12. Selected topics

Sonja Greven

Summer Term 2015

Overview Chapter 12 - Selected topics

12.1 Joint models for longitudinal and event time data → see extra material

12.2 Stochastic time-varying covariates

12.3 Sample size in longitudinal studies

Stochastic time-varying covariates

Different types of covariates:

- Time-invariant covariates for each subject, e.g. gender, race, treatment group
- Time-varying covariates:
  - design-related, e.g.
    - time since baseline and its transformations such as t^2
    - treatment in a "crossover" study
  - stochastic time-varying covariates, e.g.
    - dietary intake
    - bloodmarker
    - air pollution
    - physical activity

Stochastic time-varying covariates

- In our models, we assumed a relationship for the mean

$$g(\mathsf{E}(Y_{ij}|\mathbf{X}_i)) = \mathbf{x}_{ij}^T\boldsymbol{\beta}.$$

- This implicitly assumes that $\mathsf{E}(Y_{ij}|\mathbf{X}_i)$ depends only on $\mathbf{x}_{ij}$:

$$\mathsf{E}(Y_{ij}|\mathbf{X}_i) = \mathsf{E}(Y_{ij}|\mathbf{x}_{i1}, \ldots, \mathbf{x}_{in_i}) = \mathsf{E}(Y_{ij}|\mathbf{x}_{ij}). \tag{12.1}$$

  This is true for time-invariant variables. For time-varying stochastic covariates, however, preceding or subsequent values of $\mathbf{x}_{ij}$ can 'confound' the relationship between Y_{ij} and $\mathbf{x}_{ij}$ and $\widehat{\boldsymbol{\beta}}$ can then be biased.

External and Internal Covariates

A covariate is called exogenous or external when

$$f(\mathbf{x}_{i,j+1}|\mathbf{x}_{i1},\ldots,\mathbf{x}_{ij},Y_{i1},\ldots,Y_{ij}) = f(\mathbf{x}_{i,j+1}|\mathbf{x}_{i1},\ldots,\mathbf{x}_{ij}).$$

Otherwise, the covariate is called internal or endogenous.

Examples:

- air pollution measured at a central monitor is external, as it does not depend on health outcomes
- personal air pollution exposure is internal if subjects with poor health outcomes change their behavior to avoid high air pollution exposures.

For an external covariate (and automatically for design-related covariates),

$$\mathsf{E}(Y_{ij}|\boldsymbol{X}_i) = \mathsf{E}(Y_{ij}|\mathbf{x}_{i1},\ldots,\mathbf{x}_{in_i}) = \mathsf{E}(Y_{ij}|\mathbf{x}_{i1},\ldots,\mathbf{x}_{ij}).$$

External Covariates

For external covariates, we can focus on specifying a model for $f(Y_{ij}|\mathbf{x}_{i1}, \ldots, \mathbf{x}_{ij})$. Possible models include

- concurrent, model $\mathsf{E}(Y_{ij}|\mathbf{x}_{ij})$
- lagged, model $\mathsf{E}(Y_{ij}|\mathbf{x}_{i,j-k})$ for some k
- cumulative, model $\mathsf{E}(Y_{ij}|\sum_{k=1}^{j} \mathbf{x}_{ik})$
- distributed lags, regression coefficients for $\mathbf{x}_{ij}, \ldots, \mathbf{x}_{i,j-k}$ follow some pre-specified structure (e.g. polynomial).

Note that e.g. modeling $\mathsf{E}(Y_{ij}|\mathbf{x}_{ij})$ while Y_{ij} depends on both $\mathbf{x}_{ij}$ **and** $\mathbf{x}_{i,j-1}$ can give misleading results.

Internal Covariates

When variables are internal, we have to think both about meaningful targets of inference and valid methods of inference. Methods include causal inference, and modeling of the joint process $\{Y_{ij}, \mathbf{x}_{ij}\}$.

Overview Chapter 12 - Selected topics

12.1 Joint models for longitudinal and event time data

12.2 Stochastic time-varying covariates

12.3 Sample size in longitudinal studies

Sample size in longitudinal studies

As an example, assume that we have

- N subjects **per group**
- $n_i = n$ measurements per subject (with equal time points t_j, but not necessarily equidistant)
- Two groups: placebo and therapy
- Model: LMM with linear group-specific trend, random intercept and slope per subject
- Null hypothesis: $\delta = 0$, where δ stands for the difference between the linear trends in groups A and B.

Sample size formula

For given type 1 error α and type 2 error β, the necessary sample size N to detect a difference δ then is

$$N = \frac{(Z_{(1-\alpha/2)} + Z_{(1-\beta)})^2 2\tilde{\sigma}^2}{\delta^2},$$

where

$$\tilde{\sigma}^2 = \sigma^2 \left\{ \sum_{j=1}^{n} (t_j - \bar{t})^2 \right\}^{-1} + d_{22}$$

with $\bar{t} = \sum_{j=1}^{n} t_j / n$, error variance σ^2 and random slope variance d_{22}. Thus, one needs to make assumptions about δ, σ^2 and d_{22} to calculate N.

The t_j are often chosen equidistantly with the study duration limited by organizational reasons. Then, N needs to be greater for given smaller n.

Comments and extensions

- The formula can be "reversed" to e.g. derive the power as a function of N.
- The formula can easily be adapted for groups of different sizes.
- The formula can easily be adapted for comparing other coefficients.
- The extension to non-normal responses is also possible.

For further discussion, see e.g. Diggle et al (2002), Fitzmaurice et al (2004).