Tumor size evolution in randomized clinical trials: joint modeling approach and dynamic predictions

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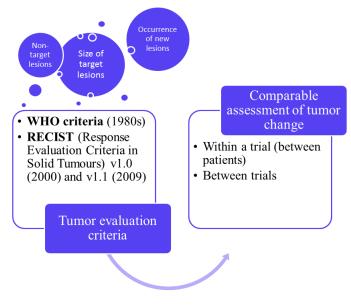
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Tumor evaluations in clinical trials



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Categorical criteria - RECIST and WHO

WHO

- Bidimensional size, target lesions determined before treatment
- Progression : >25% increase of one or more target lesions
- ▶ Appearance of new lesions → global progression

• **RECIST** (v1.1)

- Unidimensional size, max 2 lesions per organ and up to 5 total
- Progression: >20% increase over smallest sum observed (> 5 mm absolute increase)
- ▶ Appearance of new lesions → global progression
- 4 categories (Complete Response, Partial Response, Progressive Disease, Stable Disease)
 - ⇒ dichotomization : response or no response / progression or no progression

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Measurement of lesions



 The longest diameters measured in the plane in which the images were acquired

- Measure the longest diameter of a lesion
- Measure the longest perpendicular diameter to it and the burden is their product (WHO criteria)
- Total individual tumor burden is the sum (of the longest diameters - RECIST, of the products - WHO)
- Baseline: no more than 4 weeks before treatment, Follow-up: every 6-8 weeks

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Introduction

Measurability of lesions

- Measurable tumor lesions at least one diameter with a minimum size of :
 - 10 mm by CT scan
 - 10 mm caliper measurement by clinical exam
 - 20 mm by chest X-ray

Lymph nodes: >15 mm in *short* axis when assessed by CT scan

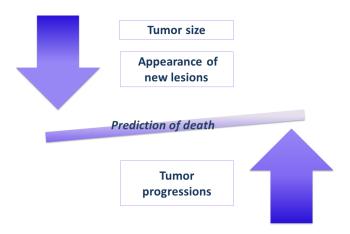
- Non-measurable tumor lesions.
 - small lesions (longest diameter <10 mm)
 - truly non-measurable lesions, eg. leptomeningeal disease, ascites, inflammatory breast disease

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Objective

Does the continuous tumor size and/or appearance of new lesions enable better prediction of the OS than times of progression?



Reference: Król et al. Biometrics, 2016.

Observed data

For individual i (i = 1, ..., N) we observe :

- Longitudinal biomarker : $Y_i(t_{ik})$
- Recurrences : $T_{ij} = \min(T_{ij}^*, C_i, T_i^*)$ and $\delta_{ij} = \mathbb{1}_{\{T_{ij}^* = T_{ij}\}}$
- Terminal event : $T_i = \min(C_i, T_i^*)$ and $\delta_i = \mathbb{1}_{\{T_i^* = T_i\}}$

Patient's death



Tumor size evolution



Appearance of new lesion

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Joint model for longitudinal data, recurrent events and a terminal event

System of linear mixed-effects model and two hazard functions:

$$\begin{cases} Y_{i}(t_{ik}) = m_{i}(t_{ik}) + \epsilon_{i}(t_{ik}) = \boldsymbol{X}_{i,l}(t_{ik})^{\top}\boldsymbol{\beta}_{l} + \boldsymbol{Z}_{i}(t_{ik})^{\top}\boldsymbol{b}_{i} + \epsilon_{i}(t_{ik}) & \text{(Biomarker)} \\ r_{ij}(t|v_{i},\boldsymbol{b}_{i}) = r_{0}(t) \exp\left(v_{i} + \boldsymbol{X}_{ij,r}^{\top}\boldsymbol{\beta}_{r} + g(\boldsymbol{b}_{i},t)^{\top}\boldsymbol{\eta}_{r}\right) & \text{(Recurrences)} \\ \lambda_{i}(t|v_{i},\boldsymbol{b}_{i}) = \lambda_{0}(t) \exp\left(\alpha v_{i} + \boldsymbol{X}_{i,t}^{\top}\boldsymbol{\beta}_{t} + h(\boldsymbol{b}_{i},t)^{\top}\boldsymbol{\eta}_{t}\right) & \text{(Death)} \end{cases}$$

- $u_i = (\boldsymbol{b}_i^T, v_i)^T \sim \mathcal{N}(\mathbf{0}, \mathbf{B})$ with $\mathbf{B} = \begin{pmatrix} \mathbf{B_1} & \mathbf{0} \\ \mathbf{0} & \sigma_v^2 \end{pmatrix}$
- measurement errors iid, $\epsilon_i(t_{ik}) \sim \mathcal{N}(0, \sigma_{\epsilon}^2)$
- $g(\mathbf{b}_i, t)$ and $h(\mathbf{b}_i, t)$ link functions
- $r_0(t)$, $\lambda_0(t)$ baseline hazard functions

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Estimation

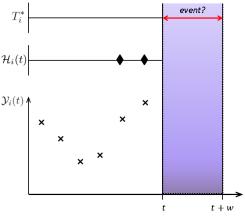
Joint marginal likelihood

$$L_i(\boldsymbol{\theta}) = \int_{\boldsymbol{u}_i} \prod_{k=1}^{n_i} f_{Y|\boldsymbol{u}_i}(Y_i(t_{ik})|\boldsymbol{u}_i;\boldsymbol{\theta}) \prod_{j=1}^{r_i} f_{T^r|\boldsymbol{u}_i}(T_{ij},\delta_{ij}|\boldsymbol{u}_i;\boldsymbol{\theta}) \cdot f_{T^t|\boldsymbol{u}_i}(T_i,\delta_i|\boldsymbol{u}_i;\boldsymbol{\theta}) f_{\boldsymbol{u}_i}(\boldsymbol{u}_i;\boldsymbol{\theta}) d\boldsymbol{u}_i$$

- n_i number of biomarker measurements of individual i. r_i - number of recurrent events of individual i
- ▶ Parameters to estimate $\theta = (\beta_t^\top, \beta_t^\top, \beta_t^\top, \eta_t^\top, \eta_t^\top, \alpha, r_0(\cdot), \lambda_0(\cdot), \mathbf{B}, \sigma_\epsilon)^\top$
- Penalized maximum likelihood estimation using Marquardt algorithm
- Baseline hazard functions approximation using splines : smooth estimation
- Integrals approximated using Gauss-Hermite quadrature

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Dynamic predictions



- \(\mathcal{H}_i(t)\) history of recurrences of individual \(i\) until \(t\)
 \(\mathcal{Y}_i(t)\) history of the biomarker of individual \(i\) until \(t\)
- Predicted probability of the terminal event T_i^* in a horizon [t, t + w]

$$\mathbb{P}(T_i^* \leq t + w | T_i^* > t, \mathcal{F}_i(t), \mathbf{X}_i; \boldsymbol{\theta})$$

$$\mathcal{F}_i(t) = \mathcal{H}_i(t),$$

$$\mathcal{F}_i(t) = \mathcal{Y}_i(t)$$

or
$$\mathcal{F}_i(t) = \{\mathcal{H}_i(t), \mathcal{Y}_i(t)\}$$

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Measures of predictive abilities

- EPOCE (Expected Prognostic Observed Cross-Entropy) Commenges et al., 2012
 - Evaluation of conditional density of the event given the individual history
 - Internal validation : approximate cross-validated estimator CVPOL_a
- Brier score
 - The inverse probability of censoring weighted error estimator (data-based Brier score) Gerds and Schumacher, 2006
 - Comparison of predictions and actual observed events
 - Internal validation : k-fold cross-validation

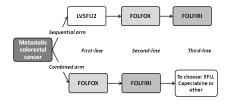
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Clinical trial FFCD 2000-05

• Follow-up:

Phase III randomized multi-center clinical trial (53 centers in France), 407 patients



- Tumor evaluation every 8 weeks, max 4 target lesions in 2 dimensions
- Change of line: progression (WHO criteria), unacceptable toxicity, decision of investigator

Ducreux et al., The Lancet Oncology, 2011

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Clinical trial FFCD 2000-05

Objectives :

- Which of longitudinal biomarker, times of appearance of new lesions or times of progression provide the most accurate prediction of the overall survival?
- To identify the prognostic factors on the outcomes of interest
- To evaluate the treatment effect.

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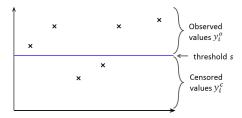
Data

Biomarker definition : sum of the longest diameters

$$SLD_{ij} = \sum_{k=1}^{n_{ij}} d_{ijk}, \ \ j = 0, 1, \dots, n_i, \ \ i = 1, \dots, 407$$

 $n_i \in \{0, 1, ..., 17\}$ - number of visits of individual i, $n_{ij} \in \{1, 2, 3, 4\}$ - number of target lesions measured during visit j, d_{ijk} - max diameter of lesion k measured during visit j of individual i

Left-censoring



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Data: FFCD 2000-05

N=402 patients analyzed. Observed:

- 6.18 tumor size measurements per patient
- 1.05 appearance of new lesions per patient
- 1.82 progression per patient
- 321 deaths
- Overall survival: 16.3 months in the combination (C) arm and 16 months in the sequential (S) arm

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Results of the trivariate model

Covariate	Biomarker : SLD		New lesions	Death
	Est. (SE)	p-value	HR (95% CI)	HR (95% CI)
Intercept	2.90 (0.29)	< 0.001	-	-
Time	-0.35(0.13)	0.006	-	-
Treatement (C/S)	-0.20(0.14)	0.16	0.96 (0.75-1.21)	1.02 (0.64-1.61)
Treatement (C/S) × Time	-0.42(0.15)	0.007	-	-
Age (60-69/<60 years)	0.23 (0.18)	0.20	0.75 (0.56-1.02)	1.04 (0.57-1.87)
Age (≥70/<60 years)	0.02 (0.16)	0.91	0.82 (0.61-1.09)	1.40 (0.79-2.49)
Sex (Women/Men)	0.27 (0.14)	0.06	0.86 (0.67-1.10)	1.02 (0.63-1.65)
Baseline WHO PS (1/0)	-0.14(0.15)	0.34	1.16 (0.89-1.51)	1.51 (0.85-2.68)
Baseline WHO PS (2/0)	0.45 (0.21)	0.035	2.15 (1.44-3.21)	10.22 (3.68-28.40)
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- Significant decreasing value of SLD with time (-0.35), and decreasing with time more pronounced for the combination arm (-0.40)
- Strong effect of WHO performance status 2 on the risk of death, new lesions and on tumor size
- No significant associations with gender and age
- Significant associations between the processes via the shared random effects (except of the link between the biomarker and recurrent events)

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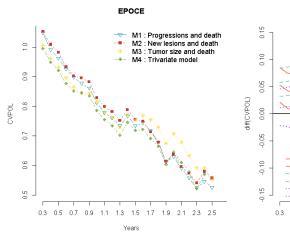
Comparison with the alternative models - predictive ability

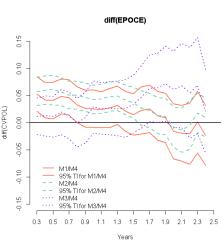
- Comparison of the models in terms of the predictive ability of the overall survival
 - Joint modelling of times of progression and time of death (M1)
 - Joint modelling of times of appearance of new lesions and time of death (M2)
 - Joint modelling of tumor size (SLD) and time of death (M3)
 - Joint modelling of tumor size (SLD), times of appearance of new lesions and time of death (M4)
- Measures of predictive ability using internal validation
 - Brier score (10-fold cross-validation)
 - ► **EPOCE** (CVPOL_a approximated cross-validation)

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Results - EPOCE

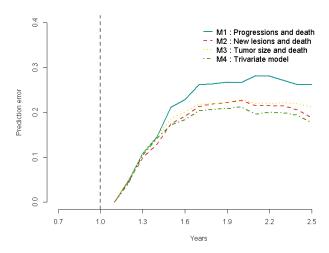




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Results - Brier score



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Conclusion

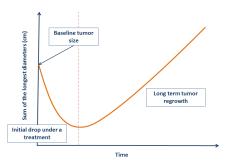
- Advantages of using joint models for simultaneous analysis of prognostic factors
- Comparison of joint models of different types in terms of predictive accuracy
- Proposition of a new trivariate joint model
- FFCD 2000-05: Improvement of predictive abilities using tumor size and appearance of new lesions
- Implementation of the proposed model into the R package frailtypack Rondeau et al., 2012

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Perspectives

- Incorporation of information on progression of non-target disease
- Application to other clinical trials, in particular to a meta-analysis
- More flexible modeling of the biomarker
 - Parametric approach : two slopes of time
 - Approximation by B-Splines
 - ► Tumor dynamics modeled using ordinary differential equations Claret et al., 2009



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