

# Two-stage estimation and composite likelihood in the Poisson correlated Gamma-frailty model

Marta Fiocco, Hein Putter, Hans van Houwelingen

Leiden University Medical Center, The Netherlands

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M. Fiocco

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### Summary

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## Recurrent event data

- ▶ In medical studies subjects can experience recurrent or repeated events
- ▶ This implies correlation of event times within an individual

### Statistical models

- ▶ Two approaches:
  - ▶ Marginal approach: dependence between recurrent events is seen as nuisance
  - ▶ Frailty approach: model explicitly the correlation
- ▶ Model the event occurrences through counts
- ▶ Or number of events over period of time

## Poisson correlated Gamma frailty model

- ▶ Vector of event counts  $Y = (Y_1, \dots, Y_T)$
- ▶ General formulation:  $Z = (Z_1, \dots, Z_T)$  multivariate gamma frailty
  - ▶  $Z_t$  mean one, variance  $\xi$
  - ▶ Correlation between  $Z_s$  and  $Z_t$  equals  $\rho^{|s-t|}$
- ▶  $Y_1, \dots, Y_T$  are assumed conditionally independent given the frailties, with

$$Y_t | Z_t \sim \text{Po}(\mu_t Z_t),$$

with

$$\mu_t = \exp(\mathbf{x}_t^\top \boldsymbol{\beta}).$$

# Properties of Poisson correlated Gamma frailty

- ▶ Marginal  $Y_t \sim \text{NB}(\mu_t, \theta)$
- ▶  $EY_t = \mu_t$ ;  $\text{var} Y_t = \mu_t + \mu_t^2 \xi$
- ▶ Full joint distribution can be derived in theory from Laplace transform

$$P(Y_1 = y_1, \dots, Y_T = y_T) = \left( \prod_{t=1}^T \frac{\mu_t^{y_t}}{y_t!} \right) \cdot E\{Z_1^{y_1} \dots Z_T^{y_T} \exp(-\boldsymbol{\mu}^\top \mathbf{Z})\},$$

but is intractable in practice

## Estimation

- ▶ Henderson & Shimakura (2003) proposed to maximize the composite log-likelihood

$$\sum_{i=1}^N \sum_{1 \leq s \leq t \leq T} \log P(Y_s = y_s, Y_t = y_t)$$

jointly over all parameters  $\beta, \theta, \rho$

- ▶ Two problems occurred when we tried to implement this
  - ▶ Serious rounding errors for high counts
  - ▶ Maximization over large number of parameters
  - ▶ (No flexible software available)

# Estimation

- ▶ A further rearrangement is possible when counts are very high
- ▶ In our case this arrangement does not work
- ▶ Normal approximation in case of high counts is not good!

# Solutions

- ▶ Rounding errors:
  - ▶ Alternative multivariate Gamma distribution: to be used as frailty vector in a Poisson model for longitudinal count data.
  - ▶ The new Gamma distribution is based on renewal processes.
- ▶ Dimension problem: composite likelihood still entails a high-dimensional maximization problem
  - ▶ Two-stage approach

# New proposal

## Resulting distribution of $Y$

- ▶ Marginal still  $NB(\mu_t, \theta)$
- ▶ Full joint distribution still intractable
- ▶ Pairwise distribution:

$$\begin{aligned}
 P(Y_s = y_s, Y_t = y_t) &= \frac{\mu_s^{y_s} \mu_t^{y_t}}{y_s! y_t!} \times E(Z_s^{y_s} Z_t^{y_t} e^{\mu_s Z_s} e^{\mu_t Z_t}) \\
 &= \sum_{k=0}^{y_s} \sum_{l=0}^{y_t} E\left( e^{-\mu_s X_s - \mu_t X_t - (\mu_s + \mu_t) X_0} \cdot \frac{X_s^k X_0^{y_s - k}}{k! (y_s - k)!} \frac{X_t^l X_0^{y_t - l}}{l! (y_t - l)!} \mu_s^{y_s} \mu_t^{y_t} \right) \\
 &= \sum_{k=0}^{y_s} \sum_{l=0}^{y_t} P_{NB}(k; \mu_s(1 - \rho_{st}), \xi) \cdot P_{NB}(l; \mu_t(1 - \rho_{st}), \xi) \cdot \\
 &\quad P_{NB}(y_s + y_t - k - l; (\mu_s + \mu_t)\rho_{st}, \xi) \cdot \\
 &\quad P_{Bin}(y_s - k; y_s + y_t - k - l, \frac{\mu_s}{\mu_s + \mu_t})
 \end{aligned}$$

# Advantages

- ▶ No rounding errors, because the terms contributing to the sum are all products of probabilities, hence between 0 and 1
- ▶ It is possible to generate data from the multivariate proposed Gamma distribution for all values of  $\theta$ , not only for  $\theta = \frac{q}{2}$  as in Henderson & Shimakura (2003)

# Estimation for the Poisson-gamma mixed model

- ▶ Parameters:  $\beta, \theta, \rho$
- ▶ Full likelihood analysis requires the joint probability  $P(Y_{i1} = y_{i1}, \dots, Y_{iT} = y_{iT})$  which is intractable (no closed form)
- ▶ Alternative: Composite likelihood approach [Lindsay 1988] and two-stage estimation procedure
- ▶ First stage: Estimate  $\eta = (\beta, \theta)$ , applying composite likelihood only using marginals
- ▶ Second stage: the estimated values  $\hat{\beta}$  and  $\hat{\theta}$  are used in the composite likelihood based on all pairwise time points for estimating the correlation parameter  $\rho$

## First stage

- ▶ Composite likelihood using marginals negative binomial
  - ▶  $Y_{it} \sim \text{NB}(\mu_{it}, \theta)$ , with mean  $\mu_{it} = \exp(\mathbf{x}_{it}^T \beta)$
- ▶ For fixed  $\theta$ , the negative binomial distribution can be formulated as a GLM (with log-link).
- ▶ Can use `glm.nb` from MASS library in R
- ▶ Fits GLM for negative binomials by exploiting GLM-structure for fixed  $\theta$  and adding maximization of log-likelihood with respect to  $\theta$
- ▶ Standard errors for  $\eta = (\beta, \theta)$  are found using a sandwich estimator

## Second stage

- ▶ Estimate  $\rho$  using again composite likelihood based on all pairs of time points
- ▶ Composite log-likelihood contribution for subject  $i$  is

$$l_{2i}(\rho, \hat{\eta}) = \sum_{1 \leq s \leq t \leq T} \log P(Y_{is} = y_{is}, Y_{it} = y_{it})$$

- ▶ Total composite log-likelihood is sum over subjects
- ▶ Estimate  $\hat{\rho}$  is found as solution to the composite score equations with the estimate  $(\hat{\theta})$  from stage one plugged in:

$$\sum_{i=1}^N \frac{\partial l_{2i}(\rho, \hat{\eta})}{\partial \rho} = 0$$

- ▶ Advantage: only single parameter  $\rho$  to be estimated at this stage

## Standard errors

- ▶ Standard errors for the estimates of the parameters of interest  $\beta$ ,  $\theta$ , and  $\rho$  can be obtained in two ways
  - ▶ Parametric bootstrap: feasible since it is possible to generate data from the proposed multivariate Gamma distribution
  - ▶ Asymptotic theory (apply sandwich methodology)
    - ▶ The asymptotic variance of  $\hat{\rho}$  can also be estimated by a sandwich estimator, which also accounts for uncertainty of first stage estimator [Andersen 2004]
    - ▶ Actual formulas:

$$\begin{aligned} \text{var}(\hat{\eta}) &\approx \frac{1}{N} \cdot \mathbf{B}_1^{-1} \mathbf{M}_1 \mathbf{B}_1^{-1} \\ \text{var}(\hat{\rho}) &\approx \frac{1}{N} \cdot \left[ \mathbf{B}_2^{-1} \mathbf{M}_2 \mathbf{B}_2^{-1} - 2\mathbf{B}_2^{-1} \mathbf{B}_{12}^\top \mathbf{B}_1^{-1} \mathbf{M}_1 \mathbf{B}_1^{-1} \mathbf{B}_{12} \mathbf{B}_2^{-1} \right. \\ &\quad \left. + \mathbf{B}_2^{-1} \mathbf{B}_{12}^\top \mathbf{B}_1^{-1} \mathbf{M}_1 \mathbf{B}_1^{-1} \mathbf{B}_{12} \mathbf{B}_2^{-1} \right] \end{aligned}$$

## Application

- ▶ Data set consists of 65 patients used before in Henderson & Shimakura
- ▶ Counts in 12 successive intervals of equal length
- ▶ Estimate the baseline rate and the effect of the treatment
- ▶ Assumed same effect of the treatment for the 12 time points
- ▶ Counting model:  $y_t \sim \text{Po}((\beta_t + \gamma Z)Z_t)$ ,
- ▶  $Z_1, \dots, Z_{12}$  multivariate serially correlated gamma-frailty vector
- ▶  $Z = 0$  or  $Z = 1$  indicates treatment

## Two–stage estimation procedure

- ▶ First-stage: the regression parameters  $\beta$ ,  $\gamma$  and the overdispersion parameter  $\theta$  are simultaneously estimated based on the marginal negative binomial distribution
- ▶ Estimation via glm with a negative binomial family
- ▶ Second-stage: estimate  $\rho$  based on the joint distribution of the pair

### Compare one stage with two-stage estimation

- ▶  $\hat{\beta}$  and  $\hat{\theta}$  obtained with the two–stage procedure were identical, up to five decimals, to those obtained in Henderson & Shimakura, even though both the underlying gamma frailty process and the estimation method differed.
- ▶  $\hat{\rho} = 0.847$  with the two-stage procedure
- ▶  $\hat{\rho} = 0.849$  with Henderson & Shimakura’s method
- ▶ Standard errors in the procedures were also quite similar



## Simulation study

### Compare one-stage vs two-stage composite likelihood

- ▶ Study the robustness of our procedure against different frailty vectors
- ▶ Results from both estimation procedures were remarkably similar
- ▶ The efficiency of our two-stage estimation was 99% compared to the one-stage composite likelihood procedure of Henderson & Shimakura
- ▶ Estimates appeared to be quite robust to misspecification of the particular multivariate frailty distribution generating the count data.

## Summary

- ▶ We propose a new multivariate gamma distribution based on renewal processes
- ▶ The construction is based on the infinite divisibility property of the Gamma distribution
- ▶ The new multivariate gamma distribution has been used as a mixing distribution in a Poisson model for longitudinal count data
- ▶ Full likelihood is intractable, applied a composite likelihood and two-stage estimation procedure for estimating the parameters in the model
- ▶ Quantification of the loss of efficiency with respect to full likelihood requires further study

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