

Fast and accurate modelling of longitudinal neuroimaging data

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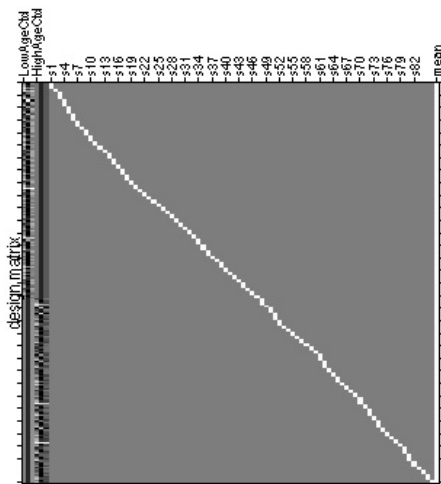
OHBM, 2012

An example of a longitudinal study in brainimaging

fMRI study of longitudinal changes in a population of adolescents at risk for alcohol abuse linked to Heitzeg et al. (2010)

- ▶ 86 subjects
- ▶ 2 groups (Low risk: 47 subj. and High risk: 39 subj.)
- ▶ Missing data (1, 2, 3 or 4 scans/subject)
- ▶ Go/No-go task
- ▶ No common time points

2nd-level standard modelling in SPM

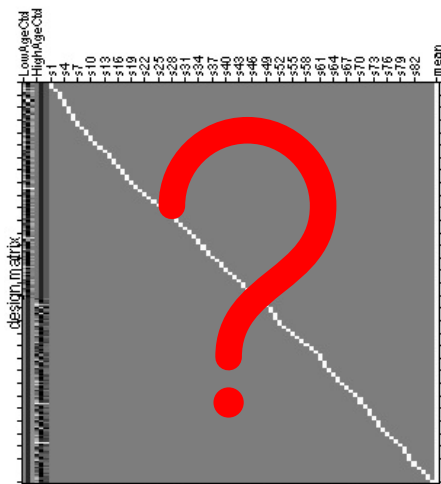


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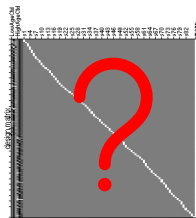


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2nd-level standard modelling in SPM



Only valid under **Compound Symmetry**:

$$\text{var}(y_i) = \sigma^2 \begin{pmatrix} 1 & \rho & \dots & \rho \\ \rho & 1 & \dots & \rho \\ \vdots & \vdots & \ddots & \vdots \\ \rho & \rho & \dots & 1 \end{pmatrix}$$

Is there an alternative method?

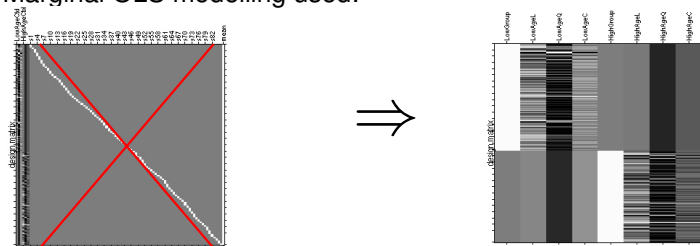
- ▶ Gold standard method for longitudinal data in Biostatistics: Linear Mixed Effects (LME) modelling (Laird and Ware, 1982) :

$$y_i = \underbrace{X_i\beta}_{\text{Fixed effects}} + \underbrace{Z_i b_i}_{\text{Random effects}} + e_i$$

- ▶ Unfortunately, LME has drawbacks:
 - ▶ Random effects not easy to specify
 - ▶ Use of iterative algorithms
 - ▶ generally slow
 - ▶ may fail to converge to a solution:
E.g., 12 subjects, 8 visits, Toeplitz (linearly decaying) correlation struct., LME with unstructured intra-visit correlation fails to converge 95 % of the time.
E.g., 12 subjects, 8 visits, Compound Symmetry , LME with random int. and random slope fails to converge 2 % of the time.

The Sandwich Estimator (SwE) method

- ▶ Marginal OLS modelling used:



$$y_i = \underbrace{X_i \beta}_{\text{Fixed effects}} + \underbrace{\beta_{0i}}_{\text{Subject indicator covariates}} + e_i$$

- ▶ β estimated by OLS estimate $\hat{\beta}_{OLS}$
- ▶ $\text{var}(\hat{\beta}_{OLS})$ estimated by the Sandwich Estimator (Eicker, 1963):

$$\text{SwE} = \underbrace{\left(\sum_{i=1}^M X_i' X_i \right)^{-1}}_{\text{Bread}} \underbrace{\left(\sum_{i=1}^M X_i' \hat{V}_i X_i \right)}_{\text{Meat}} \underbrace{\left(\sum_{i=1}^M X_i' X_i \right)^{-1}}_{\text{Bread}}$$

$$\text{with } \hat{V}_i = r_i r_i' \text{ and } r_i = y_i - X_i \hat{\beta}$$

The adjusted Sandwich Estimator (SwE) method

- ▶ SwE property:

$$\lim_{M \rightarrow +\infty} \text{SwE} = \text{var}(\hat{\beta}_{OLS})$$

→ **Large sample assumption**

- ▶ In order to enhance the accuracy of the SwE method in **small samples**, we propose to use:
 - ▶ Small sample bias adjustment (MacKinnon and White, 1985)
 - ▶ Small sample distributional adjustment of the statistical test Null distribution (Waldorp, 2009)
 - ▶ Assumption of a common covariance matrix among subjects

Assessment method

- ▶ Methods accuracy assessed by Null Gaussian Monte Carlo simulations (10,000 realizations)
- ▶ Metric used:

$$\text{Relative False Positive Rate (rel. FPR)} = \frac{E(\text{FPR}_{\text{Method}})}{\text{Nominal FPR}}$$

- ▶ 2 correlation structures tested:

Compound Symmetry

E.g., for subject 1:

$$\begin{pmatrix} 1 & 0.8 & 0.8 & 0.8 \\ 0.8 & 1 & 0.8 & 0.8 \\ 0.8 & 0.8 & 1 & 0.8 \\ 0.8 & 0.8 & 0.8 & 1 \end{pmatrix}$$

Non Compound Symmetry

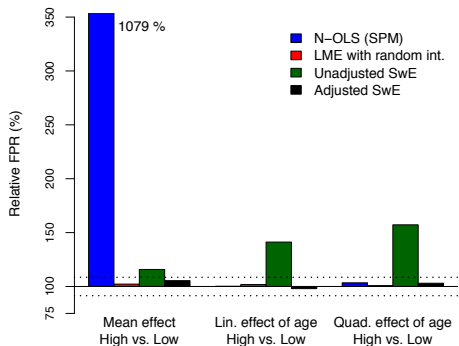
E.g., for subject 1:

$$\begin{pmatrix} 1 & 0.7 & 0.51 & 0.31 \\ 0.7 & 1 & 0.81 & 0.61 \\ 0.51 & 0.81 & 1 & 0.8 \\ 0.31 & 0.61 & 0.8 & 1 \end{pmatrix}$$

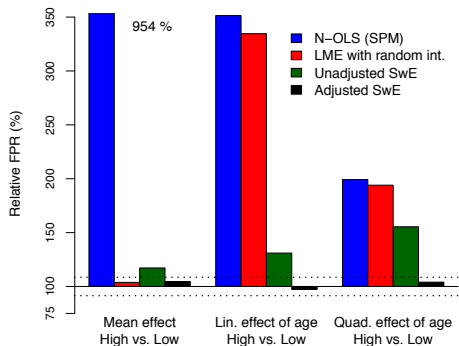
Simulation results

- ▶ F-test at 0.05 as level of significance

Compound Symmetry
Constant intra-visit correlation of 0.8



Non Compound Symmetry
Linear decay of the intra-visit correlation of 0.1/year



Summary

- ▶ Longitudinal standard methods not really appropriate to neuroimaging data:
 - ▶ LME
 - ▶ Difficult to specify
 - ▶ generally slow
 - ▶ Convergence issues
 - ▶ N-OLS
 - ▶ Issues when Compound Symmetry does not hold
 - ▶ Cannot accommodate pure between covariates (e.g., gender)
- ▶ The SwE method, particularly with small samples adjustments,
 - ▶ Accurate in a large range of settings
 - ▶ Easy to specify
 - ▶ No iteration needed
 - ▶ Quite fast
 - ▶ No convergence issues
 - ▶ Can accommodate pure between covariates (e.g., gender)

Acknowledgment

- ▶ Data
 - ▶ M. Heitzeg

- ▶ Funding
 - ▶ GlaxoSmithKline through the Marie Curie Initial Training Network "Neurophysics"