2020 Joint Statistical Meetings

Simon Bussy

simon.bussy@gmail.com

Lights: a generalized joint model for high-dimensional multivariate longitudinal data and censored durations

S. Bussy [1,2], A. Barbieri [3], S. Zohar [1], A.S. Jannot [1,4]

[1] INSERM, UMRS 1138, Centre de Recherche des Cordeliers, Paris, France.
[2] Califrais' Machine Learning Lab, Paris, France.
[3] INSERM, UMR 1219, Bordeaux Population Health Research Center, Univ. Bordeaux, France.
[4] Biomedical Informatics and Public Health Department, EGPH, APHP, Paris, France.

I. Introduction

Overview

- Deal with the problem of joint modeling of longitudinal data and censored durations

Overview

- Deal with the problem of joint modeling of longitudinal data and censored durations
- Large number of both longitudinal and time-independent features are available

Overview

- Deal with the problem of joint modeling of longitudinal data and censored durations
- Large number of both longitudinal and time-independent features are available
- Flexibility in modeling the dependency between the longitudinal features and the event time with appropriate penalties

Overview

- Deal with the problem of joint modeling of longitudinal data and censored durations
- Large number of both longitudinal and time-independent features are available
- Flexibility in modeling the dependency between the longitudinal features and the event time with appropriate penalties
- Inference achieved using an efficient and novel Quasi-Newton Monte Carlo Expectation Maximization algorithm

Use cases

- Predict the risk for an event of interest to occur quickly, taking into account simultaneously a huge number of longitudinal signals in a high-dimensional context

Use cases

- Predict the risk for an event of interest to occur quickly, taking into account simultaneously a huge number of longitudinal signals in a high-dimensional context
- Provides powerful interpretability by automatically pinpointing significant time-dependent and time-independent features

Use cases

- Predict the risk for an event of interest to occur quickly, taking into account simultaneously a huge number of longitudinal signals in a high-dimensional context
- Provides powerful interpretability by automatically pinpointing significant time-dependent and time-independent features

Real-time decision support

- Medical context $\rightarrow$ event of interest: survival time, re-hospitalization, relapse or disease progression ; longitudinal data: biomarkers or vital parameters measurements

Use cases

- Predict the risk for an event of interest to occur quickly, taking into account simultaneously a huge number of longitudinal signals in a high-dimensional context
- Provides powerful interpretability by automatically pinpointing significant time-dependent and time-independent features

Real-time decision support

- Medical context $\rightarrow$ event of interest: survival time, re-hospitalization, relapse or disease progression ; longitudinal data: biomarkers or vital parameters measurements
- Customer's satisfaction monitoring context $\rightarrow$ event of interest: time when a client churns ; longitudinal data: the client's activity recorded from account opening throughout the duration of the business relationship

High-dimensional framework

- Survival analysis

$$T = T^\star \wedge C \quad \text{and} \quad \Delta = \mathbb{1}_{\{T^\star \leq C\}}$$

High-dimensional framework

- Survival analysis

$$T = T^\star \wedge C \quad \text{and} \quad \Delta = \mathbb{1}_{\{T^\star \leq C\}}$$

- Time-independent features $X \in \mathbb{R}^p$ with $p \gg n$

High-dimensional framework

- Survival analysis

$$T = T^\star \wedge C \quad \text{and} \quad \Delta = \mathbb{1}_{\{T^\star \leq C\}}$$

- Time-independent features $X \in \mathbb{R}^p$ with $p \gg n$
- L longitudinal outcomes such that $L \gg n$ and

$$Y(t) = \big(Y^1(t), \dots, Y^L(t)\big)^\top \in \mathbb{R}^L$$

High-dimensional framework

- Survival analysis

$$T = T^\star \wedge C \quad \text{and} \quad \Delta = \mathbb{1}_{\{T^\star \leq C\}}$$

- Time-independent features $X \in \mathbb{R}^p$ with $p \gg n$
- L longitudinal outcomes such that $L \gg n$ and

$$Y(t) = \big(Y^1(t), \dots, Y^L(t)\big)^\top \in \mathbb{R}^L$$

- Heterogeneity of the population: latent subgroups

$$G \in \{0, \dots, K-1\}$$

High-dimensional framework

- Survival analysis

$$T = T^\star \wedge C \quad \text{and} \quad \Delta = \mathbb{1}_{\{T^\star \leq C\}}$$

- Time-independent features $X \in \mathbb{R}^p$ with $p \gg n$
- L longitudinal outcomes such that $L \gg n$ and

$$Y(t) = \big(Y^1(t), \dots, Y^L(t)\big)^\top \in \mathbb{R}^L$$

- Heterogeneity of the population: latent subgroups

$$G \in \{0, \dots, K-1\}$$

- Softmax link function for the latent class membership probability given time-independent features

$$\pi_{\xi_k}(x) = \mathbb{P}[G = k | X = x] = \frac{e^{x^\top \xi_k}}{\sum_{k=0}^{K-1} e^{x^\top \xi_k}}$$

II. Model

Submodels

Group-specific marker trajectories

- $h_l\Big(\mathbb{E}[Y^l(t)|b^l, G=k]\Big) = m_k^l(t) = u^l(t)^\top \beta_k^l + v^l(t)^\top b^l$
  with fixed effect parameters $\beta_k^l \in \mathbb{R}^{q_l}$ and subject-and-longitudinal outcome specific random effects $b^l \in \mathbb{R}^{r_l} \sim \mathcal{N}(0, D_{ll})$

Submodels

Group-specific marker trajectories

- $h_l\big(\mathbb{E}[Y^l(t)|b^l, G=k]\big) = m_k^l(t) = u^l(t)^\top \beta_k^l + v^l(t)^\top b^l$
  with fixed effect parameters $\beta_k^l \in \mathbb{R}^{q_l}$ and subject-and-longitudinal outcome specific random effects $b^l \in \mathbb{R}^{r_l} \sim \mathcal{N}(0, D_{ll})$
- $\mathrm{Cov}[b^l, b^{l'}] = D_{ll'}$ and

$$D = \begin{bmatrix} D_{11} & \cdots & D_{1L} \\ \vdots & \ddots & \vdots \\ D_{1L}^\top & \cdots & D_{LL} \end{bmatrix}$$

  the global variance-covariance matrix

Submodels

Group-specific marker trajectories

- $h_l\big(\mathbb{E}[Y^l(t)|b^l, G=k]\big) = m_k^l(t) = u^l(t)^\top \beta_k^l + v^l(t)^\top b^l$
  with fixed effect parameters $\beta_k^l \in \mathbb{R}^{q_l}$ and subject-and-longitudinal outcome specific random effects $b^l \in \mathbb{R}^{r_l} \sim \mathcal{N}(0, D_{ll})$
- $\mathrm{Cov}[b^l, b^{l'}] = D_{ll'}$

Group-specific risk of event

- $\lambda(t|G=k) = \lambda_0(t)\exp\left\{x^\top \gamma_{k,0} + \sum_{l=1}^{L}\sum_{a=1}^{\mathcal{A}} {\gamma_{k,a}^l}^\top \varphi_a(t, \beta_k^l, b^l)\right\}$

Submodels

Group-specific marker trajectories

- $h_l\big(\mathbb{E}[Y^l(t)|b^l, G=k]\big) = m_k^l(t) = u^l(t)^\top \beta_k^l + v^l(t)^\top b^l$ with fixed effect parameters $\beta_k^l \in \mathbb{R}^{q_l}$ and subject-and-longitudinal outcome specific random effects $b^l \in \mathbb{R}^{r_l} \sim \mathcal{N}(0, D_{ll})$
- $\mathrm{Cov}[b^l, b^{l'}] = D_{ll'}$

Group-specific risk of event

- $\lambda(t|G=k) = \lambda_0(t) \exp\Big\{x^\top \gamma_{k,0} + \sum_{l=1}^L \sum_{a=1}^{\mathcal{A}} {\gamma_{k,a}^l}^\top \varphi_a(t, \beta_k^l, b^l)\Big\}$
- Functionals $(\varphi_a)_{a\in\mathcal{A}}$

Description	$\varphi_a(t,\beta_k^l,b^l)$	$\frac{\partial\varphi_a(t,\beta_k^l,b^l)}{\partial\beta_k^l}$	Reference
Linear predictor	$m_k^l(t)$	$u^l(t)$	Chi and Ibrahim [2]
Random effects	b^l	$\mathbf{0}_{q_l}$	Hatfield et al. [3]
Time-dependent slope	$\frac{\mathrm{d}}{\mathrm{d}t} m_k^l(t)$	$\frac{\mathrm{d}}{\mathrm{d}t} u^l(t)$	Rizopoulos and Ghosh [4]
Cumulative effect	$\int_0^t m_k^l(s)\mathrm{d}s$	$\int_0^t u^l(s)\mathrm{d}s$	Andrinopoulou et al. [1]

Notations

- $\mathcal{D}_n = \big\{(x_1, y_1^1, \ldots, y_1^L, t_1, \delta_1), \ldots, (x_n, y_n^1, \ldots, y_n^L, t_n, \delta_n)\big\}$ with $y_i^l = (y_{i1}^l, \ldots, y_{in_i^l}^l)^\top \in \mathbb{R}^{n_i^l}$ and $y_{ij}^l = Y_i^l(t_{ij}^l)$

Notations

- $\mathcal{D}_n = \left\{(x_1, y_1^1, \ldots, y_1^L, t_1, \delta_1), \ldots, (x_n, y_n^1, \ldots, y_n^L, t_n, \delta_n)\right\}$ with $y_i^l = (y_{i1}^l, \ldots, y_{in_i^l}^l)^\top \in \mathbb{R}^{n_i^l}$ and $y_{ij}^l = Y_i^l(t_{ij}^l)$
- $y_i = ({y_i^1}^\top \cdots {y_i^L}^\top)^\top \in \mathbb{R}^{n_i}$ with $n_i = \sum_{l=1}^L n_i^l$

Notations

- $\mathcal{D}_n = \{(x_1, y_1^1, \dots, y_1^L, t_1, \delta_1), \dots, (x_n, y_n^1, \dots, y_n^L, t_n, \delta_n)\}$ with $y_i^l = (y_{i1}^l, \dots, y_{in_i^l}^l)^\top \in \mathbb{R}^{n_i^l}$ and $y_{ij}^l = Y_i^l(t_{ij}^l)$
- $y_i = ({y_i^1}^\top \cdots {y_i^L}^\top)^\top \in \mathbb{R}^{n_i}$ with $n_i = \sum_{l=1}^L n_i^l$
- $b_i = ({b_i^1}^\top \cdots {b_i^L}^\top)^\top \in \mathbb{R}^r$ with $r = \sum_{l=1}^L r_l$

Notations

- $\mathcal{D}_n = \big\{(x_1, y_1^1, \ldots, y_1^L, t_1, \delta_1), \ldots, (x_n, y_n^1, \ldots, y_n^L, t_n, \delta_n)\big\}$ with $y_i^l = (y_{i1}^l, \ldots, y_{in_i^l}^l)^\top \in \mathbb{R}^{n_i^l}$ and $y_{ij}^l = Y_i^l(t_{ij}^l)$
- $y_i = ({y_i^1}^\top \cdots {y_i^L}^\top)^\top \in \mathbb{R}^{n_i}$ with $n_i = \sum_{l=1}^L n_i^l$
- $b_i = ({b_i^1}^\top \cdots {b_i^L}^\top)^\top \in \mathbb{R}^{r}$ with $r = \sum_{l=1}^L r_l$
- Design matrices

$$U_i = \begin{bmatrix} U_{i1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & U_{iL} \end{bmatrix} \in \mathbb{R}^{n_i \times q} \text{ and } V_i = \begin{bmatrix} V_{i1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & V_{iL} \end{bmatrix} \in \mathbb{R}^{n_i \times r}$$

with $q = \sum_{l=1}^L q_l$ and where for all $l = 1, \ldots, L$, one writes

$$\begin{cases} U_{il} & = \big(u_i^l(t_{i1}^l)^\top \cdots u_i^l(t_{in_i^l}^l)^\top\big)^\top \in \mathbb{R}^{n_i^l \times q_l}, \\ V_{il} & = \big(v_i^l(t_{i1}^l)^\top \cdots v_i^l(t_{in_i^l}^l)^\top\big)^\top \in \mathbb{R}^{n_i^l \times r_l}. \end{cases}$$

Notations

- $\mathcal{D}_n = \left\{(x_1, y_1^1, \ldots, y_1^L, t_1, \delta_1), \ldots, (x_n, y_n^1, \ldots, y_n^L, t_n, \delta_n)\right\}$ with $y_i^l = (y_{i1}^l, \ldots, y_{in_i^l}^l)^\top \in \mathbb{R}^{n_i^l}$ and $y_{ij}^l = Y_i^l(t_{ij}^l)$
- $y_i = ({y_i^1}^\top \cdots {y_i^L}^\top)^\top \in \mathbb{R}^{n_i}$ with $n_i = \sum_{l=1}^L n_i^l$
- $b_i = ({b_i^1}^\top \cdots {b_i^L}^\top)^\top \in \mathbb{R}^{r}$ with $r = \sum_{l=1}^L r_l$
- Design matrices

$$U_i = \begin{bmatrix} U_{i1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & U_{iL} \end{bmatrix} \in \mathbb{R}^{n_i \times q} \text{ and } V_i = \begin{bmatrix} V_{i1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & V_{iL} \end{bmatrix} \in \mathbb{R}^{n_i \times r}$$

with $q = \sum_{l=1}^L q_l$ and where for all $l = 1, \ldots, L$, one writes

$$\begin{cases} U_{il} &= \left(u_i^l(t_{i1}^l)^\top \cdots u_i^l(t_{in_i^l}^l)^\top\right)^\top \in \mathbb{R}^{n_i^l \times q_l}, \\ V_{il} &= \left(v_i^l(t_{i1}^l)^\top \cdots v_i^l(t_{in_i^l}^l)^\top\right)^\top \in \mathbb{R}^{n_i^l \times r_l}. \end{cases}$$

- $\beta_k = ({\beta_k^1}^\top \cdots {\beta_k^L}^\top)^\top \in \mathbb{R}^{q}$

Notations

- $\mathcal{D}_n = \left\{(x_1, y_1^1, \ldots, y_1^L, t_1, \delta_1), \ldots, (x_n, y_n^1, \ldots, y_n^L, t_n, \delta_n)\right\}$ with $y_i^l = (y_{i1}^l, \ldots, y_{in_i^l}^l)^\top \in \mathbb{R}^{n_i^l}$ and $y_{ij}^l = Y_i^l(t_{ij}^l)$
- $y_i = ({y_i^1}^\top \cdots {y_i^L}^\top)^\top \in \mathbb{R}^{n_i}$ with $n_i = \sum_{l=1}^L n_i^l$
- $b_i = ({b_i^1}^\top \cdots {b_i^L}^\top)^\top \in \mathbb{R}^r$ with $r = \sum_{l=1}^L r_l$
- Design matrices

$$U_i = \begin{bmatrix} U_{i1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & U_{iL} \end{bmatrix} \in \mathbb{R}^{n_i \times q} \text{ and } V_i = \begin{bmatrix} V_{i1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & V_{iL} \end{bmatrix} \in \mathbb{R}^{n_i \times r}$$

with $q = \sum_{l=1}^L q_l$ and where for all $l = 1, \ldots, L$, one writes

$$\begin{cases} U_{il} &= \left(u_i^l(t_{i1}^l)^\top \cdots u_i^l(t_{in_i^l}^l)^\top\right)^\top \in \mathbb{R}^{n_i^l \times q_l}, \\ V_{il} &= \left(v_i^l(t_{i1}^l)^\top \cdots v_i^l(t_{in_i^l}^l)^\top\right)^\top \in \mathbb{R}^{n_i^l \times r_l}. \end{cases}$$

- $\beta_k = ({\beta_k^1}^\top \cdots {\beta_k^L}^\top)^\top \in \mathbb{R}^q$
- $M_{ik} = U_i \beta_k + V_i b_i \in \mathbb{R}^{n_i}$

Likelihood

- $\theta = \left(\xi_0^\top \cdots \xi_{K-1}^\top, \beta_0^\top \cdots \beta_{K-1}^\top, \phi^\top, \mathrm{vech}(D), \lambda_0(t), \gamma_0^\top \cdots \gamma_{K-1}^\top\right) \in \mathbb{R}^\vartheta$

Likelihood

- $\theta = \left(\xi_0^\top \cdots \xi_{K-1}^\top, \beta_0^\top \cdots \beta_{K-1}^\top, \phi^\top, \mathrm{vech}(D), \lambda_0(t), \gamma_0^\top \cdots \gamma_{K-1}^\top\right) \in \mathbb{R}^\vartheta$
- $f(y_i|b_i, G_i = k) = \exp\left\{(y_i \odot \Phi_i)^\top M_{ik} - c_\phi(M_{ik}) + d_\phi(y_i)\right\}$ with $\Phi_i = (\phi_1^{-1}\mathbf{1}_{n_i^1}{}^\top \cdots \phi_L^{-1}\mathbf{1}_{n_i^L}{}^\top)^\top \in \mathbb{R}^{n_i}$

Likelihood

- $\theta = \left(\xi_0^\top \cdots \xi_{K-1}^\top, \beta_0^\top \cdots \beta_{K-1}^\top, \phi^\top, \text{vech}(D), \lambda_0(t), \gamma_0^\top \cdots \gamma_{K-1}^\top\right) \in \mathbb{R}^\vartheta$
- $f(y_i|b_i, G_i = k) = \exp\left\{(y_i \odot \Phi_i)^\top M_{ik} - c_\phi(M_{ik}) + d_\phi(y_i)\right\}$ with $\Phi_i = (\phi_1^{-1}\mathbf{1}_{n_i^1}{}^\top \cdots \phi_L^{-1}\mathbf{1}_{n_i^L}{}^\top)^\top \in \mathbb{R}^{n_i}$
- Survival part:

$$f(t_i, \delta_i|b_i, G_i = k; \theta) = \left[\lambda(t_i|\mathcal{M}_k(t_i), G_i = k)\right]^{\delta_i} \times \exp\left\{-\int_0^{t_i} \lambda(s|\mathcal{M}_k(s), G_i = k)\mathrm{d}s\right\}$$

Likelihood

- $\theta = \left(\xi_0^\top \cdots \xi_{K-1}^\top, \beta_0^\top \cdots \beta_{K-1}^\top, \phi^\top, \mathrm{vech}(D), \lambda_0(t), \gamma_0^\top \cdots \gamma_{K-1}^\top\right) \in \mathbb{R}^\vartheta$
- $f(y_i|b_i, G_i = k) = \exp\left\{(y_i \odot \Phi_i)^\top M_{ik} - c_\phi(M_{ik}) + d_\phi(y_i)\right\}$ with $\Phi_i = (\phi_1^{-1}\mathbf{1}_{n_i^1}{}^\top \cdots \phi_L^{-1}\mathbf{1}_{n_i^L}{}^\top)^\top \in \mathbb{R}^{n_i}$
- Survival part:

$$f(t_i, \delta_i|b_i, G_i = k; \theta) = \Big[\lambda(t_i|\mathcal{M}_k(t_i), G_i = k)\Big]^{\delta_i} \times \exp\left\{-\int_0^{t_i} \lambda(s|\mathcal{M}_k(s), G_i = k)\mathrm{d}s\right\}$$

- Then, the likelihood writes

$$\ell_n(\theta) = n^{-1}\sum_{i=1}^n \log \int_{\mathbb{R}^r} \sum_{k=0}^{K-1} \pi_{\xi_k}(x_i) f(t_i, \delta_i|b_i, G_i = k; \theta) \times f(y_i|b_i, G_i = k; \theta) f(b_i; \theta)\mathrm{d}b_i$$

III. Inference

Penalization

- Penalized objective

$$\ell_n^{\mathrm{pen}}(\theta) = -\ell_n(\theta) + \sum_{k=0}^{K-1} \zeta_{1,k}\|\xi_k\|_{\mathrm{en},\eta} + \zeta_{2,k}\|\gamma_k\|_{\mathrm{sg}l_1,\tilde\eta} + \zeta_{3,k}\|\beta_k\|_{\mathrm{sg}l_1,\tilde\eta}$$

with the elasticnet penalty

$$\|z\|_{\mathrm{en},\eta} = (1-\eta)\|z\|_1 + \frac{\eta}{2}\|z\|_2^2$$

and the sparse group lasso penalty

$$\|z\|_{\mathrm{sg}l_1,\tilde\eta} = (1-\tilde\eta)\|z\|_1 + \tilde\eta \sum_{l=1}^{L} \|z^l\|_2$$

Penalization

- Penalized objective

$$\ell_n^{\text{pen}}(\theta) = -\ell_n(\theta) + \sum_{k=0}^{K-1} \zeta_{1,k}\|\xi_k\|_{\text{en},\eta} + \zeta_{2,k}\|\gamma_k\|_{\text{sg}l_1,\tilde{\eta}} + \zeta_{3,k}\|\beta_k\|_{\text{sg}l_1,\tilde{\eta}}$$

with the elasticnet penalty

$$\|z\|_{\text{en},\eta} = (1-\eta)\|z\|_1 + \frac{\eta}{2}\|z\|_2^2$$

and the sparse group lasso penalty

$$\|z\|_{\text{sg}l_1,\tilde{\eta}} = (1-\tilde{\eta})\|z\|_1 + \tilde{\eta}\sum_{l=1}^{L}\|z^l\|_2$$

- Resulting optimization problem

$$\hat{\theta} \in \text{argmin}_{\theta\in\mathbb{R}^{\vartheta}}\, \ell_n^{\text{pen}}(\theta)$$

QNMCEM algorithm (1/2)

- $\ell_n^{\mathsf{comp}}(\theta) = \ell_n^{\mathsf{comp}}(\theta; \mathcal{D}_n, \boldsymbol{b}, \boldsymbol{G})$

QNMCEM algorithm (1/2)

- $\ell_n^{\text{comp}}(\theta) = \ell_n^{\text{comp}}(\theta; \mathcal{D}_n, \boldsymbol{b}, \boldsymbol{G})$

Monte Carlo E-step

- $\mathcal{Q}_n(\theta, \theta^{(w)}) = \mathbb{E}_{\theta^{(w)}}[\ell_n^{\text{comp}}(\theta) | \mathcal{D}_n]$

QNMCEM algorithm (1/2)

- $\ell_n^{\text{comp}}(\theta) = \ell_n^{\text{comp}}(\theta; \mathcal{D}_n, \boldsymbol{b}, \boldsymbol{G})$

Monte Carlo E-step

- $\mathcal{Q}_n(\theta, \theta^{(w)}) = \mathbb{E}_{\theta^{(w)}}[\ell_n^{\text{comp}}(\theta) | \mathcal{D}_n]$
- Requires to compute expectations of the form

$$\mathbb{E}_{\theta^{(w)}}[g(b_i, G_i) | t_i, \delta_i, y_i] = \sum_{k=0}^{K-1} \pi_{ik}^{\theta^{(w)}} \int_{\mathbb{R}^r} g(b_i, G_i) f(b_i | t_i, \delta_i, y_i; \theta^{(w)}) \mathrm{d} b_i$$

for different functions g, where we denote

$$\pi_{ik}^{\theta^{(w)}} = \mathbb{P}_{\theta^{(w)}}[G_i = k | t_i, \delta_i, y_i]$$

QNMCEM algorithm (1/2)

- $\ell_n^{\text{comp}}(\theta) = \ell_n^{\text{comp}}(\theta; \mathcal{D}_n, \boldsymbol{b}, \boldsymbol{G})$

Monte Carlo E-step

- $\mathcal{Q}_n(\theta, \theta^{(w)}) = \mathbb{E}_{\theta^{(w)}}[\ell_n^{\text{comp}}(\theta) | \mathcal{D}_n]$
- Requires to compute expectations of the form

$$\mathbb{E}_{\theta^{(w)}}[g(b_i, G_i)|t_i, \delta_i, y_i] = \sum_{k=0}^{K-1} \pi_{ik}^{\theta^{(w)}} \int_{\mathbb{R}^r} g(b_i, G_i) f(b_i|t_i, \delta_i, y_i; \theta^{(w)}) \mathrm{d}b_i$$

for different functions g, where we denote

$$\pi_{ik}^{\theta^{(w)}} = \mathbb{P}_{\theta^{(w)}}[G_i = k|t_i, \delta_i, y_i]$$

- Monte Carlo approximations used for untractable integrals

QNMCEM algorithm (2/2)

Quasi-Newton M-step

- $\theta^{(w+1)} \in \text{argmin}_\theta \, \mathcal{Q}_n(\theta, \theta^{(w)}) + \sum_{k=0}^{K-1} \zeta_{1,k} \|\xi_k\|_{\text{en},\eta} + \zeta_{2,k} \|\gamma_k\|_{\text{sg}l_1,\tilde{\eta}} + \zeta_{3,k} \|\beta_k\|_{\text{sg}l_1,\tilde{\eta}}$

QNMCEM algorithm (2/2)

Quasi-Newton M-step

- $\theta^{(w+1)} \in \mathrm{argmin}_\theta \, \mathcal{Q}_n(\theta, \theta^{(w)}) + \sum_{k=0}^{K-1} \zeta_{1,k} \|\xi_k\|_{\mathrm{en},\eta} + \zeta_{2,k} \|\gamma_k\|_{\mathrm{sg}l_1,\tilde{\eta}} + \zeta_{3,k} \|\beta_k\|_{\mathrm{sg}l_1,\tilde{\eta}}$
- $D^{(w+1)} = n^{-1} \sum_{i=1}^{n} \hat{\mathbb{E}}_{\theta^{(w)}} [b_i b_i^\top | t_i, \delta_i, y_i]$

QNMCEM algorithm (2/2)

Quasi-Newton M-step

- $\theta^{(w+1)} \in \text{argmin}_\theta \ \mathcal{Q}_n(\theta, \theta^{(w)}) + \sum_{k=0}^{K-1} \zeta_{1,k} \|\xi_k\|_{\text{en},\eta} + \zeta_{2,k} \|\gamma_k\|_{\text{sg}l_1,\tilde{\eta}} + \zeta_{3,k} \|\beta_k\|_{\text{sg}l_1,\tilde{\eta}}$
- $D^{(w+1)} = n^{-1} \sum_{i=1}^n \hat{\mathbb{E}}_{\theta^{(w)}}[b_i b_i^\top | t_i, \delta_i, y_i]$
- $P_{n,k}^{(w)}(\xi_k) = -n^{-1} \sum_{i=1}^n \hat{\pi}_{ik}^{\theta^{(w)}} \log \pi_{\xi_k}(x_i)$

QNMCEM algorithm (2/2)

Quasi-Newton M-step

- $\theta^{(w+1)} \in \text{argmin}_\theta \, \mathcal{Q}_n(\theta, \theta^{(w)}) + \sum_{k=0}^{K-1} \zeta_{1,k} \|\xi_k\|_{\text{en},\eta} + \zeta_{2,k} \|\gamma_k\|_{\text{sg}l_1,\tilde{\eta}} + \zeta_{3,k} \|\beta_k\|_{\text{sg}l_1,\tilde{\eta}}$
- $D^{(w+1)} = n^{-1} \sum_{i=1}^n \hat{\mathbb{E}}_{\theta^{(w)}}[b_i b_i^\top | t_i, \delta_i, y_i]$
- $P_{n,k}^{(w)}(\xi_k) = -n^{-1} \sum_{i=1}^n \hat{\pi}_{ik}^{\theta^{(w)}} \log \pi_{\xi_k}(x_i)$
- $\xi_k^{(w+1)} \in \text{argmin}_{\xi_k \in \mathbb{R}^p} P_{n,k}^{(w)}(\xi_k) + \zeta_{1,k} \|\xi_k\|_{\text{en},\eta}$

QNMCEM algorithm (2/2)

Quasi-Newton M-step

- $\theta^{(w+1)} \in \operatorname{argmin}_\theta \mathcal{Q}_n(\theta, \theta^{(w)}) + \sum_{k=0}^{K-1} \zeta_{1,k} \|\xi_k\|_{\text{en},\eta} + \zeta_{2,k} \|\gamma_k\|_{\text{sg}l_1,\tilde{\eta}} + \zeta_{3,k} \|\beta_k\|_{\text{sg}l_1,\tilde{\eta}}$
- $D^{(w+1)} = n^{-1} \sum_{i=1}^n \hat{\mathbb{E}}_{\theta^{(w)}} [b_i b_i^\top | t_i, \delta_i, y_i]$
- $P_{n,k}^{(w)}(\xi_k) = -n^{-1} \sum_{i=1}^n \hat{\pi}_{ik}^{\theta^{(w)}} \log \pi_{\xi_k}(x_i)$
- $\xi_k^{(w+1)} \in \operatorname{argmin}_{\xi_k \in \mathbb{R}^p} P_{n,k}^{(w)}(\xi_k) + \zeta_{1,k} \|\xi_k\|_{\text{en},\eta}$
- L-BFGS-B to solve the problem

$$\begin{aligned} \text{minimize} \quad & P_{n,k}^{(w)}(\xi_k^+ - \xi_k^-) + \zeta_{1,k} \Big((1-\eta) \sum_{j=1}^p (\xi_{k,j}^+ + \xi_{k,j}^-) + \frac{\eta}{2} \|\xi_k{}^+ - \xi_k{}^-\|_2^2 \Big) \\ \text{subject to} \quad & \xi_{k,j}^+ \geq 0 \text{ and } \xi_{k,j}^- \geq 0 \text{ for } j = 1, \dots, p \end{aligned}$$

QNMCEM algorithm (2/2)

Quasi-Newton M-step

- $\theta^{(w+1)} \in \text{argmin}_\theta \, \mathcal{Q}_n(\theta, \theta^{(w)}) + \sum_{k=0}^{K-1} \zeta_{1,k} \|\xi_k\|_{\text{en},\eta} + \zeta_{2,k} \|\gamma_k\|_{\text{sg}l_1,\tilde{\eta}} + \zeta_{3,k} \|\beta_k\|_{\text{sg}l_1,\tilde{\eta}}$
- $D^{(w+1)} = n^{-1} \sum_{i=1}^n \hat{\mathbb{E}}_{\theta^{(w)}}[b_i b_i^\top | t_i, \delta_i, y_i]$
- $P_{n,k}^{(w)}(\xi_k) = -n^{-1} \sum_{i=1}^n \hat{\pi}_{ik}^{\theta^{(w)}} \log \pi_{\xi_k}(x_i)$
- $\xi_k^{(w+1)} \in \text{argmin}_{\xi_k \in \mathbb{R}^p} P_{n,k}^{(w)}(\xi_k) + \zeta_{1,k} \|\xi_k\|_{\text{en},\eta}$
- L-BFGS-B to solve the problem

$$\begin{aligned} &\text{minimize} \quad && P_{n,k}^{(w)}(\xi_k^+ - \xi_k^-) + \zeta_{1,k}\Big((1-\eta)\sum_{j=1}^p (\xi_{k,j}^+ + \xi_{k,j}^-) + \frac{\eta}{2}\|\xi_k{}^+ - \xi_k{}^-\|_2^2\Big) \\ &\text{subject to} \quad && \xi_{k,j}^+ \geq 0 \text{ and } \xi_{k,j}^- \geq 0 \text{ for } j = 1, \ldots, p \end{aligned}$$

- Similar tricks for $\beta_k^{(w+1)}$ and $\gamma_k^{(w+1)}$

QNMCEM algorithm (2/2)

Quasi-Newton M-step

- $\theta^{(w+1)} \in \text{argmin}_\theta\ \mathcal{Q}_n(\theta, \theta^{(w)}) + \sum_{k=0}^{K-1} \zeta_{1,k} \|\xi_k\|_{\text{en},\eta} + \zeta_{2,k} \|\gamma_k\|_{\text{sg}l_1,\tilde\eta} + \zeta_{3,k} \|\beta_k\|_{\text{sg}l_1,\tilde\eta}$
- $D^{(w+1)} = n^{-1} \sum_{i=1}^n \hat{\mathbb{E}}_{\theta^{(w)}}[b_i b_i^\top | t_i, \delta_i, y_i]$
- $P_{n,k}^{(w)}(\xi_k) = -n^{-1} \sum_{i=1}^n \hat\pi_{ik}^{\theta^{(w)}} \log \pi_{\xi_k}(x_i)$
- $\xi_k^{(w+1)} \in \text{argmin}_{\xi_k \in \mathbb{R}^p} P_{n,k}^{(w)}(\xi_k) + \zeta_{1,k} \|\xi_k\|_{\text{en},\eta}$
- L-BFGS-B to solve the problem

$$\begin{aligned} &\text{minimize} && P_{n,k}^{(w)}(\xi_k^+ - \xi_k^-) + \zeta_{1,k}\Big((1-\eta)\sum_{j=1}^p (\xi_{k,j}^+ + \xi_{k,j}^-) + \frac{\eta}{2}\|\xi_k{}^+ - \xi_k{}^-\|_2^2\Big) \\ &\text{subject to} && \xi_{k,j}^+ \geq 0 \text{ and } \xi_{k,j}^- \geq 0 \text{ for } j = 1, \ldots, p \end{aligned}$$

- Similar tricks for $\beta_k^{(w+1)}$ and $\gamma_k^{(w+1)}$
- Predictive marker $\hat{\mathcal{R}}_{ik} = \dfrac{\pi_{\hat\xi_k}(x_i)\hat f(t_i^{max}, y_i | b_i, G_i = k; \hat\theta)}{\sum_{k=0}^{K-1} \pi_{\hat\xi_k}(x_i)\hat f(t_i^{max}, y_i | b_i, G_i = k; \hat\theta)}$, which is an estimate of $\mathbb{P}_\theta[G_i = k | T_i^\star > t_i^{max}, y_i]$

V. Conclusion

Conclusion

- Prognostic method called lights introduced to deal with the problem of joint modeling of longitudinal data and censored durations, where a large number of longitudinal features are available

Conclusion

- Prognostic method called lights introduced to deal with the problem of joint modeling of longitudinal data and censored durations, where a large number of longitudinal features are available
- Penalization of the likelihood in order to perform feature selection and to prevent overfitting

Conclusion

- Prognostic method called lights introduced to deal with the problem of joint modeling of longitudinal data and censored durations, where a large number of longitudinal features are available
- Penalization of the likelihood in order to perform feature selection and to prevent overfitting
- New efficient estimation algorithm (QNMCEM) has been derived

Conclusion

- Prognostic method called lights introduced to deal with the problem of joint modeling of longitudinal data and censored durations, where a large number of longitudinal features are available
- Penalization of the likelihood in order to perform feature selection and to prevent overfitting
- New efficient estimation algorithm (QNMCEM) has been derived
- Automatically determines significant prognostic longitudinal features

Conclusion

- Prognostic method called lights introduced to deal with the problem of joint modeling of longitudinal data and censored durations, where a large number of longitudinal features are available
- Penalization of the likelihood in order to perform feature selection and to prevent overfitting
- New efficient estimation algorithm (QNMCEM) has been derived
- Automatically determines significant prognostic longitudinal features

Python 3 package

- Available at `https://github.com/Califrais/lights`

Conclusion

- Prognostic method called lights introduced to deal with the problem of joint modeling of longitudinal data and censored durations, where a large number of longitudinal features are available
- Penalization of the likelihood in order to perform feature selection and to prevent overfitting
- New efficient estimation algorithm (QNMCEM) has been derived
- Automatically determines significant prognostic longitudinal features

Python 3 package

- Available at `https://github.com/Califrais/lights`
- Applications of the model available soon on an `arXiv` paper.

Thank you!

References

[1] Eleni-Rosalina Andrinopoulou, Dimitris Rizopoulos, Johanna JM Takkenberg, and Emmanuel Lesaffre. Combined dynamic predictions using joint models of two longitudinal outcomes and competing risk data. *Statistical methods in medical research*, 26(4):1787–1801, 2017.

[2] Yueh-Yun Chi and Joseph G Ibrahim. Joint models for multivariate longitudinal and multivariate survival data. *Biometrics*, 62(2):432–445, 2006.

[3] Laura A Hatfield, Mark E Boye, and Bradley P Carlin. Joint modeling of multiple longitudinal patient-reported outcomes and survival. *Journal of Biopharmaceutical Statistics*, 21(5): 971–991, 2011.

[4] Dimitris Rizopoulos and Pulak Ghosh. A bayesian semiparametric multivariate joint model for multiple longitudinal outcomes and a time-to-event. *Statistics in medicine*, 30(12):1366–1380, 2011.