

Modeling Integrated Data

John M. Abowd
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Outline

- Application of the grouping algorithm
- Further discussion of the methods
- Discussion of software

Characteristics of the Groups

Table 4: Results of Applying the Grouping Algorithm to the Pooled Data Set

	<i>Largest Group</i>	<i>Second Largest Group</i>	<i>Average of All Other Groups</i>	<i>Total of All Groups</i>
Observations	285,402,315	90	4.3	287,241,891
Persons	64,441,382	38	1.5	68,329,212
Firms	3,200,067	8	1.1	3,662,974
Groups	1	1	430,529	430,531
Estimable Effects	67,641,448	45		71,992,185

Notes: The "pooled" data are comprised of annual observations from California, Florida, Illinois, Maryland, Minnesota, North Carolina, and Texas over the period 1986-2000. No single state contributed observations for all years. See Table 1. *Sources:* Author's calculations using the LEHD Program data base.

Estimation by Direct Solution of Least Squares

- Once the grouping algorithm has identified all estimable effects, we solve for the least squares estimates by direct minimization of the sum of squared residuals.
- This method, widely used in animal breeding and genetics research, produces a unique solution for all estimable effects.

Least Squares Conjugate Gradient Algorithm

- The matrix Δ is chosen to precondition the normal equations.

$$\Delta = \text{diagonal elements of } \begin{bmatrix} X'X & X'D & X'F \\ D'X & D'D & D'F \\ F'X & F'D & F'F \end{bmatrix}$$

- The data matrices and parameter vectors are redefined as shown.

$$y = [X \mid D \mid F] \Delta^{-1/2} \Delta^{1/2} \begin{bmatrix} \beta \\ \theta \\ \psi \end{bmatrix} + \varepsilon \equiv Z\delta + \varepsilon$$

$$Z \equiv [X \mid D \mid F] \Delta^{-1/2} \text{ and } \delta \equiv \Delta^{1/2} \begin{bmatrix} \beta \\ \theta \\ \psi \end{bmatrix}$$

LSCG (II)

- The goal is to find δ to solve the least squares problem shown.
- The gradient vector g figures prominently in the equations.
- The initial conditions for the algorithm are shown.
 - e is the vector of residuals.
 - d is the direction of the search.

$$\hat{\delta} = \operatorname{argmin}_{\delta} [(y - Z\delta)'(y - Z\delta)]$$

$$0 = \frac{1}{2} \frac{\partial (y - Z\delta)'(y - Z\delta)}{\partial \delta} = Z'(y - Z\delta) \equiv g$$

$$\tau_{-1} = 0$$

$$d_{-1} = 0$$

$$\delta_0 = 0$$

$$e_0 = y - Z\delta_0$$

$$g_0 = Z'e_0 = Z'y - Z'Z\delta_0$$

$$d_0 = g_0$$

$$\rho_0 = g_0'g_0$$

$$\lambda_0 = 0$$

LSCG (III)

- The loop shown has the following features:
 - The search direction d is the current gradient plus a fraction of the old direction.
 - The parameter vector δ is updated by moving a positive amount in the current direction.
 - The gradient, g , and residuals, e , are updated.
 - The original parameters are recovered from the preconditioning matrix.

For $\ell = 0, 1, 2, 3, \dots$

$$d_\ell = g_\ell + \tau_{\ell-1} d_{\ell-1}$$

$$q_\ell = Z d_\ell$$

$$\lambda_\ell = \rho_\ell / (q_\ell' q_\ell)$$

$$\delta_{\ell+1} = \delta_\ell + \lambda_\ell d_\ell$$

$$e_{\ell+1} = e_\ell - \lambda_\ell q_\ell$$

$$g_{\ell+1} = Z' e_{\ell+1}$$

$$\begin{bmatrix} \beta_{\ell+1} \\ \theta_{\ell+1} \\ \psi_{\ell+1} \end{bmatrix} = \Delta^{-1/2} \delta_{\ell+1}$$

LSCG (IV)

- Verify that the residuals are uncorrelated with the three components of the model.
 - Yes: the LS estimates are calculated as shown.
 - No: certain constants in the loop are updated and the next parameter vector is calculated.

$$[X\beta_{\ell+1} \quad D\theta_{\ell+1} \quad F\psi_{\ell+1}]' e_{\ell+1} \begin{cases} < \begin{bmatrix} c \\ c \\ c \end{bmatrix}, \text{ stop } \hat{\delta} = \delta_{\ell+1} \\ \text{else, continue} \end{cases}$$

$$\rho_{\ell+1} = (g_{\ell+1}' g_{\ell+1})$$

$$\tau_{\ell} = \rho_{\ell+1} / \rho_{\ell}$$

$$\begin{bmatrix} \hat{\beta} \\ \hat{\theta} \\ \hat{\psi} \end{bmatrix} = \Delta^{-1/2} \hat{\delta}$$

$$S = (y - Z\hat{\delta})(y - Z\hat{\delta})'$$

Mixed Effects Assumptions

$$\Lambda = \begin{bmatrix} \Sigma_1 & 0 & \dots & 0 \\ 0 & \Sigma_2 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & \Sigma_N \end{bmatrix} \quad \mathbb{E} \begin{bmatrix} \theta \\ \psi \end{bmatrix} \Big| X = 0 \quad \mathbb{V} \begin{bmatrix} \theta \\ \psi \end{bmatrix} \Big| X = \Omega$$

- The assumptions above specify the complete error structure with the firm and person effects random.
- For maximum likelihood or restricted maximum likelihood estimation assume joint normality.

Estimation by Mixed Effects Methods

$$\begin{bmatrix} X' \Lambda^{-1} X & X' \Lambda^{-1} [D \mid F] \\ \left[\begin{array}{c} D' \\ \hline F' \end{array} \right] \Lambda^{-1} X & \left[\begin{array}{c} D' \\ \hline F' \end{array} \right] \Lambda^{-1} [D \mid F] + \Omega^{-1} \end{bmatrix} \begin{bmatrix} \beta \\ \theta \\ \psi \end{bmatrix} = \begin{bmatrix} X' \Lambda^{-1} y \\ \left[\begin{array}{c} D' \\ \hline F' \end{array} \right] \Lambda^{-1} y \end{bmatrix}$$

- Solve the mixed effects equations
- Techniques: Bayesian EM, Restricted ML

Relation Between Fixed and Mixed Effects Models

$$\Lambda = \sigma_{\varepsilon}^2 I_{N^*} \quad |\Omega| \rightarrow \infty$$

- Under the conditions shown above, the ME and estimators of all parameters approaches the FE estimator

Correlated Random Effects vs. Orthogonal Design

$X'D = 0$ orthogonal personal characteristics and person - effect design

$X'F = 0$ orthogonal personal characteristics and firm - effect design

$D'F = 0$ orthogonal person - effect and firm - effect designs

- Orthogonal design means that characteristics, person design, firm design are orthogonal.
- Uncorrelated random effects means that Ω is diagonal.

Software

- SAS: proc mixed
- ASREML
- aML
- SPSS: Linear Mixed Models
- STATA: xtreg, glamm, xtmixed
- R: the lme() function
- S+: linear mixed models
- Gauss
- Matlab
- Genstat: REML