MULTILEVEL MODELLING NEWSLETTER

The Multilevel Models Project:

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Graphing Made Easy with *ML3*

MULTILEVEL

OLS

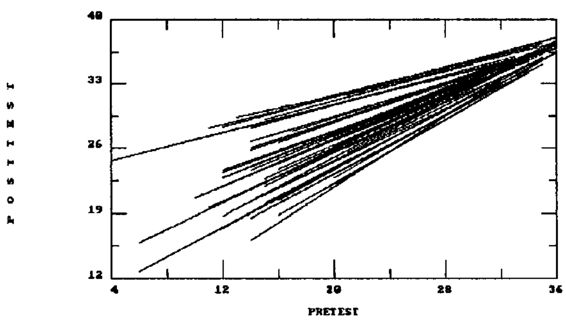

Fig 1. ML predicted postest vs pretest for 50 schools

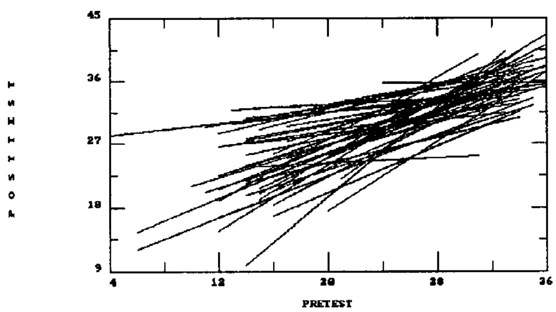

FIG 2. OLS predicted posttest vs pretest for 50 schools

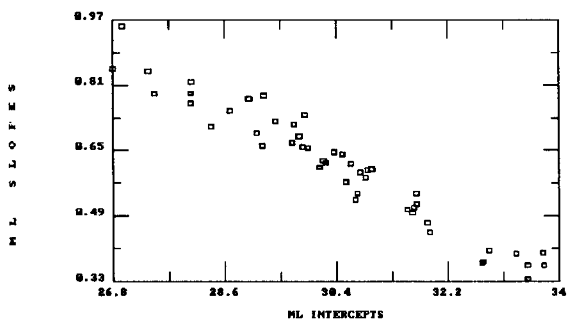

Fig. 3 ML slopes vs intercepts

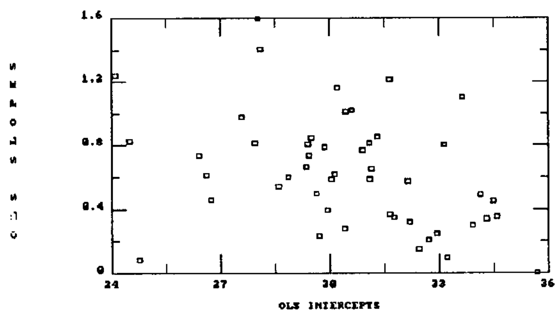

Fig 4. OLS intercepts vs. slopes

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GRAPHING WITH *ML3*

Jon Rasbash

Many *ML3* users are unaware of some powerful graphing capabilities of the program. All four graphs on the front cover, showing the results of a multilevel analysis compared to a set of school by school OLS analyses, are produced by only nine *ML3* commands. This short note shows how these graphs were constructed.

Let's start after we have just run the multilevel model:

$$(POSTTEST)_{ij} = \beta_{0j} + \beta_{1j}(PRETEST)_{ij} + e_{ij}$$

and obtained the results

RANDOM PARAMETERS

LEVEL 2

PARAMETER	ESTIMATE	S. ERROR
INTERCPT /INTERCPT	4.408	1.238
PRETEST /INTERCPT	-0.336	0.114
1PRETEST /PRETEST	0.0349	0.0166

LEVEL 1

PARAMETER	ESTIMATE	S. ERROR
INTERCPT /INTERCPT	27.21	1.305

FIXED PARAMETERS

PARAMETER	ESTIMATE	S. ERROR
INTERCPT	30.43	0.357
PRETEST	0.612	0.0422

The data set used here has fifty schools.

Figure 1. shows the multilevel prediction lines for our fifty schools. To construct this graph we must

- i Calculate the school level intercept and slope residuals.
- ii Add these residuals to the population intercept and slope forming fifty prediction equations, one for each school; apply each schools prediction equation to each schools data producing a prediction line for each school.
- iii Plot out the resulting fifty prediction lines.

The following three commands perform these three tasks.

RESIduals 2 2 'INTERCPT' 'PRETEST' results to C50 C51

PREDict 'INTERCPT' C50 'PRETEST' C51 results to c60

PLGL 'SCHOOL' C60 'PRETEST'

The PREDict command predicts a value of POSTTEST for every individual in the data set. These predictions are placed in column 60.

We now have fifty sets of (x,y) data points stacked up in columns ('PRETEST', C60), one set for each school. The PLGL plots out these fifty lines. The PLGL command provides an easy way to graph the relationship between two variables across a large number of higher level units.

GRAPHING WITH *ML3*

Figure 2. is produced by applying the PLGL command to a column of OLS predictions. These predictions are formed from fifty separate OLS analysis, one analysis for each school in the data set. We can form these OLS predictions by the command,

OLSEstimates at level 2 predictions to c70 coefficients c71-c72

Now we can graph the OLS predictions for each school,

PLGL 'SCHOOL' c70 'PRETEST'

Figure 3. is a plot of the multilevel intercepts versus slopes for our fifty schools. We can form this graph by adding the intercept and slope residuals in columns 50 and 51 to the average intercept and slope:

CALC C50 = C50 + 30.43

CALC C51 = C51 + 6.12

PLTP C51 c50

Figure 4. is a plot of the OLS intercepts versus the OLS slopes which are in C71 and C72 respectively. These are plotted out by typing :

PLTP C72 C71

RELEASE 2.2 of *ML3* now available

The major enhancements in version 2.2 are

* colour graphics support for EGA/VGA graphics adaptors
* commands to calculate likelihood values around model solutions
* invoking other programs, for example, an editor, from inside *ML3-E*

Any users who have bought a previous copy of *ML3* can upgrade to V2.2 for £10 (£15 / US$ 25 for users based outside the UK).

Please fill the following form, make cheques payable to ***The Multilevel Models Project***, and send it to the address on the front page if you wish to order.

....

Name ________________________________

I enclose payment of ________. Please send _______ copies of *ML3* V2.2 to the following address:

REVIEW ARTICLE

For many new readers of the Newsletter, the following introductory article to multilevel modelling may be of interest. It is based on a longer paper to appear in the British Educational Research Journal (1992).

New Statistical Methods for Analysis Social Structures: an introduction to multilevel models

Lindsay Paterson & Harvey Goldstein

Introduction

Recent developments in multilevel modelling have made available to social scientists powerful statistical techniques for analysing individuals as members of social groups. The techniques are also especially useful for repeated measures data. This note is an outline of the concepts of multilevel modelling. A fuller account and technical details can be found in, for example, *Goldstein (1987a)* and *Raudenbush and Bryk (1986).*

As a generalisation of ordinary regression

Consider a survey of 5000 pupils drawn from 100 schools; thus the groups are the schools. Suppose we wish to investigate the relationship between a score based on examination attainment at age 16 (y_i for pupil i) and a measure of verbal - reasoning ability (x_i) on entry to secondary school. Ordinary regression would estimate a single equation by pooling all 5000 cases, expressing the examination attainment as a linear function of ability:

$$y_i = b_0 + b_1 x_i + e_i \qquad (1)$$

where b_0 is the 'intercept' and b_1 is the slope coefficient. The term e_i is a random variable, often called a residual and usually assumed to be Normally distributed with mean 0 and a constant variance. Equation (1) simply says that the exam score (y_i) increases by a fixed amount (b_1) for a unit increase in verbal reasoning score (x_i) without allowing for school differences.

A multilevel model provides the appropriate generalisation of (1) to take account of school differences. Changing the suffixes so that y_{ij} is the attainment of the i-th pupil in the j-th school, we can incorporate school membership into the model by writing:

$$y_{ij} = b_0 + b_1 x_{ij} + u_j + e_{ij} \qquad (2)$$

where the addition of a term specific to each school, u_j, indicates that over and above any given verbal reasoning score each school has its own contribution.

The key technical advance of multilevel modelling is to assume that the u_j vary randomly across schools with a zero mean and a constant variance in order to make inferences about the variation between all schools not merely the 100 which have been sampled. One of the aims of the data analysis will be to see whether the addition of further variables to the model (for example social status) reduces or 'explains' any of the between-school variation. Extensions to further levels of nesting (for example education authorities) are straightforward, as are extensions which assume that coefficients such as b_1 are random variables, varying across schools. Thus multilevel modelling can respect the heterogeneous of social experience. Populations need not be treated as homogeneous, and the methods yield statistical tests of differences between groups in the model and confidence intervals for the extent of any differences.

Since all data analysis in the social sciences deals with populations where there are inbuilt hierarchies, the scope for application of multilevel models is very wide. More examples can be found in economics, in political science, in geography and repeated measures data analysis (*Raffe & Willims, 1989; Garner & Raudenbush, 1990;).*

REVIEW ARTICLE

What is lost by not using multilevel techniques?

A common approach to analysing hierarchical data has been to aggregate to group level and then use only group means. Thus instead of using information about the 5000 pupils in the above example, only the 100 school means would be used, and ordinary regression would be used to relate the mean attainment to the mean score.

There are two drawbacks to this approach, one technical and the other substantive. The technical one is that the statistical estimates can be very unreliable in the sense that slight perturbations to the data or to the model can produce markedly different results. This shows up as large standard errors for estimates, and as high collinearity among predictors. The second drawback is that aggregate data are removed from the social and educational processes that are of interest. For example, learning is done by children, not schools or LEAs, and we can not offer explanations based upon aggregate level analyses that would make explanatory sense. Details are given by *Woodhouse and Goldstein (1988)*.

If we let the regression relationship vary among groups by means of multilevel analysis, we can see where effects are occurring, and understand how they are occurring. Allowing individual relationships to vary among groups is necessary for technical reasons as well, because the grouping might have an effect on standard errors. This is a well-known issue in design-based inference from clustered data, and a problem also for model-based inference, because in practice no model can incorporate all group-level influences on individual behaviour, and so such influences become part of the random error.

Multilevel analysis allows characteristics of the group to be incorporated into models of individual behaviour, while also producing correct estimates of standard errors so that valid tests and intervals can be constructed.

Time

Repeated measures on individuals can be represented as grouping time-points or occasions within people. *Goldstein (1989)* has explained how this representation can be used to gain insights into the physical growth of children. The two levels of random variation-among individuals, and among occasions within individuals-take account of the fact that growth characteristics of individual children, such as their average growth rate, vary around a population mean, and also that each child's observed measurements vary around his or her own growth trajectory. Furthermore, characteristics at higher levels can be used to explain processes at lower levels. *Raudenbush (1988)*, for example, reports a study which found greater variation among children in reading growth than in arithmetic growth. The reading growth itself could be predicted by characteristics of the child's home, such as the educational level of the mother.

Time can be incorporated even if multiple measurements are not available on individuals. For example, regular cohorts of school leavers are sampled by the *Scottish Young People's Survey* from secondary schools in Scotland. The multilevel structure is thus pupils within time points within school, and not all schools need to be represented at each time point. The advantage of this structure is that time-related characteristics can be incorporated without ignoring also the issue of whether schools remain stable institutionally over time. Many publications are related to this issue (*Paterson 1991; Willims & Raudenbush 1989; Coopers & Lybrand 1988; Nuttall et al 1989;)*

Non-linear models and Random cross classifications

The equation (2) makes the tacit assumption that the response variable (y_{ij}) is continuous, but many social scientists need methods for proportions, or simply variables scored as 0 or 1, and there are cases where a non-linear model relationship might be appropriate. Multilevel analogues of generalised linear models are

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being developed at the *Institute of Education in London University*. In particular, multilevel log-linear modelling can be carried out using the program *ML3 (Goldstein 1991 and see page 2 of this Newsletter).*

Software and further information

The three main programs for carrying out multilevel analysis are available as follows; each comes with a manual containing worked examples of how to use it, and describing some of the theory of the techniques:

ML3: The Multilevel Models Project,
Department of Mathematics, Statistics and Computing
Institute of Education, University of London
20 Bedford Way, London. WC1H 0AL, U.K.

HLM: S.W.Raudenbush,
Department of Counselling, Educational Psychology and Special Education
460 Erikon Hall, Michigan State University
East Lansing, Michigan 48824. U.S.A.

VARCL: N.T.Longford
Educational Testing Service
Princeton
New Jersey. U.S.A.

References

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Garner, C.L. And Raudenbush,S.W..(1990). Neighbourhood effects on educational attainment. *Sociology of education*,(to appear).

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Goldstein, H.(1987b).Multilevel covariance components. *Biometrika*, 74,430-431.

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Nuttall, D.L., Goldstein,H., Prosser, R., And Rasbash,J. (1990). Differential school effectiveness. *International Journal of Educational Research*, 13,769-776.

Paterson,L.(1989). Trends in attainment in Scottish secondary schools. In: *Schools, classrooms and pupils: international studies of schooling from a multilevel perspective, eds S.W.Raudenbush and J.D.Willms. New York: Academic Press*,85-100.

Raffe, D. And Willms, J.D.(1989). Schooling the discouraged worker:local-labour-market effects on educational participation. *Sociology*, 23,559-581.

Raudenbush, S.W.(1988). The analysis of longitudinal, multilevel data. (Available from the Centre for Educational Sociology, Edinburgh University.)

Raudenbush, S.W.,and Bryk, A.S.(1986). A Hierarchical model for studying school effects. *Sociology of education*, 59,1-17.

Willms, J.D. And Raudenbush,S.W.(1989). A longitudinal hierarchical linear model for estimating school effects and their stability. *Journal of Educational Measurement*, 26,1-24.

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PROJECT NEWS

Logit models for proportions using *ML3*

Harvey Goldstein

In the January 1990 newsletter, I described how a multilevel logit-linear model for proportions could be fitted using *ML3*. The procedure for doing this is described in the most recent *ML3* manual (for version 2 of the program) and has also been incorporated into a set of macros which can handle quite general models (*Goldstein, H. 1991. Nonlinear multilevel models, with an application to discrete response data, Biometrika, 78,45-51*). The macros, with a description of how to use them, are available from the multilevel models project at the Institute of Education.

Health Information Research Services and Multilevel models

Kelvyn Jones & Graham Moon

Health Information Research Services is a group based at Portsmouth Polytechnic, researching the production of ill-health and the consumption of health care. Due to the disciplinary background of the team, attention has focused on quantitative analysis of health information in its geographical context. Consequentially, we have found multilevel modelling to be an extremely useful tool in the disentangling of composition and contextual effects. Currently, multilevel models are being used on three research projects.

The first project is concerned with the variation in uptake of childhood immunization among clients (level 1) and between clinics (level 2). The response variable is the binary outcome, immunised or not. There are a number of predictors at each level. These include a variety of social indicators for the child's parents at level 1, and organisational variables at level 2. The multilevel models reveal substantial effects for client characteristics as well as interactions between the client and clinic. Some clinics perform well with socially disadvantage groups, others do not. These results have particular importance in the light of recent changes in health legislation. General practitioners are to be remunerated in relation to broad bands of crude average immunization uptake. Those with returns between 70 and 90 percent be paid at a lower rate, and those with returns above 90 percent receiving a higher rate. Our study indicates that crude averages are substantially an outcome of client composition and are therefore an inadequate measure of clinic performance. General practitioners have intuitively realised this. There are documented cases of GP's excluding certain groups (eg travellers) and areas (council estates). This is an example of an inadequate quantitative criterion producing results that were not intended.

The other two projects are at an early stage of development. One concerns the continued use of folk-healers in different regions of Saudi Arabia. The data consists of a large-scale survey of respondents (level 1), attending western-style clinics (level 2) and in different areas (level 3). It has been found that while the overall fixed term for the level-1 predictor, Momad/Settled, is not significantly different from zero, there are substantial random effects if this variable is allowed to vary at the area level. Similarly, as shown in the figure, the relationship between age and continued use of folk-healing varies from area to area. The higher intercepts and steeper slops being for the rural areas.

PROJECT NEWS

The third one is a cooperation study with researchers at the Netherlands Institute of Primary Care. The Institute has undertaken a mammoth survey of mobility and medical interventions which cost 10 million guilders. There are two inter-linked surveys. One consists of 300,000 episodes of illness (level 1) for 161 GP's (level 2) in 103 practices (level 3). The other survey consists of 13,000 health survey questionnaires for the same GP's and practices. We are beginning this project with the simpler second data set, focusing on the existence of geographical differences in morbidity for such illness as hypertension, heart disease and bronchitis when respondent-level composition effects of age, gender and occupation are taken into account.

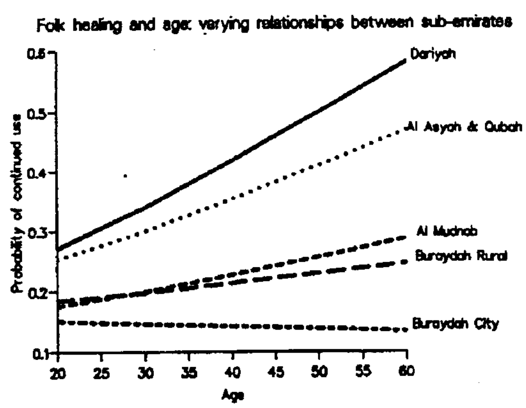

Figure for project two

Monthly Data Analysis Clinic Continuing in London

Having started last December, the monthly data analysis clinic has worked with a number of *ML3* users. Most of them came to talk to members of the Project team about non-linear curve modelling and multilevel models for repeated measures data.

The clinic, held in Room 683 at the Institute of Education is free for users of *ML3*. Hours are 10:00 am to 5:00 pm. The next dates are as follows:

<u>Tuesday November 26 1991</u>
<u>Tuesday December 10 1991</u>
<u>Tuesday January 14 1992</u>
<u>Tuesday February 11 1992</u>
<u>Tuesday March 10 1992</u>

Persons wishing to participate please call *Min Yang on 071 612 6682* first to make an appointment.

LONDON WORKSHOP NOTICE

On 3-5 December, 1991, the Multilevel Models Project will offer another workshop on three-level models at the Institute of Education of the University of London. The three-day session is designed to present the fundamentals of multilevel modelling together with some more advanced topics such as non-linear curve modelling and multivariate modelling. The emphasis is on data analytic practice rather than theoretic methodology. No fee is charged for attending the workshop. The tentative timetable is as follows:

3rd (a.m.) Registration, introductory seminar and hands-on practice with example data set by using *ML3*.
3rd (aft.) Modelling of repeated measures data and practice in using *ML3* to analyze repeated measures data.
3rd (eve.) Analysis of participants' data.
4th (a.m.) Three-level modelling with examples, and practice in analyzing three-level data by using *ML3*.
4th (aft.) Multivariate multilevel models with examples.
4th (eve.) Analysis of participants' data.
5th (a.m.) Continuing analysis of participants' data.
5th (aft.) Participants present results of analysis.

NEWS & BOOKS

Further information and application form are available from *Min Yang* at the address on the front page.

It is hoped to mount a further workshop *19-21 May 1992.*

New Book Concerned with Effects of Schooling

Edited by *J Douglas Willms, Monitoring School Performance: A Non-technical Guide for Educational Administrators,* is published by *Falmer Press,* due late Autumn 1991.

Douglas Willms is an associate professor in University of British Columbia, and member of the Centre for Educational Sociology. His book evaluates methods of establishing and monitoring school systems either at the school, district, authority or state level, from a practical and theoretical viewpoint.

Intended as a general reference guide for determining the strengths and limitations of methods for making school comparisons, the book covers the analysis and interpretation of data on school performance. This has been facilitated by recent improvements in tests and survey instruments and in statistical methods and research design.

The contents consist of the following chapters:

*Introduction:Developing a System
*The Social and Political Context of Monitoring Systems
*Monitoring Systems and the Input-Output Model
*The Estimation of School Effects
*Schooling Outcomes
*Measures of School Progress
*Measuring Schooling Inputs
*A monitoring System for Elementary Schools in Canada
*A monitoring System for Secondary Schools in Scotland
*Descriptive Analyses for an Annual Report: Five Types of Analyses
*A Research Program Based on Performance Monitoring
*Summary and Appendix

The book will be of interest to Head Teachers, LEA administrators and other educationists who seek a better understanding of the validity of assessment derived from monitoring systems. An order form can be obtained from following address :

Alison Woodhead
Falmer Press, FREEPOST
Ranking Road
Basingstoke
Hampshire, RG240BR
ENGLAND

Data Analysis with ML3 Out Now

This is a sister book to *ML3-Software for Three-level Analysis, Users' Guide for V.2.* It will be published by the Multilevel Model Project team in the late Autumn.

As *ML3* has become more widely used, the team has become aware that many users have experienced difficulties with the specification, running and interpreting of their data. This can be put down partly to the novelty of the methodology but also to the complexity of *ML3*'s command language. Therefore this book is designed to be used as a supplement to the *ML3* manual. It has contributions from six experienced users working in substantive applied areas with detailed descriptions of an analysis of one of their own data sets. These descriptions are designed to take the reader through the process of setting up the model, carrying out the data analysis and interpreting the results. The readers will

NEWS & BOOKS

find something here which matches their own problems closely enough to provide a starting point and ideas to pursue. The contents are as follows:

*Multilevel Logistic Regression, by *Lindsay Paterson*
*Multilevel Item Response Models, by *Geoffrey Woodhouse*
*Repeated Measures Models, by *Ian Plewis*
*A Multilevel Analysis of Social Attitude Data, by *Karl Ashworth & Richard Wiggins*
*A Multilevel Bivariate Model, by *Michael Creswell*
*A Multilevel Model with Missing Data, by *Bob Prosser*

The price is £ 20 with 40% academic discount. An order form can be obtained by contacting the Multilevel Models Project at the address on the front page.

For those readers who are interested in carrying out the analyses described in this volume, a copy of some of the datasets used can be made available.

Replacement

Dr. *Min Yang* replaced *Bob Prosser* on the multilevel models project in September 1991.

IN THE NEXT ISSUE

* The Summer Holiday Effect and Multilevel Growth, a multilevel analysis

* Multilevel Modelling and Segregation Indices

* Book Review

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