<<多层统计分析模型>>

图书基本信息

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前言

Interest in multilevel statistical models for social science and public health studies has been aroused dramatically since the mid-1980s. New multilevel modeling techniques are giving researchers tools for analyzing data that have a hierarchical or clustered structure. Multilevel models are now applied to a wide range of studies in sociology, population studies, education studies, psychology, economics, epidemiology, and public health.Individuals and social contexts （e.g., communities, schools, organizations, or geographic locations） to which individuals belong are conceptualized as a hierarchical system, in which individuals are micro units and contexts are macro units. Research interest often centers on whether and how individual outcome varies across contexts, and how the variation is explained by contextual factors; what and how the relationships between the outcome measures and individual characteristics vary across contexts, and how the relationships are influenced or moderated by contextual factors. To address these questions, studies often employ data collected from more than one level of observation units, i.e., observations are collected at both an individual level （e.g., students） and one or more contextual levels （e.g., schools, cities）. As a result, the data are characterized by a hierarchical structure in which individuals are nested within units at the higher levels. This kind of data is called hierarchically structured data or multilevel data. The conventional single-level statistical methods, such as ordinary least square（OLS） regression are inappropriate for analysis of multilevel data because observations are nonindependent and the contextual effects cannot be addressed appropriately in such models. Multilevel modeling not only takes into account observation dependence in the multilevel data, but also provides a more meaningful conceptual framework by allowing assessment of both individual and contextual effects, as well as cross-level interaction effects.This book covers a broad range of topics about multilevel modeling. Our goal is to help students and researchers who are interested in analysis of multilevel data to understand the basic concepts, theoretical frameworks and application methods of multilevel modeling. This book is written in non-mathematical terms, focusing on the methods and application of various multilevel models, using the internationally widely used statistical software, the Statistics Analysis System （SAS）. Examples are drawn from analysis of real-world research data. We focus on twolevel models in this book because it is most frequently encountered situation in real research. These models can be readily expanded to models with three or more levels when applicable. A wide range of linear and non-linear multilevel models are introduced and demonstrated.

内容概要

Multilevel Models: Appfications Using SAS is written in nontechnical terms, focuses on the methods and applications of various multilevel models, including liner multilevel models,multilevel logistic regression models, multilevel Poisson regression models, multilevel negative binomial models, as well as some cutting-edge applications, such as multilevel zero-inflated Poisson (ZIP) model, random effect zero-inflated negative binomial model (RE-ZINB), mixed-effect mixed-distribution models, bootstrapping multilevel models, and group-based trajectory models. Readers will learn to build and apply multilevel models for hierarchically structured cross-sectional data and longitudinal data using the internationally distributed software package Statistics Analysis System (SAS). Detailed SAS syntax and output are provided for model applications, providing students, research scientists and data analysts with ready templates for their applications.

作者简介

作者：王济川 谢海义 (美国) 费舍余 (Fisher.J.) Dr. Jichuan Wang is a professor in the Center for Clinical and Community Research, the Children's National Medical Center, the George Washington Universty School of Medicine.Dr. Haiyi Xie is an associate professor of Community and Family Medicine, Dartmouth Medical School, Dartmouth College.Dr. James Henry Fisher is a senior planner for the HancockCounty Planning Commission in EIIsworth, Maine.

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章节摘录

插图：In the linear model case, this integral can be solved in closed form, and the resulting likelihood or restricted likelihood can be maximized directly. For nonlinear multilevel models, however, the integral is usually unknown and must be approximated. Many methods have been proposed for such maximization approximation. Two basic methods are: 1） linearizati'on, which approximates the integrated likelihood function using techniques such as Taylor series expansion, 2） integral approximation with numerical methods. These approaches are implemented in two SAS procedures, PROC GLIMMIX and PROC NLMIXED and two macros, %GLIMMIX and %NLMIXED, respectively.Prior to the current version of SAS （SAS 9.2） （SAS Institute Inc., 2008）, PROC GLIMMIX is solely based on linearization methods. In version 9.2 of PROC GLIMMIX, linearization is the default estimation method, and two numerical integration methods——Laplace approximation method and adaptive Gauss-Hermite quadrature have been added as options. The linearization method is also called a pseudo-likelihood method, in which pseudo-data are generated from the original data, and likelihood function is approximated using Taylor series expansions （Schabenberger, 2005）. The essential idea of the linearization method is to approximate GLMM using normal linear mixed model estimates repeatedly. Among the various linearization methods available in the procedure, the default method is the restricted or residual pseudo-likelihood （REPL） （Wolfinger & O'Connell, 1993）. The maximization of the pseudo-likelihood can be carried out by various optimization techniques in PROC GLIMMIX. The default optimization technique is the Newton-Raphson algorithm.The major advantages of linearization-based methods include: First, they can fit models for which the joint distribution is difficult or impossible to ascertain. Second, compared with numerical integration methods, they allow a larger number of random effects to be estimated in the model. Third, the variance/covariance structure of the level-1 residual matrix （i.e., R matrix） can be readily accommodated. Fourth, the model is iteratively estimated based on the linear mixed model, thus both ML and REML are available for model estimation （Schabenberger, 2005）. In addition, in our experience, linearization based models are much faster to run.The disadvantages of linearization-based methods include: First, they are based on iterative model estimation using pseudo-data constructed from the original data; as such, they do not have a real likelihood, and therefore -2LL or deviance statistic cannot be used for model comparisons. Second, PROC GLIMMIX does not support a broad array of variance/covariance structures of the R matrix that you can draw on with the PROC MIXED procedure （Schabenberger, 2005）.

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