture departures from normality depending on the data.

Application of 'BUGS' to the problem of nonrandom attrition in the Manchester and Newcastle longitudinal studies of cognitive aging (*Scott Hofer & David Spiegelhalter, University of Manchester, HOFER@hera.psy.man.ac.uk*)

The goal of longitudinal studies of cognitive functioning is to make valid inferences about rates, patterns, causes, and concomittants of age-related changes in cognitive capabilities. One of the greatest obstacles to achieving this goal is that of subject attrition. Indeed, results based on such progressively elite longitudinal samples make generalizations to the target population very difficult to justify. Our focus is on the application of methods to correct for the biasing effect of nonrandom attrition on estimates of age-related changes in cognitive functioning-specifically where the causes of dropout are directly or indirectly related to performance on cognitive tests. Growth curve (hierarchical random effects) models are used to estimate the initial level, age-changes gradient, and covariate relationships in P. Rabbitt's Manchester and Newcastle longitudinal studies. Results will be presented from analyses using Markov Chain Monte Carlo techniques (i.e., Gibbs Sampling using BUGS), as well as likelihood-based procedures, allowing a wide range of realistic models for ignorable and nonignorable nonrandom attrition to be examined.

Gibbs Sampling for multilevel logistic models of infant mortality (*Toby Prevost, University of Southampton, ATP@alcd.soton.ac.uk*)

We use retrospective data from the 1988 Tunisian demographic and Health Survey. The hierarchical structure consists of about 3,000 women providing information about 8,500 children. Other studies have identified correlation between binary outcomes of siblings. We adopt a multilevel logistic model to incorporate this 'maternal heterogeneity'. Siblings share the random effect that their mother draws from an iid normal distribution.

We compare one Bayesian and two classical approaches to the estimation of the random intercepts model, which are implemented in BUGS, *MLn* and EGRET. The Gibbs Sampling approach is preferred for its flexibility in this area of application.

Multilevel multivariate logistic models in study of attitudes and vote over the electoral cycle (*M. Yang, A. Heath and H. Goldstein, Institute of Education, TEMSMYA@ioe.ac.uk*)

Opinion polls regularly show swings against the government in the middle of the electoral cycle. One explanation for this is that in the middle of the cycle voters are more influenced by transitory factors whereas at general election time they are more influenced by their fundamental values and interests. To test this hypothesis we use the 1983-86-87 British Election Panel Study data. The dataset contains measures both of voters' attitudes towards enduring political issues as well as more changable perceptions of the parties and party leaders in that period. It has three aspects: (i) three-level hierarchy with voters nested within constituencies, and repeated measures within voters; (ii) the outcomes are repeatedly measured binary variables for a party voting; and (iii) all covariates are time-dependent.

We apply multilevel multivariate models to study the variance-covariance structure of the binary outcomes at voter level, to model the random contextural effects of attitudes and to compare the change of effects of covariates over the electoral cycle. The model descriptions and output interpretation are emphasised from the applied point of view. Practical evaluation on the adequacy of the model estimates have been carried out. We are studying the validity of the standard distributional assumption in logistic repeated measures models.

Comparison of repeated measures ANOVA and multilevel linear model for analysis of longitudinal data (*Egon Durban, University of Texas, EDURBAN@bcm.tmc.edu*)

In this study, two different statistical models were utilized to evaluate data from a longitudinal clinical trial and results are compared. The data were chosen from the Trial of Antihypertension Intervention and Management (TAIM) and modeled by a balanced repeated measures 3x3 factorial ANOVA (2 factors, drug and diet, each at 3 levels) with a third factor, time, nested in each drug/diet treatment combination. This model was compared with a two-stage hierarchical model. The multilevel analysis was found superior to the repeated measures ANOVA in several respects: 1) All data were utilized in fitting the multilevel model regardless of an individual's time of repeat visit or number of repeat visits, an important consideration in the design of clinical trials; 2) error variances were considerably reduced compared with the repeated measures design; and 3) the multilevel analysis provided a convenient and comprehensive graphical summary of the analysis.

Index of Articles Appearing in the Multilevel Modelling Newsletter (1989-1995)