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Semi- and non-parametric competing risks analysis
of right censored data and failure cause
missing completely at random

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Abstract

We consider a nonparametric and a semiparametric (in presence of covariates) additive hazards rate competing risks model with censoring and failure cause possibly missing completely at random. Estimators of the unknown parameters are proposed in order to satisfy some optimality criteria. Large sample results are given for all the estimators. Our nonparametric method is applied to a real data set and the behavior of the semiparametric estimators are analyzed through a Monte Carlo study.

Key words: Additive hazards, competing risks, counting processes, missing failure cause, reliability, survival analysis.

1 Introduction

We consider $p \geq 2$ independent competing failure causes. We assume that to each failure time T_j is associated a hazard rate function (risk function) λ_j with $1 \leq j \leq p$. The failure time T is the minimum of the p failure times associated to the p failure causes (this can be seen as a 1-out-of- p system in reliability), then we have $T = T_1 \wedge \dots \wedge T_p$. The failure time T can be censored by a censoring time C , then we observe $X = T \wedge C$ and $\delta = 1(T \leq C)$

where $1(\cdot)$ is the indicator function. Generally, when T is uncensored, that is for $\delta = 1$, the failure cause is known, which means that $\sum_{j=1}^p j1(T_j = T)$ is observed, but from times to times, it may happen that the failure cause is unknown and no partial information about the failure cause is available. In addition, a vector of explanatory variables denoted by Z and having potentially significant effects on the p failure times may be observed. In this paper we propose a model that allows to analyze such lifetime data from a semiparametric point of view in presence of covariates, and from a nonparametric point of view otherwise. We need to emphasize that our model extends some existing models in the semi-/non-parametric direction, however, the missingness mechanism is accounted here in the simplest way.

The problem of competing risks is not new and during the last two decades many models have been proposed in order to account that a system or an individual may fail or dead from several causes (see Crowder, 2001, for a large overview on the topic). In a number of real applications of competing risks models the authors have to face the problem of missing information (e.g. Miyakawa, 1984; Usher and Hodgson, 1988; Lin *et al.*, 1993; Schabe, 1994; Goetghebeur and Ryan, 1995; Guttman *et al.*, 1995; Reiser *et al.*, 1996; Basu *et al.*, 1999; Flehinger *et al.*, 2002; Craiu and Duchesne, 2004; Craiu and Reiser, 2007).

Among the great amount of paper dealing with competing risks model some of them focus on nonparametric estimation methods (see e.g. Lo, 1991 and Schabe, 1994). Because in many case partial information about the failure cause can only be obtained (e.g. masked cause of failure), a large number of works developed some specific methods with accurate modeling of the missingness mechanism. Most of these models are parametric and when a latent variable represents the missingness mechanism an EM-type algorithm can be proposed to estimate the model parameters. In Craiu and Duchesne (2004) such estimation procedure is proposed and the missingness may depend both on the failure cause and the failure time. Recently, Craiu and Reiser (2007) considered a very complete parametric model including dependence of failure causes.

Some authors developed estimation procedures in the semi-/non-parametric framework for two or more failure causes (see e.g. Myakawa, 1984; Dinse, 1986; Lo, 1991, Schabe, 1994). The special case of a possibly censored single failure cause differs from the competing risks model only by the fact that in this case the censoring time is not an event of interest. However, when the censoring information is missing, we are close to the competing risks situation where failure causes are possibly missing. Some specific methods has been derived in Gijbels *et al.* (1993), McKeague and Subramanian (1998), van der Laan and McKeague (1998), Sun and Zhou (2003) and Subramanian (2004) for various models including or not covariates, and several missingness mechanisms.

Goetghebeur and Ryan (1995) proposed a competing risks model with proportional hazards assumption for the different failure causes. In their model the mechanism of missingness may depend on the failure time (this is the missing at random assumption) while in the model we propose it is independent of everything (this is the missing completely at random assumption). In our model each failure type has its own semiparametric additive hazards rate model and at the contrary to Goetghebeur and Ryan (1995), these failure rates are not linked.

The paper is organized as follows. In Section 2 we describe the model and we point out that each data resulting from the model can be seen as the realization of a nonhomogeneous Markov process. In Section 3 the estimators are defined. Because data for which the failure cause is missing are informative for the whole parameters of the model, we develop a method that allows to account this information in an optimal way with respect to an efficiency criterium. In Section 4, for the Euclidean parameters, and in Section 5 for the functional parameters, the corresponding estimators are shown to be consistent and asymptotically Gaussian. For each estimator, a consistent estimator of the asymptotic variance is provided. Section 6 is devoted to numerical examples. A Monte Carlo study is performed for the case including covariates whereas our estimation method is applied to a real data set that does not include covariates. Some concluding remarks are given in the last Section.

2 Framework

Consider a population in which each individual is liable to die from any of $p \geq 2$ causes D_1, \dots, D_p . The causes are not necessarily independent but each death is due to a single cause. Let us denote by T the individual lifetime and $d \in \{1, \dots, p\}$ its cause of death. Suppose that our interest focuses on the effect of a time-varying covariate vector $Z(\cdot)$ of dimension k . More precisely, let $\mathbb{Z}(t) = \{Z(u); u \leq t\}$ denote the history up to time t of this covariate process and assume that an additive hazard model holds on the cause specific hazard rate function, that is:

$$\lambda_j(t|\mathbb{Z}) = \lim_{h \rightarrow 0^+} \frac{1}{h} P(T \in [t, t+h[, d = j | T \geq t, \mathbb{Z}(t)) = \lambda_{0j}(t) + \beta_j^T Z(t), \quad t \geq 0, \quad (1)$$

for $j = 1, \dots, p$ where $\lambda_{0j}(\cdot)$ is the baseline j th cause specific hazard rate function and $\beta_j \in \mathbb{R}^k$ is the regression parameter associated to the j th cause.

Suppose also that the lifetime T is right-censored by a random variable (r.v.) C and write

$$X = T \wedge C \equiv \min(T, C) \text{ and } \delta = I\{T \leq C\},$$

where $I(A)$ is the indicator of the set A . Let $\lambda_C(\cdot)$ denote the hazard rate function of the r.v. C and assume that C is, conditionally on \mathbb{Z} , independent from (T, d) .

Of course the cause of death is not known if C is observed rather than T for a given individual. But in some situations it might be the case that d is also not known even if T is observed. Let M denote the missing indicator, i.e. $M = 1$ if the cause is known and $M = 0$ otherwise. Thus we are in a situation where the available observation for an individual is

$$(X, \delta, D, \mathbb{Z}(X)),$$

where $D = \delta M d$ reveals the failure cause d when the failure time is uncensored ($\delta = 0$) and $M = 1$ and is equal to zero otherwise. In the following we assume that the missing mechanism is such that:

$$P(M = 1|X, \mathbb{Z}, \delta = 1) = P(M = 1|\delta = 1) = \alpha \in [0, 1],$$

where α is an unknown parameter, and

$$P(M = 0|X, \mathbb{Z}, \delta = 0) = P(M = 0|\delta = 0) = 1.$$

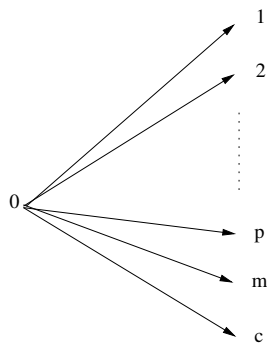
One can see the observation of the vector (X, δ, D) , conditionally on \mathbb{Z} , as the realization of a $(p + 3)$ -states nonhomogeneous Markov process (see Fig. 1) with space set $\{0, 1, \dots, p, m, c\}$: state 0 is the initial state; state i , for $i = 1, \dots, p$, corresponds to the observation of the lifetime T with known cause of death i ; state m to the observation of the lifetime with missing cause; state c to a censored observation. Except 0, all the states are absorbant. From the assumptions on M and the independence between (T, d) and C , conditionally on Z , one can easily get that the instantaneous transition rates of this Markov process are, conditionally on \mathbb{Z} :

$$\begin{cases} \lambda'_j(t|\mathbb{Z}) &= \alpha \lambda_j(t|\mathbb{Z}), \text{ for } j \in \{1, \dots, p\}, \\ \lambda'_m(t|\mathbb{Z}) &= (1 - \alpha) \sum_{j=1}^p \lambda_j(t|\mathbb{Z}), \\ \lambda'_c(t|\mathbb{Z}) &= \lambda_C(t|\mathbb{Z}). \end{cases}$$

It is important to note that, up to a multiplicative constant (α or $1 - \alpha$), the additive form of the instantaneous rates is preserved (except for the transition $0 \rightarrow c$). It is obvious for $\lambda'_j(t|\mathbb{Z})$ with $1 \leq j \leq p$ but also for $\lambda'_m(\cdot|\mathbb{Z})$ since

$$\lambda'_m(t|\mathbb{Z}) = (1 - \alpha) (\lambda_{0m}(t) + \beta_m^T Z(t)),$$

where $\lambda_{0m}(\cdot) = \sum_{j=1}^p \lambda_{0j}(\cdot)$ et $\beta_m = \sum_{j=1}^p \beta_j$. This will help us to estimate the regression parameters β_1, \dots, β_p .

Figure 1: Markov graph associated to (X, δ, D)

Now, let us suppose that we observe a sample $(X_i, \delta_i, D_i, \mathbb{Z}_i(X_i))_{1 \leq i \leq n}$ of $(X, \delta, D, \mathbb{Z}(X))$. Let $\tau < +\infty$ be the upper bound of the interval of study which means that individuals are only observed on the time interval $[0, \tau]$. Let $N_{ij}(\cdot)$, for $j \in \{1, \dots, p, m\}$, be the counting processes defined by:

$$\begin{aligned} N_{ij}(t) &= 1(X_i \leq t, D_i = j) \text{ for } j \neq m, \\ \text{and } N_{im}(t) &= 1(X_i \leq t, \delta_i = 1, D_i = 0). \end{aligned}$$

Finally write $Y_i(t) = 1(X_i \geq t)$ the individual risk process, for $i = 1, \dots, n$.

From Andersen *et al.* (1993) or Fleming and Harrington (1991), we know that, conditionally on \mathbb{Z} , the processes $M_{ij}(\cdot)$, for $j = 1, \dots, p$, and $M_{im}(\cdot)$ defined respectively by

$$M_{ij}(t) = N_{ij}(t) - \int_0^t Y_i(s) \lambda'_j(s|\mathbb{Z}) ds \text{ and } M_{im}(t) = N_{im}(t) - \int_0^t Y_i(s) \lambda'_m(s|\mathbb{Z}) ds,$$

for $t \geq 0$, are mean-zero martingales with respect to the filtration $(\mathcal{F}_t)_{t \geq 0}$ defined by

$$\mathcal{F}_t = \sigma\{N_{ij}(s), N_{im}(s), Y_i(s); s \leq t; 1 \leq i \leq n, j \in \{1, \dots, p\}\}.$$

3 Statistical Inference on the euclidean parameters

3.1 Estimators

The finite dimensional parameters of our model are: the probability α to know the cause of death, and the regression parameters β_1, \dots, β_p of each cause specific hazard rate functions. Recall that $\alpha = P(M = 1|\delta = 1)$. Thus, one can estimate empirically α by the proportion of lifetimes with known cause of death among the uncensored lifetimes, that is:

$$\hat{\alpha} = \frac{\sum_{i=1}^n 1(D_i > 0)}{\sum_{i=1}^n 1(\delta_i = 1)} = \frac{\sum_{j=1}^p N_{.j}(\tau)}{N_{..}(\tau)},$$

where

$$N_{\cdot j}(t) = \sum_{i=1}^n N_{ij}(t) \text{ and } N_{\cdot\cdot}(t) = \sum_{j=1}^p N_{\cdot j}(t) + \sum_{i=1}^n N_{im}(t), \text{ for all } t.$$

Extending an approach used by Lin et Ying (1994) in case of a single cause of death, one can estimate β_j , for $j = 1, \dots, p$, as the solution $\hat{\beta}_j$ of the estimating equation $\mathcal{U}_j(\beta, \hat{\alpha}, \tau) = 0$ where

$$\mathcal{U}_j(\beta, \hat{\alpha}, \tau) = \sum_{i=1}^n \int_0^\tau [Z_i(s) - \bar{Z}(s)] [dN_{ij}(s) - \hat{\alpha} \beta^T Z_i(s) Y_i(s) ds],$$

and

$$\bar{Z}(s) = \frac{\sum_{i=1}^n Y_i(s) Z_i(s)}{\sum_{i=1}^n Y_i(s)}.$$

Now, since it has been seen that the cause specific hazard rate function $\lambda'_m(\cdot)$ associated to a missing cause has an additive form too, one can also estimate β_m by the solution $\hat{\beta}_m$ of the estimating equation $\mathcal{U}_m(\beta, \hat{\alpha}, \tau) = 0$ where

$$\mathcal{U}_m(\beta, \hat{\alpha}, \tau) = \sum_{i=1}^n \int_0^\tau [Z_i(s) - \bar{Z}(s)] [dN_{im}(s) - (1 - \hat{\alpha}) \beta^T Z_i(s) Y_i(s) ds].$$

Explicit expressions of these estimators are available and given below (see equation (10)).

At this stage, we are in a situation where each parameter β_j , for $j = 1, \dots, p$, has its own estimator $\hat{\beta}_j$. But we also have an estimator $\hat{\beta}_m$ of their sum $\beta_m = \beta_1 + \dots + \beta_p$. It is of course of interest to use it in order to improve the estimation of the first parameters β_j , for $j = 1, \dots, p$. In this order, we suggest to find the linear transformation of our estimator $(\hat{\beta}_1^T, \dots, \hat{\beta}_p^T, \hat{\beta}_m^T)^T$ which will give us an estimator of $(\beta_1^T, \dots, \beta_p^T)^T$ with minimum asymptotic variance. More precisely, let \mathcal{H} be the family of all the block matrices

$$H = \begin{pmatrix} H_{11} & H_{12} & \cdots & H_{1p} & H_{1m} \\ H_{21} & H_{22} & \cdots & H_{2p} & H_{2m} \\ \vdots & \vdots & & \vdots & \vdots \\ H_{p1} & H_{p2} & \cdots & H_{pp} & H_{pm} \end{pmatrix},$$

where the H_{ij} , for $i = 1, \dots, p$ and $j = 1, \dots, p, m$, are real matrices of dimension $k \times k$, such that

$$H \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_p \\ \beta_m \end{pmatrix} = \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_p \end{pmatrix} \quad (2)$$

for all vectors β_1, \dots, β_p in \mathbb{R}^k and $\beta_m = \beta_1 + \dots + \beta_p$. Write

$$\hat{q}(H) = \text{trace}(H \hat{\Sigma}_{\hat{\beta}, \infty} H^T),$$

where $\hat{\Sigma}_{\hat{\beta}, \infty}$ is an estimator of the asymptotic covariance matrix of $(\hat{\beta}_1^T, \dots, \hat{\beta}_p^T, \hat{\beta}_m^T)^T$. With

$$\hat{H} = \underset{H \in \mathcal{H}}{\text{Argmin}} \hat{q}(H),$$

an estimator of $(\beta_1^T, \dots, \beta_p^T)$ with minimal asymptotic variance is given by:

$$\begin{pmatrix} \tilde{\beta}_1 \\ \vdots \\ \tilde{\beta}_p \end{pmatrix} = \hat{H} \begin{pmatrix} \hat{\beta}_1 \\ \vdots \\ \hat{\beta}_p \\ \hat{\beta}_m \end{pmatrix}.$$

Thus, the optimal estimators of the regression parameters are: $\tilde{\beta}_i = \sum_{j=1}^p \hat{H}_{ij} \hat{\beta}_j + \hat{H}_{im} \hat{\beta}_m$, for $i = 1, \dots, p$.

Note that the constraints on H given by (2) are linear and do not link its lines between them. Indeed, denoting by I_k the identity matrix of order k , these constraints may be written

$$\begin{cases} H_{ii} + H_{im} &= I_k \\ H_{ij} + H_{im} &= 0, \end{cases}$$

for $1 \leq i \leq p$ and $j \in \{1, \dots, p\} \setminus \{i\}$.

On the other hand, we have

$$\hat{q}(H) = \sum_{i=1}^p \text{trace}(H_{i\bullet} \hat{\Sigma}_{\hat{\beta}, \infty} H_{i\bullet}^T) = \sum_{i=1}^p \hat{q}_i(H)$$

where $\hat{q}_i(H) = \text{trace}(H_{i\bullet} \hat{\Sigma}_{\hat{\beta}, \infty} H_{i\bullet}^T)$ and $H_{i\bullet}$ is the i th line block of H .

Thus, it is sufficient to solve separately the following problems (P_i) , for $i = 1, \dots, p$:

$$(P_i) \begin{cases} \text{Find } H_{i1}, \dots, H_{im} \text{ which minimize } \text{trace}(H_{i\bullet} \hat{\Sigma}_{\hat{\beta}, \infty} H_{i\bullet}^T) \\ \text{such that : } H_{ii} + H_{im} = I_k, \\ H_{ij} + H_{im} = 0, \text{ for } j \neq i, \end{cases}$$

3.2 Example for $p = k = 2$

As an example, let us show how to solve problems (P_1) and (P_2) when $p = k = 2$. Since in this case (P_1) and (P_2) are identical, we only have to consider problem (P_1) . Let us introduce other temporary notations. For $j = 1, 2, m$, write

$$H^{(j)} = H_{1j} = \begin{pmatrix} h_{11}^{(j)} & h_{12}^{(j)} \\ h_{21}^{(j)} & h_{22}^{(j)} \end{pmatrix}.$$

Let

$$\hat{Q} = \begin{pmatrix} \hat{\Sigma}_{\hat{\beta}, \infty} & 0 \\ 0 & \hat{\Sigma}_{\hat{\beta}, \infty} \end{pmatrix}$$

and

$$L = \left(h_{11}^{(1)}, h_{12}^{(1)}, h_{11}^{(2)}, h_{12}^{(2)}, h_{11}^{(m)}, h_{12}^{(m)}, h_{21}^{(1)}, h_{22}^{(1)}, h_{21}^{(2)}, h_{22}^{(2)}, h_{21}^{(m)}, h_{22}^{(m)} \right) = (l_1, \dots, l_{12}).$$

One can rewrite the function $\hat{q}_1(H)$ to be minimized like:

$$\hat{q}_1(H) = \text{trace} \left(\left(H^{(1)} \ H^{(2)} \ H^{(m)} \right) \hat{\Sigma}_{\hat{\beta}, \infty} \left(H^{(1)} \ H^{(2)} \ H^{(m)} \right)^T \right) = L \hat{Q} L^T.$$

Now, since the constraints on H are

$$\begin{cases} H^{(1)} + H^{(m)} = I_2 \\ H^{(2)} + H^{(m)} = 0 \end{cases} \Leftrightarrow \begin{cases} h_{ij}^{(1)} + h_{ij}^{(m)} = 1 \text{ for } 1 \leq i, j \leq 2 \\ h_{ij}^{(2)} + h_{ij}^{(m)} = 0 \text{ for } 1 \leq i, j \leq 2 \end{cases},$$

they can be rewritten $CL = d$ where

$$C = \begin{pmatrix} 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 \end{pmatrix} \quad \text{and} \quad d = \begin{pmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{pmatrix}.$$

Thus the Lagrange function for this optimization problem with linear constraints is given by

$$\ell(L, \lambda) = \frac{1}{2} L^T \hat{Q} L + (CL - d)^T \lambda$$

where λ is a Lagrange multiplier vector. The optimal parameters \hat{L} and $\hat{\lambda}$ necessarily satisfy the first-order conditions

$$\begin{cases} \frac{\partial \ell}{\partial L}(L, \lambda) = 0 = \hat{Q} L + C^T \lambda \\ CL = d \end{cases},$$

which give

$$\hat{\lambda} = -[C \hat{Q}^{-1} C^T]^{-1} d,$$

and

$$\hat{L} = \hat{Q}^{-1} C^T [C \hat{Q}^{-1} C^T]^{-1} d.$$

It has to be noted that \hat{Q} is invertible whenever $\hat{\Sigma}_{\hat{\beta}, \infty}$ is.

4 Asymptotic behavior of the regression parameters estimators

4.1 Additional notations or assumptions, preliminary results

In order to simplify the notation in the following derivations, let us denote by $p + 1$ the index corresponding to a missing cause (previously denoted by m). Let

$$\beta = \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_p \\ \beta_{p+1} \end{pmatrix} \text{ and } \hat{\beta} = \begin{pmatrix} \hat{\beta}_1 \\ \vdots \\ \hat{\beta}_p \\ \hat{\beta}_{p+1} \end{pmatrix}.$$

If z is a column vector in \mathbb{R}^k , let us write

$$x^{\otimes l} = \begin{cases} 1 & \text{when } l = 0, \\ z & \text{when } l = 1, \\ zz^T & \text{when } l = 2. \end{cases}$$

Finally, let us denote by $S_l(\cdot)$, for $l = 0, 1, 2$, the processes defined by

$$S_l(s) = \frac{1}{n} \sum_{i=1}^n Y_i(s) Z_i^{\otimes l}(s),$$

for $0 \leq s \leq \tau$ and for b in \mathbb{R}^k the process $S_3(\cdot; b)$ defined by

$$S_3(s; b) = \frac{1}{n} \sum_{i=1}^n Y_i(s) Z_i^{\otimes 2}(s) b^T Z_i(s).$$

From now on we make the following assumptions.

- A1. The probability α to get a known cause of death is strictly positive.
- A2. The upper bound τ of the time interval of study is such that $0 < \int_0^\tau \lambda_{0j}(s) ds < +\infty$, for $j = 1, \dots, p$, and the covariate processes $Z_i(\cdot)$ are $(\mathcal{F}_t)_{t \geq 0}$ -predictable and uniformly bounded with respect to $i = 1, \dots, n$.
- A3. For $0 \leq l \leq 2$, there exists functions $s_k(\cdot)$ defined on $[0, \tau]$ such that

$$\max_{0 \leq l \leq 2} \sup_{s \in [0, \tau]} \|S_l(s) - s_l(s)\| \xrightarrow{P} 0, \text{ when } n \rightarrow +\infty.$$

Moreover, the function $s_0(\cdot)$ is bounded below by a strictly positive real number.

A4. With the notations $a(u) = s_2(u) - s_1^{\otimes 2}(u)/s_0(u)$,

$$A(t) = \int_0^t a(u)du \text{ and } \theta(t) = \int_0^t [s_0(u)\lambda_{0p+1}(u)du + \beta_{p+1}^T s_1(u)] du, \quad (3)$$

the matrix $A(\tau)$ is positive definite and the real $\theta(\tau)$ is strictly positive.

The matrix

$$\int_0^\tau [S_2(s) - S_1^{\otimes 2}(s)/S_0(s)] ds$$

is also positive definite. Note that, from previous assumptions, it was already true asymptotically.

A5. For all $b \in \mathbb{R}^k$, let $S_4(\cdot; b)$ be the process defined by

$$S_4(s; b) = \frac{1}{n} \sum_{i=1}^n (b^T Z_i(s)) Y_i(s) (s_1(s) Z_i^T(s) / s_0(s)).$$

There exist functions $s_3(\cdot; b)$ and $s_4(\cdot; b)$ such that, for all $b \in \mathbb{R}^k$,

$$\max_{3 \leq l \leq 4} \sup_{s \in [0, \tau]} \|S_l(s; b) - s_l(s; b)\| \xrightarrow{P} 0, \text{ when } n \rightarrow +\infty.$$

A6. The following functions are integrable on $[0, \tau]$:

$$a(\cdot), a(\cdot)\lambda_{0j}(\cdot), s_0(\cdot)\lambda_{0j}(\cdot), s_1(\cdot), \frac{s_1^{\otimes 2}(\cdot)}{s_0^2(\cdot)}, s_3(\cdot; \beta_j) \text{ and } s_4(\cdot; \beta_j), \text{ for } j = 1, \dots, p.$$

Now, let us introduce, for all $b \in \mathbb{R}^k$, the processes $\mathcal{U}_j(b, \alpha_j, \cdot)$ defined, for $j = 1, \dots, p+1$ and $t \in [0, \tau]$, by:

$$\mathcal{U}_j(b, \alpha_j, t) = \sum_{i=1}^n \int_0^t (Z_i(s) - \bar{Z}(s)) (dN_{ij}(s) - \alpha_j b^T Z_i(s) Y_i(s) ds),$$

where

$$\alpha_j = \begin{cases} \alpha & \text{if } 1 \leq j \leq p, \\ 1 - \alpha & \text{if } j = p + 1. \end{cases}$$

Note that values of these processes at $s = \tau$ appear in the estimating equations of Section 3.1.

It is easily seen that these processes can be rewritten like

$$\mathcal{U}_j(b, \alpha_j, \cdot) = \sum_{i=1}^n \int_0^\cdot (Z_i(s) - \bar{Z}(s)) dM_{ij}(s),$$

for $j = 1, \dots, p+1$. Hence they are local square integrable $(\mathcal{F}_t)_{t \geq 0}$ -martingales as sum of stochastic integrals of predictable and bounded processes with respect to local square integrable martingales.

We are now in a position to introduce our preliminary technical results which, as all the following in this paper, take place in the Skorohod space of cadlag functions $D[0, \tau]$.

Proposition 4.1 *The multivariate process $\mathbb{U}_n(\cdot)$ defined, for all $t \in [0, \tau]$, by*

$$\mathbb{U}_n(t) = \frac{1}{\sqrt{n}} \begin{pmatrix} \mathcal{U}_1(\beta_1, \alpha_1, t) \\ \vdots \\ \mathcal{U}_{p+1}(\beta_{p+1}, \alpha_{p+1}, t) \\ \sum_{j=1}^{p+1} \frac{\alpha_j^*}{\theta(\tau)} M_j(t) \end{pmatrix},$$

where $\alpha_j^* = 1 - \alpha$ for $1 \leq j \leq p$ and $\alpha_{p+1}^* = -\alpha$, converges weakly in $D^{k(p+1)+1}[0, \tau]$, as n tends to ∞ , to a mean zero multivariate gaussian martingale $\mathbb{U}_\infty(\cdot)$ with covariance matrix given, for all $t \in [0, \tau]$, by

$$\Sigma_{\mathbb{U}_\infty}(t) = \begin{pmatrix} \Theta_1(t) & 0 & 0 & \xi_1(t) \\ 0 & \ddots & 0 & \vdots \\ 0 & 0 & \Theta_{p+1}(t) & \xi_{p+1}(t) \\ \xi_1^T(t) & \cdots & \xi_{p+1}^T(t) & \xi_\alpha(t) \end{pmatrix},$$

where, for $j = 1, \dots, p+1$,

$$\Theta_j(t) = \alpha_j \int_0^t [a(s)\lambda_{0j}(s) + s_3(s; \beta_j) - s_4(s; \beta_j) - s_4^T(s; \beta_j) + (\beta_j^T s_1(s))s_1^{\otimes 2}(s)/s_0^2(s)] ds,$$

$$\xi_j(t) = \kappa_j \frac{\alpha(1-\alpha)}{\theta(\tau)} A(t)\beta_j, \text{ with } \kappa_j = 1, \text{ for } 1 \leq j \leq p \text{ and } \kappa_{p+1} = -1,$$

$$\xi_\alpha(t) = \frac{\alpha(1-\alpha)}{\theta^2(\tau)} \theta(t)$$

and $A(\cdot)$ as well as $\theta(\cdot)$ are defined in (3).

Proof. As in Andersen and Gill (1982), the main idea is to apply Rebolledo's Theorem (see Rebolledo, 1980, or Andersen *et al.*, 1993, p. 83-84). Since this theorem is now of classical use, we only derive here the limit of the predictable variation process associated to \mathbb{U}_n . This will give us the asymptotic covariance matrix function $\Sigma_{\mathbb{U}_\infty}(\cdot)$ of \mathbb{U}_n .

On one hand, straightforward calculations show that we have, for $j = 1, \dots, p+1$,

$$\begin{aligned} \left\langle \frac{1}{\sqrt{n}} \mathcal{U}_j(\beta_j, \alpha, \cdot) \right\rangle (t) &= \frac{1}{n} \sum_{i=1}^n \int_0^t (Z_i(s) - \bar{Z}(s)) (Z_i(s) - \bar{Z}(s))^T Y_i(s) \lambda_j'(s|Z) ds \\ &= \alpha_j \int_0^t [S_2(s) - S_1^{\otimes 2}(s)/S_0(s)] \lambda_{0j}(s) ds \\ &+ \alpha_j \int_0^t [S_3(s; \beta_j) - S_4(s; \beta_j) - S_4^T(s; \beta_j) + (\beta_j^T S_1(s))S_1^{\otimes 2}(s)/S_0^2(s)] ds + o_P(1), \end{aligned}$$

which, by Assumptions A2-A6, converges in probability, as n tends to $+\infty$, to $\Theta_j(t)$ given in the Theorem.

On the other hand, since the martingales M_{ij} and $M_{i'j'}$ are orthogonal for all $1 \leq i, i' \leq n$ and $1 \leq j \neq j' \leq p+1$, we have:

$$\langle \mathcal{U}_j(\beta_j, \alpha_j, \cdot), \mathcal{U}_{j'}(\beta_{j'}, \alpha_{j'}, \cdot) \rangle(t) = 0,$$

as soon as j is different from j' and for all $t \in [0, \tau]$. This justifies the null terms in the asymptotic covariance matrix $\Sigma_{\mathbb{U}_\infty}(t)$.

Now, thanks again to the orthogonality between martingales with different indices, it is easy to show that, for $1 \leq l \leq p+1$, we have

$$\frac{1}{n} \left\langle \mathcal{U}_l(\cdot), \sum_{j=1}^{p+1} \frac{\alpha_j^* M_{.j}(\cdot)}{\theta(\tau)} \right\rangle(t) = \frac{\alpha_l^*}{n\theta(\tau)} \sum_{i=1}^n \int_0^t (Z_i(s) - \bar{Z}(s)) Y_i(s) \lambda_j'(s|\mathbb{Z}) ds$$

which converges in probability to

$$\xi_l(t) = \kappa_l \frac{\alpha(1-\alpha)}{\theta(\tau)} A(t) \beta_l,$$

when n tends to $+\infty$. Finally, with the same kind of arguments we have

$$\left\langle \frac{1}{\sqrt{n}} \sum_{j=1}^{p+1} \frac{\alpha_j^* M_{.j}(\cdot)}{\theta(\tau)} \right\rangle(t) = \frac{1}{n} \sum_{j=1}^{p+1} \frac{\alpha_j^*}{\theta^2(\tau)} \sum_{i=1}^n \int_0^t Y_i(s) \lambda_j'(s|\mathbb{Z}) ds \xrightarrow{P} \xi_\alpha(t) = \frac{\alpha(1-\alpha)}{\theta(\tau)} \theta(t),$$

when n tends to $+\infty$. □

4.2 Large sample behaviour of $\hat{\alpha}$

Lemma 4.2 *We have:*

$$\sqrt{n}(\hat{\alpha} - \alpha) = \sum_{j=1}^{p+1} \frac{\alpha_j^*}{\theta(\tau)} \frac{1}{\sqrt{n}} M_{.j}(\tau) + o_P(1). \quad (4)$$

And thus, $\sqrt{n}(\hat{\alpha} - \alpha)$ converges weakly to a $N(0, \alpha(1-\alpha)/\theta(\tau))$ distribution when $n \rightarrow +\infty$.

Remark. The second result of this lemma is obvious and doesn't need the first step. A straightforward application of the central limit theorem will give it. But the first result will be itself of interest in the following section.

Proof. From the definition of $\hat{\alpha}$ we can write:

$$\begin{aligned}
\hat{\alpha} &= \frac{\sum_{i=1}^n \sum_{j=1}^p \int_0^\tau dN_{ij}(s)}{\sum_{i=1}^n \sum_{j=1}^{p+1} \int_0^\tau dN_{ij}(s)} \\
&= \frac{\sum_{i=1}^n \sum_{j=1}^p \int_0^\tau dM_{ij}(s) + \sum_{i=1}^n \sum_{j=1}^p \int_0^\tau Y_i(s) \lambda'_j(s|\mathbb{Z}) ds}{\sum_{i=1}^n \sum_{j=1}^{p+1} \int_0^\tau dM_{ij}(s) + \sum_{i=1}^n \sum_{j=1}^{p+1} \int_0^\tau Y_i(s) \lambda'_j(s|\mathbb{Z}) ds} \\
&= \frac{\sum_{j=1}^p M_{\cdot j}(\tau) + \alpha \sum_{i=1}^n \sum_{j=1}^p \int_0^\tau Y_i(s) \lambda_j(s|\mathbb{Z}) ds}{M_{\cdot\cdot}(\tau) + \sum_{i=1}^n \sum_{j=1}^p \int_0^\tau Y_i(s) \lambda_j(s|\mathbb{Z}) ds} \\
&= \frac{\sum_{j=1}^p M_{\cdot j}(\tau) + \alpha n \int_0^\tau [S_0(u) \lambda_{0_{p+1}}(u) + \beta_{p+1}^T S_1(u)] du}{M_{\cdot\cdot}(\tau) + n \int_0^\tau [S_0(u) \lambda_{0_{p+1}}(u) + \beta_{p+1}^T S_1(u)] du},
\end{aligned}$$

where $M_{\cdot\cdot}(\cdot)$ denotes the process $\sum_{i=1}^n \sum_{j=1}^{p+1} M_{ij}(\cdot)$. It follows that

$$\begin{aligned}
&\sqrt{n}(\hat{\alpha} - \alpha) \\
&= \frac{\frac{1-\alpha}{\sqrt{n}} \sum_{j=1}^p M_{\cdot j}(\tau) - \frac{\alpha}{\sqrt{n}} M_{\cdot p+1}(\tau)}{\frac{1}{n} M_{\cdot\cdot}(\tau) + \int_0^\tau [S_0(u) \lambda_{0_{p+1}}(u) + \beta_{p+1}^T S_1(u)] du} 1(N_{\cdot\cdot}(\tau) > 0) - \sqrt{n} \alpha 1(N_{\cdot\cdot}(\tau) = 0) \\
&= \frac{\frac{1-\alpha}{\sqrt{n}} \sum_{j=1}^p M_{\cdot j}(\tau) - \frac{\alpha}{\sqrt{n}} M_{\cdot p+1}(\tau)}{\frac{1}{n} M_{\cdot\cdot}(\tau) + \int_0^\tau [S_0(u) \lambda_{0_{p+1}}(u) + \beta_{p+1}^T S_1(u)] du} + o_P(1).
\end{aligned}$$

Moreover, using Lenglar's inequality and Assumption A3, it is easily seen that

$$\frac{1}{n} M_{\cdot\cdot}(\tau) \xrightarrow{P} 0, \text{ as } n \rightarrow +\infty. \quad (5)$$

These two last results with Assumptions A3 and A4 complete the proof of (4).

Then the asymptotic normality of $\hat{\alpha}$ is obtained thanks to Proposition 4.1 . \square

4.3 Large sample behaviour of $\hat{\beta}$

Theorem 4.3 *Under Assumptions A1-A5, the random vector $\sqrt{n}(\hat{\beta} - \beta)$ is asymptotically gaussian, with mean zero and positive definite covariance matrix*

$$\Sigma_{\hat{\beta}, \infty} = \Sigma_1(\tau) \Sigma_{U_\infty}(\tau) \Sigma_1^T(\tau),$$

where

$$\Sigma_1(\tau) = \begin{pmatrix} \frac{A^{-1}(\tau)}{\alpha} & 0 & \dots & 0 & -\frac{\beta_1}{\alpha} \\ 0 & \ddots & \ddots & \vdots & \vdots \\ \vdots & \ddots & \frac{A^{-1}(\tau)}{\alpha} & 0 & -\frac{\beta_p}{\alpha} \\ 0 & \dots & 0 & \frac{A^{-1}(\tau)}{1-\alpha} & \frac{\beta_{p+1}}{1-\alpha} \end{pmatrix}.$$

Proof. Write

$$\hat{\alpha}_j = \begin{cases} \hat{\alpha} & \text{if } 1 \leq j \leq p \\ 1 - \hat{\alpha} & \text{if } j = p + 1 \end{cases}.$$

From their definition, the estimators $\hat{\beta}_j$, for $j = 1, \dots, p$, are such that $\mathcal{U}_j(\hat{\beta}_j, \hat{\alpha}_j, \tau) = 0$.

Thus, one can write :

$$\begin{aligned} \frac{1}{\sqrt{n}}\mathcal{U}_j(\beta_j, \alpha_j, \tau) &= \frac{1}{\sqrt{n}} \sum_{i=1}^n \int_0^\tau (Z_i(s) - \bar{Z}(s)) \left(\hat{\alpha}_j \hat{\beta}_j^T Z_i(s) Y_i(s) ds - \alpha_j \beta_j^T Z_i(s) Y_i(s) ds \right) \\ &= \left[\int_0^\tau \frac{1}{n} \sum_{i=1}^n (Z_i(s) Z_i^T(s) - \bar{Z}(s) \bar{Z}^T(s)) Y_i(s) ds \right] \times \left[\sqrt{n}(\hat{\alpha}_j - \alpha_j) \hat{\beta}_j + \sqrt{n} \alpha_j (\hat{\beta}_j - \beta_j) \right]. \end{aligned}$$

With the notation

$$\hat{A}(\tau) = \int_0^\tau [S_2(s) - S_1^{\otimes 2}(s)/S_0(s)] ds,$$

we obtain

$$\frac{1}{\sqrt{n}}\mathcal{U}_j(\beta_j, \alpha_j, \tau) = \hat{A}(\tau) \left[\sqrt{n}(\hat{\alpha}_j - \alpha_j) \hat{\beta}_j + \alpha_j \sqrt{n}(\hat{\beta}_j - \beta_j) \right].$$

It follows that

$$\hat{\beta}_j - \beta_j = \frac{1}{\hat{\alpha}_j} \hat{A}^{-1}(\tau) \frac{1}{n} \mathcal{U}_j(\beta_j, \alpha_j, \tau) + \left(\frac{\alpha_j}{\hat{\alpha}_j} - 1 \right) \beta_j, \quad (6)$$

thanks to Assumption A4 which insures that $\hat{A}(\tau)$ is invertible. Now, using Assumptions A3 and A4, Proposition 4.1 and Lemma 4.2, it is easily seen that the right-hand side of (6) converges to zero when n tends to $+\infty$. Thus $\hat{\beta}$ is consistent.

Furthermore, after some straightforward calculations on equation (6), one can write, for $j = 1, \dots, p + 1$:

$$\begin{aligned} \sqrt{n}(\hat{\beta}_j - \beta_j) &= \frac{1}{\alpha_j} \left(A^{-1}(\tau) \frac{\mathcal{U}_j(\beta_j, \alpha_j, \tau)}{\sqrt{n}} - \beta_j \sqrt{n}(\hat{\alpha}_j - \alpha_j) \right) \\ &\quad + \frac{1}{\alpha_j} \left((\hat{A}^{-1}(\tau) - A^{-1}(\tau)) \frac{\mathcal{U}_j(\beta_j, \alpha_j, \tau)}{\sqrt{n}} - \sqrt{n}(\hat{\alpha}_j - \alpha_j)(\hat{\beta}_j - \beta_j) \right). \end{aligned}$$

Using again Assumptions A3 and A4 (which ensures that $A^{-1}(\tau)$ converges in probability to $A^{-1}(\tau)$), Proposition 4.1 and Lemma 4.2 as well as the consistency of $\hat{\beta}$, one can prove

that the second term of the right-hand side of this last equality is an $o_P(1)$. Thus we can write:

$$\sqrt{n}(\hat{\beta}_j - \beta_j) = \frac{1}{\alpha} \left(A^{-1}(\tau) \frac{\mathcal{U}_j(\beta_j, \alpha_j, \tau)}{\sqrt{n}} - \beta_j \sqrt{n}(\hat{\alpha} - \alpha) \right) + o_P(1), \quad (7)$$

for $j = 1, \dots, p$, and

$$\begin{aligned} & \sqrt{n}(\hat{\beta}_{p+1} - \beta_{p+1}) \\ &= \frac{1}{1-\alpha} \left(A^{-1}(\tau) \frac{\mathcal{U}_{p+1}(\beta_{p+1}, \alpha_{p+1}, \tau)}{\sqrt{n}} + \beta_{p+1} \sqrt{n}(\hat{\alpha} - \alpha) \right) + o_P(1). \end{aligned} \quad (8)$$

Hence, from (4), (7) and (8) we finally obtain

$$\sqrt{n}(\hat{\beta} - \beta) = \Sigma_1(\tau) \mathbb{U}_n(\tau) + o_P(1), \quad (9)$$

where $\Sigma_1(\tau)$ is given in Theorem 4.3. This and Proposition 4.1 complete the proof. Note that the matrix $\Sigma_{\hat{\beta}, \infty}$ is positive definite since it is the case for $\Sigma_{\mathbb{U}, \infty}(\tau)$. \square

4.4 The optimal estimator $\tilde{\beta}$

Recall that our optimal estimator is $\tilde{\beta} = \hat{H}\hat{\beta}$, where

$$\hat{H} = \text{Argmin}_{H \in \mathcal{H}} \hat{q}(H) = \text{Argmin}_{H \in \mathcal{H}} \text{trace}(H \hat{\Sigma}_{\hat{\beta}, \infty} H^T)$$

and $\hat{\Sigma}_{\hat{\beta}, \infty}$ is required to be an estimator of the asymptotic covariance matrix $\Sigma_{\hat{\beta}, \infty}$ given in Theorem 4.3. Thus, we first have to find such an estimator of $\Sigma_{\hat{\beta}, \infty}$.

It is easy to check from their definition that the explicit expressions of the estimators $\hat{\beta}_j$, for $j = 1, \dots, p+1$, are

$$\hat{\beta}_j = \frac{1}{\hat{\alpha}_j} \hat{A}^{-1}(\tau) \frac{1}{n} \sum_{i=1}^n \int_0^\tau (Z_i(s) - \bar{Z}(s)) dN_{ij}(s). \quad (10)$$

Furthermore, let

$$\hat{\Theta}_j(\tau) = \frac{1}{n} \sum_{i=1}^n \int_0^\tau (Z_i(s) - \bar{Z}(s))^{\otimes 2} dN_{ij}(s),$$

and

$$\hat{\xi}_j(\tau) = \kappa_j \frac{\hat{\alpha}(1-\hat{\alpha})}{\hat{\theta}(\tau)} \hat{A}(\tau) \hat{\beta}_j,$$

where $\hat{\theta}(\tau) = N_{..}(\tau)/n$, and finally

$$\hat{\xi}_\alpha(\tau) = \frac{\hat{\alpha}(1-\hat{\alpha})}{\hat{\theta}(\tau)}.$$

Therefore, one can use respectively

$$\hat{\Sigma}_1(\tau) = \begin{pmatrix} \frac{\hat{A}^{-1}(\tau)}{\hat{\alpha}} & 0 & \dots & 0 & -\frac{\hat{\beta}_1}{\hat{\alpha}} \\ 0 & \ddots & & \vdots & \vdots \\ \vdots & & \frac{\hat{A}^{-1}(\tau)}{\hat{\alpha}} & 0 & -\frac{\hat{\beta}_p}{\hat{\alpha}} \\ 0 & \dots & 0 & \frac{\hat{A}^{-1}(\tau)}{1-\hat{\alpha}} & \frac{\hat{\beta}_{p+1}}{1-\hat{\alpha}} \end{pmatrix}$$

and

$$\hat{\Sigma}_{\mathbb{U}_\infty}(\tau) = \begin{pmatrix} \hat{\Theta}_1(\tau) & 0 & 0 & \hat{\xi}_1(\tau) \\ 0 & \ddots & 0 & \vdots \\ 0 & 0 & \hat{\Theta}_{p+1}(\tau) & \hat{\xi}_{p+1}(\tau) \\ \hat{\xi}_1^T(\tau) & \cdots & \hat{\xi}_{p+1}^T(\tau) & \hat{\xi}_\alpha(\tau) \end{pmatrix}$$

as estimators of $\Sigma_1(\tau)$ and $\Sigma_{\mathbb{U}_\infty}(\tau)$. Finally, let $\beta^* = (\beta_1^T, \dots, \beta_p^T)^T$.

Theorem 4.4 *Under Assumptions A1-A5, the estimator*

$$\hat{\Sigma}_{\hat{\beta}, \infty} = \hat{\Sigma}_1(\tau) \hat{\Sigma}_{\mathbb{U}_\infty}(\tau) \hat{\Sigma}_1^T(\tau)$$

converges in probability to the matrix $\Sigma_{\hat{\beta}, \infty}$. If $\Sigma_{\hat{\beta}, \infty}$ is invertible, then $\sqrt{n}(\tilde{\beta} - \beta^*)$ is asymptotically mean-zero gaussian distributed with covariance matrix whose trace minimizes $q(H) = \text{trace}(H \Sigma_{\hat{\beta}, \infty} H^T)$ for all $H \in \mathcal{H}$. Such an estimator is said asymptotically T -optimal.

Proof. We know from Lemma 4.2 that $\hat{\alpha}$ converges in probability to α . We have also seen in the proof of Theorem 4.3 that $\hat{A}^{-1}(\tau)$ and $\hat{\beta}_j$, for $j = 1, \dots, p+1$, converge in probability respectively to $A^{-1}(\tau)$ and β_j . Thus, we thus get the convergence in probability of $\hat{\Sigma}_1(\tau)$ to $\Sigma_1(\tau)$.

Moreover, we have seen in the proof of Lemma 4.2 that

$$N_{..}(\tau) = M_{..}(\tau) + n \int_0^\tau [S_0(u) \lambda_{0p+1}(u) + \beta_{p+1}^T S_1(u)] du.$$

Thanks to Assumptions A3 and A4, the integral in the right-hand side of the last equation converges in probability to $\theta(\tau)$. This and (5) give the convergence in probability of $\hat{\theta}(\tau)$ to $\theta(\tau)$.

From the above convergences we have the convergence in probability of $\hat{\xi}_j(\tau)$ to $\xi_j(\tau)$, for $j = 1, \dots, p+1$, as well as the one of $\hat{\xi}_\alpha$ to ξ_α .

On the other hand, one can write, for $j = 1, \dots, p$:

$$\hat{\Theta}_j(\tau) = \frac{1}{n} \sum_{i=1}^n \int_0^\tau (Z_i(s) - \bar{Z}(s))^{\otimes 2} dM_{ij}(s) + \frac{1}{n} \sum_{i=1}^n \int_0^\tau (Z_i(s) - \bar{Z}(s))^{\otimes 2} Y_i(s) \lambda'_j(s|\mathbb{Z}) ds. \quad (11)$$

With the notation $A^{\otimes 2} = AA^T$ when A is also a matrix, it is easily seen that, for all $t \in [0, \tau]$

$$\left\langle \frac{1}{n} \sum_{i=1}^n \int_0^t (Z_i(s) - \bar{Z}(s))^{\otimes 2} dM_{ij}(s) \right\rangle = \frac{1}{n^2} \sum_{i=1}^n \int_0^t \left((Z_i(s) - \bar{Z}(s))^{\otimes 2} \right)^{\otimes 2} Y_i(s) \lambda'_j(s|\mathbb{Z}) ds,$$

which in $t = \tau$ converges to zero in probability when n tends to $+\infty$, by Assumptions A2 and A3. This and Lenglart inequality yield the convergence in probability to zero of the first

term of (11). Moreover, we have seen in the proof of Proposition 4.1 that the second term of (11) is equal to $\langle \mathcal{U}_j(\beta_j, \alpha, \tau) / \sqrt{n} \rangle$ and converges in probability to $\Theta_j(\tau)$, when n tends to $+\infty$. These two last convergences prove that $\hat{\Theta}_j(\tau)$ converges to $\Theta_j(\tau)$, for $j = 1, \dots, p+1$. Thus we get the consistency of the estimator $\hat{\Sigma}_{U_\infty}(\tau)$ and finally the one of $\hat{\Sigma}_{\hat{\beta}, \infty}$.

From the above and the continuous dependency of \hat{H} on $\hat{\Sigma}_{\hat{\beta}, \infty}$ we deduce that \hat{H} converges in probability to the matrix H_{opt} in \mathcal{H} which minimizes $\text{trace}(H \Sigma_{\hat{\beta}, \infty} H^T)$. Recall that the existence of such an optimal matrix is ensured because $\Sigma_{\hat{\beta}, \infty}$ is positive definite. Since $\hat{H}\beta = \beta^*$, we get from the above and Theorem 4.3 that $\sqrt{n}(\tilde{\beta} - \beta^*) = \hat{H}\sqrt{n}(\hat{\beta} - \beta)$ converges to a mean zero gaussian distribution with covariance matrix $H_{opt}\Sigma_{\hat{\beta}, \infty}H_{opt}^T$ which is optimal in the sense defined earlier. \square

5 Statistical inference on the functional parameters

Even if it is not the model considered at the beginning of this paper, we will first consider the fully nonparametric case, that is a model without covariates where only functional parameters have to be estimated. Of course, this is also of interest for applications. Then we will come back to our semiparametric model and will see how to estimate its functional parameters.

5.1 Inference in the nonparameteric model

In this case no parametric form is assumed on the cause specific hazard rate functions $\lambda_j(\cdot)$, for $j = 1, \dots, p$ and we also do not take into account any covariate. Let $\Lambda_j(\cdot)$, for $j = 1, \dots, p$, denote the cause specific cumulative hazard rate functions defined by:

$$\Lambda_j(t) = \int_0^t \lambda_j(u) du,$$

for t in $[0, \tau]$ and

$$\Lambda_{p+1}(t) = \sum_{j=1}^p \Lambda_j(t).$$

With the assumption on M and the hypothesis of independence between (T, d) and C , the instantaneous transition rates of the Markov process with graph given in Figure 1 are:

$$\begin{cases} \lambda'_j(t) &= \alpha \lambda_j(t), \text{ for } j = 1, \dots, p, \\ \lambda'_{p+1}(t) &= (1 - \alpha) \sum_{j=1}^p \lambda_j(t) = (1 - \alpha) \lambda_{p+1}(t), \\ \lambda'_C(t) &= \lambda_C(t). \end{cases}$$

At the contrary to the model by Goetghebeur and Ryan (1995), when there is no covariate in the data, the model is still of interest because it allows different failure rates for failure causes.

5.1.1 First estimators of the cause specific cumulative hazard rate functions

By standard arguments, one can easily estimate $\Lambda_j(t)$, for $j = 1, \dots, p+1$ and $t \in [0, \tau]$, by

$$\hat{\Lambda}_j(t) = \frac{1}{\hat{\alpha}_j} \hat{\Lambda}'_j(t),$$

where $\hat{\alpha}_j$ is defined at the beginning of the proof of Theorem 4.3, $Y(s) = \sum_{i=1}^n Y_i(s)$ is the number at risk at time s and

$$\hat{\Lambda}'_j(t) = \sum_{i=1}^n \int_0^t \frac{dN_{ij}(s)}{Y(s)}$$

is the well-known Nelson-Aalen estimator of

$$\Lambda'_j(t) = \int_0^t \lambda'_j(u) du.$$

Write:

$$\Lambda(\cdot) = \begin{pmatrix} \Lambda_1(\cdot) \\ \vdots \\ \Lambda_p(\cdot) \\ \Lambda_{p+1}(\cdot) \end{pmatrix} \text{ and } \hat{\Lambda}(\cdot) = \begin{pmatrix} \hat{\Lambda}_1(\cdot) \\ \vdots \\ \hat{\Lambda}_p(\cdot) \\ \hat{\Lambda}_{p+1}(\cdot) \end{pmatrix}.$$

Let us introduce two classical assumptions that allow to obtain the following asymptotic results.

B1. τ satisfies $0 < \Lambda_j(\tau) < +\infty$, for $j = 1, \dots, p$.

B2. There exists a function $s_0(\cdot)$, defined on $[0, \tau]$, and bounded away from 0, such that

$$\sup_{s \in [0, \tau]} \left| \frac{Y(s)}{n} - s_0(s) \right| \xrightarrow{P} 0, \text{ when } n \rightarrow +\infty.$$

Note that these assumptions are nothing but respectively the assumptions A2 and A3 of Section 4 adapted to this new model. It is wellknown that Assumptions B1 and B2 are fulfilled whenever τ is such that $S(\tau)\bar{G}(\tau) > 0$, where S and \bar{G} are respectively the survival functions of T and C .

Note also that the functions $s_0(\cdot)\lambda_j(\cdot)$ and $\lambda_j(\cdot)/s_0(\cdot)$ are integrable on $[0, \tau]$.

Finally, let us define:

$$\begin{aligned}\eta_j(\cdot) &= \alpha_j \int_0^\cdot \lambda_j(u)/s_0(u)du, \text{ for } j = 1, \dots, p, \\ \eta_{p+1}(\cdot) &= \sum_{j=1}^p \eta_j(\cdot), \\ \theta_0(\cdot) &= \int_0^\cdot s_0(u)\lambda_m(u)du \\ \rho_j(\cdot) &= \kappa_j \alpha(1-\alpha)\Lambda_j(\cdot)/\theta_0(\tau), \text{ for } 1 \leq j \leq p+1, \\ \text{and } \rho_\alpha(\tau) &= \alpha(1-\alpha)/\theta_0(\tau).\end{aligned}$$

Theorem 5.1 *Under Assumptions A1, B1 and B2, the process $\sqrt{n}(\hat{\Lambda}(\cdot) - \Lambda(\cdot))$ converges weakly in $D^{p+1}[0, \tau]$ to a mean zero gaussian process $\mathbb{L}(\cdot)$ with covariance matrix function*

$$\Sigma_{\mathbb{L}}(t) = \Sigma_2(t)\Sigma_{V_\infty}(t)\Sigma_2^T(t),$$

where

$$\Sigma_2(t) = \begin{pmatrix} \frac{1}{\alpha} & 0 & \cdots & 0 & -\frac{\Lambda_1(t)}{\alpha} \\ 0 & \ddots & & \vdots & \vdots \\ \vdots & & \frac{1}{\alpha} & 0 & -\frac{\Lambda_p(t)}{\alpha} \\ 0 & \cdots & 0 & \frac{1}{1-\alpha} & \frac{\Lambda_{p+1}(t)}{1-\alpha} \end{pmatrix}$$

and

$$\Sigma_{V_\infty}(t) = \begin{pmatrix} \eta_1(t) & 0 & 0 & \rho_1(t) \\ 0 & \ddots & 0 & \vdots \\ 0 & 0 & \eta_{p+1}(t) & \rho_{p+1}(t) \\ \rho_1(t) & \cdots & \rho_{p+1}(t) & \rho_\alpha(\tau) \end{pmatrix}.$$

Proof. Our proof starts with the observation that:

$$\hat{\Lambda}_j(t) - \Lambda_j(t) = \frac{1}{\hat{\alpha}_j} \left(\hat{\Lambda}'_j(t) - \Lambda'_j(t) \right) - \frac{\Lambda'_j(t)}{\sqrt{n}\alpha_j\alpha'_j} \sqrt{n}(\hat{\alpha}_j - \alpha). \quad (12)$$

A straightforward application of the central limit theorem gives the \sqrt{n} -asymptotical normality of $\hat{\alpha}$ and thus that $\sqrt{n}(\hat{\alpha} - \alpha)$ is an $O_p(1)$. Moreover, under the hypotheses B1 and B2, the Nelson-Aalen estimators $\hat{\Lambda}_j(\cdot)$, for $j = 1, \dots, p+1$, are well-known to be uniformly consistent (see *e.g.* Andersen *et al.*, 1993). Hence, under the hypotheses of Theorem 5.3, one can get easily from (12) the uniform convergence in $D[0, \tau]$ of $\hat{\Lambda}_j(\cdot)$ to $\Lambda_j(\cdot)$, for $j = 1, \dots, p+1$. These convergences and (12) yield

$$\sqrt{n}(\hat{\Lambda}_j(\cdot) - \Lambda_j(\cdot)) = \frac{\sqrt{n}}{\alpha_j} \int_0^\cdot \frac{dM_{\cdot j}(s)}{Y(s)} - \frac{\Lambda_j(\cdot)}{\alpha_j} \sqrt{n}(\hat{\alpha}_j - \alpha) + o_P(1), \quad (13)$$

in $D[0, \tau]$ and for $j = 1, \dots, p+1$.

But, following the lines of Lemma 4.2, one can show that we have

$$\sqrt{n}(\hat{\alpha} - \alpha) = \sum_{j=1}^{p+1} \frac{\alpha_j^*}{\theta_0(\tau)} \frac{1}{\sqrt{n}} M_{\cdot j}(\tau) + o_P(1), \quad (14)$$

where $\theta_0(\tau) > 0$ by B1 and B2. From this and (13), we deduce that

$$\sqrt{n}(\hat{\Lambda}(t) - \Lambda(t)) = \Sigma_2(t) \mathbb{V}_n(t) + o_P(1), \quad (15)$$

in $D^{p+1}[0, \tau]$, where $\Sigma_2(t)$ is defined in Theorem 5.3 and

$$\mathbb{V}_n(t) = \sqrt{n} \begin{pmatrix} \int_0^t \frac{dM_{\cdot 1}(s)}{Y(s)} \\ \vdots \\ \int_0^t \frac{dM_{\cdot p+1}(s)}{Y(s)} \\ \frac{1}{n} \sum_{j=1}^{p+1} \frac{\alpha_j^*}{\theta_0(\tau)} M_{\cdot j}(\tau) \end{pmatrix}.$$

Using Rebolledo's Theorem or an approach given in Dauxois (2000) one can easily prove that $\mathbb{V}_n(\cdot)$ converges weakly in $D^{p+2}[0, \tau]$ to a mean zero gaussian process $\mathbb{V}_\infty(\cdot)$. It remains to specify its covariance function $\Sigma_{\mathbb{V}_\infty}(\cdot)$. First, note that we can write $\mathbb{V}_n(t) = \mathbb{V}_{1,n}(t) + \mathbb{V}_{2,n}(t)$ where

$$\mathbb{V}_{1,n}(t) = \sqrt{n} \begin{pmatrix} \int_0^t \frac{dM_{\cdot 1}(s)}{Y(s)} \\ \vdots \\ \int_0^t \frac{dM_{\cdot p+1}(s)}{Y(s)} \\ \frac{1}{n} \sum_{j=1}^{p+1} \frac{\alpha_j^*}{\theta_0(\tau)} M_{\cdot j}(t) \end{pmatrix}$$

and

$$\mathbb{V}_{2,n}(t) = \frac{1}{\sqrt{n}} \begin{pmatrix} 0 \\ \vdots \\ 0 \\ \sum_{j=1}^{p+1} \frac{\alpha_j^*}{\theta_0(\tau)} (M_{\cdot j}(\tau) - M_{\cdot j}(t)) \end{pmatrix}.$$

Since the martingales $M_{\cdot j}$ are orthogonal, for $j = 1, \dots, p+1$, we have

$$\mathbb{E} [\mathbb{V}_n^{\otimes 2}(t)] = \mathbb{E} [\mathbb{V}_{1,n}^{\otimes 2}(t)] + \mathbb{E} [\mathbb{V}_{2,n}^{\otimes 2}(t)]$$

and thus

$$\Sigma_{\mathbb{V}_\infty}(t) = \lim_{n \rightarrow \infty} \mathbb{E} [\mathbb{V}_{1,n}^{\otimes 2}(t)] + \lim_{n \rightarrow \infty} \mathbb{E} [\mathbb{V}_{2,n}^{\otimes 2}(t)].$$

Straightforward calculus lead to the expression of $\Sigma_{\mathbb{V}_\infty}(\cdot)$ given in the theorem. From this and (15) we get the desired result. \square

One can get a consistent estimator of the covariance function $\Sigma_{\mathbb{L}}(\cdot)$ of the limiting process $\mathbb{L}(\cdot)$. In this order, let us define, for $j = 1, \dots, p+1$:

$$\hat{\eta}_j(t) = n \int_0^t \frac{dN_{\cdot j}(s)}{Y^2(s)}.$$

Define also:

$$\hat{\rho}_j(t) = \kappa_j \frac{\hat{\alpha}(1 - \hat{\alpha}) \hat{\Lambda}_j(t)}{\hat{\theta}_0(\tau)}, \text{ for } j = 1, \dots, p, \text{ and } \hat{\rho}_\alpha = \frac{\hat{\alpha}(1 - \hat{\alpha})}{\hat{\theta}_0(\tau)},$$

where $\hat{\theta}_0(\tau) = N_{\cdot}(\tau)/n$.

Then, plug-in estimators of $\Sigma_2(t)$ and $\Sigma_{\mathbb{V}_\infty}(t)$, for $t \in [0, \tau]$, are respectively

$$\hat{\Sigma}_2(t) = \begin{pmatrix} \frac{1}{\hat{\alpha}} & 0 & \cdots & 0 & -\frac{\hat{\Lambda}_1(t)}{\hat{\alpha}} \\ 0 & \ddots & & \vdots & \vdots \\ \vdots & & \frac{1}{\hat{\alpha}} & 0 & -\frac{\hat{\Lambda}_p(t)}{\hat{\alpha}} \\ 0 & \cdots & 0 & \frac{1}{1-\hat{\alpha}} & \frac{\hat{\Lambda}_{p+1}(t)}{1-\hat{\alpha}} \end{pmatrix}$$

and

$$\hat{\Sigma}_{\mathbb{V}_\infty}(t) = \begin{pmatrix} \hat{\eta}_1(t) & 0 & 0 & \hat{\rho}_1(t) \\ 0 & \ddots & 0 & \vdots \\ 0 & 0 & \hat{\eta}_{p+1}(t) & \hat{\rho}_{p+1}(t) \\ \hat{\rho}_1(t) & \cdots & \hat{\rho}_{p+1}(t) & \hat{\rho}_\alpha \end{pmatrix}.$$

Finally, an empirical estimator of $\Sigma_{\mathbb{L}}(\cdot)$ is given by:

$$\hat{\Sigma}_{\mathbb{L}}(\cdot) = \hat{\Sigma}_2(\cdot) \hat{\Sigma}_{\mathbb{V}_\infty}(\cdot) \hat{\Sigma}_2^T(\cdot).$$

5.1.2 Optimal estimators of the cause specific cumulative hazard rate functions

We are in the same kind of situation than the one of Section 3.1. Indeed, our multivariate functional estimator $\hat{\Lambda}(\cdot)$ gives us estimators $\hat{\Lambda}_1(\cdot), \dots, \hat{\Lambda}_p(\cdot)$ of $\Lambda_1(\cdot), \dots, \Lambda_p(\cdot)$ respectively and an estimator $\hat{\Lambda}_{p+1}(\cdot)$ of their sum $\Lambda_{p+1}(\cdot) = \sum_{i=1}^p \Lambda_i(\cdot)$. Here also we will look for a linear transformation of $\hat{\Lambda}(\cdot)$ which will give us an optimal estimator of $\Lambda^*(\cdot) = (\Lambda_1(\cdot), \dots, \Lambda_p(\cdot))^T$.

In this order, let us define \mathcal{H}' as the set of $p \times (p+1)$ matrices such that $Ha = a^*$ for all $a^* = (a_1, \dots, a_p)^T \in \mathbb{R}^p$ and $a = (a^{*T}, \sum_{j=1}^p a_j)^T$. Let

$$\hat{H}(t) = \underset{H \in \mathcal{H}'}{\text{Argmin}} \text{trace}(H \hat{\Sigma}_{\mathbb{L}}(t) H^T) \quad (16)$$

and choose $\tilde{\Lambda}(\cdot) = \hat{H}(\cdot) \hat{\Lambda}(\cdot)$ as a new estimator of $\Lambda^*(\cdot)$. The next theorem proves that it is asymptotically normal and T -optimal.

Theorem 5.2 *Under Assumptions A1, B1 and B2, the matrix $\hat{\Sigma}_{\mathbb{L}}(t)$ converges in probability to the matrix $\Sigma_{\mathbb{L}}(t)$, for all $t \in [0, \tau]$.*

Moreover, let us assume that the matrix $\Sigma_{\mathbb{L}}(t)$ is invertible, for all $t \in]0, \tau]$. If, for all $t \in [0, \tau]$, the matrix $\hat{H}(t)$ is the unique solution of (16), then $\tilde{\Lambda}(\cdot)$ is asymptotically normal and T -optimal. More precisely, the process $\sqrt{n}(\tilde{\Lambda}(\cdot) - \Lambda^*(\cdot))$ converges weakly in $D^p[0, \tau]$ to a centered gaussian process $\mathbb{L}'(\cdot) = H_{\Sigma_{\mathbb{L}}}(\cdot)\mathbb{L}(\cdot)$ with covariance function $H_{\Sigma_{\mathbb{L}}}(\cdot)\Sigma_{\mathbb{L}}(\cdot)H_{\Sigma_{\mathbb{L}}}^T(\cdot)$ where

$$H_{\Sigma_{\mathbb{L}}}(t) = \underset{H \in \mathcal{H}'}{\text{Argmin}} \text{trace}(H\Sigma_{\mathbb{L}}(t)H^T).$$

Proof. The proof is omitted since it follows the lines of the proof of Theorem 4.4. \square

Let us denote by L the column vector in $\mathbb{R}^{p(p+1)}$ defined by $L = (H_1, \dots, H_p)$ where H_i is the i th line of $H \in \mathcal{H}'$. The link between $L = (l_i)_{1 \leq i \leq p(p+1)}$ and $H = (h_{i,j})_{1 \leq i \leq p; 1 \leq j \leq p+1}$ is therefore $h_{i,j} = l_{(i-1)(p+1)+j}$. One can see that the linear constraints on H may be written on L as $CL = d$ where C and d are given. Indeed

$$\begin{aligned} & \begin{cases} h_{i,i} + h_{i,p+1} = 1, & \text{for } 1 \leq i \leq p, \\ h_{i,j} + h_{i,p+1} = 0, & \text{for } 1 \leq i \leq p, 1 \leq j \leq p+1 \text{ and } i \neq j, \end{cases} \\ \Leftrightarrow & \begin{cases} l_{(i-1)(p+1)+i} + l_{i(p+1)} = 1, & \text{for } 1 \leq i \leq p, \\ l_{(i-1)(p+1)+j} + l_{(i+1)p} = 0, & \text{for } 1 \leq i \leq p, 1 \leq j \leq p+1 \text{ and } i \neq j, \end{cases} \\ \Leftrightarrow & CL = d, \end{aligned}$$

where the matrix C and the vector d are obvious. Moreover, let $\hat{Q}(t)$ be the block diagonal matrix defined by

$$\hat{Q}(t) = \left(\begin{array}{ccc} \hat{\Sigma}_{\mathbb{L}}(t) & & \\ & \ddots & \\ & & \hat{\Sigma}_{\mathbb{L}}(t) \end{array} \right) \Bigg\} p\text{-times}$$

and note that

$$\text{trace}(H\hat{\Sigma}_{\mathbb{L}}(t)H^T) = L^T \hat{Q}(t)L.$$

Thus, in order to find our optimal estimator, we have to solve the following optimization problems

$$(P_t) \quad \begin{cases} \text{Find } L(t) \text{ which minimizes } L^T \hat{Q}(t)L \\ \text{such that : } CL = d \end{cases},$$

for $t \in [0, \tau]$.

Following the method of Section 3.2, the solution of (P_t) is:

$$\hat{L}(t) = \hat{Q}^{-1}(t)C^T(C\hat{Q}^{-1}(t)C^T)^{-1}d$$

and $\hat{H}(t)$ is therefore defined by $\hat{h}_{ij}(t) = \hat{l}_{(i-1)(p+1)+j}(t)$ for $1 \leq i \leq p$ and $1 \leq j \leq p+1$.

Remark. Since $\hat{\Sigma}_{\perp}(t)$ is piecewise constant, it is sufficient to calculate the matrix $\hat{H}(t)$ at points $t \in [0, \tau]$ where the counting process N_{\cdot} has jumps, that is at points $X_i \in [0, \tau]$ such that $\delta_i = 1$.

5.1.3 Estimation of the Cumulative Incidence Functions and the survival function of T

Our aim in this section is to introduce estimators of the survival function $S(\cdot)$ of the lifetime T as well as estimators of the Cumulative Incidence Functions $F_j(\cdot)$ defined, for all t and $j = 1, \dots, p$, by:

$$F_j(t) = P(T \leq t, d = j).$$

In this order, let us recall that $\Lambda(\cdot) = \sum_{j=1}^p \Lambda_j(\cdot)$ is the cumulative hazard rate function of the survival time T . It is well known that one can write the survival function in terms of the cumulative hazard rate function:

$$S(t) = \prod_{u \in]0, t]} (1 - d\Lambda(u)),$$

where \prod denotes the product integral (see Gill & Johansen, 1990). Using a plug-in method on this last equation, one can get the Kaplan-Meier estimator of $S(t)$:

$$\hat{S}(t) = \prod_{u \in]0, t]} (1 - d\tilde{\Lambda}(u)),$$

where $\tilde{\Lambda}(\cdot)$ is the optimal estimator of the previous paragraph and

$$\tilde{\Lambda}(\cdot) = \sum_{j=1}^p \tilde{\Lambda}_j(\cdot).$$

On the other hand, it is also well-known that one can write, for $t \in [0, t]$ and $j = 1, \dots, p$:

$$F_j(t) = \int_0^t S(u^-) d\Lambda_j(u)$$

and that an estimator of this cumulative incidence function is given by the Aalen-Johansen estimator (see Andersen *et al.*, 1993):

$$\hat{F}_j(t) = \int_0^t \hat{S}(u^-) d\tilde{\Lambda}_j(u).$$

The asymptotic behaviour of these estimators is given by the following theorem.

Theorem 5.3 *Under Assumptions A1, B1 and B2, we have the following weak convergence in $D^{p+1}[0, \tau]$, when $n \rightarrow +\infty$:*

$$\sqrt{n} \left[\begin{pmatrix} \hat{F}_1(\cdot) \\ \vdots \\ \hat{F}_p(\cdot) \\ \hat{S}(\cdot) \end{pmatrix} - \begin{pmatrix} F_1(\cdot) \\ \vdots \\ F_p(\cdot) \\ S(\cdot) \end{pmatrix} \right] \rightarrow \begin{pmatrix} \int_0^\cdot S(u) d\mathbb{L}'_1(u) - \int_0^\cdot S(u) \mathbb{L}'(u) d\Lambda_1(u) \\ \vdots \\ \int_0^\cdot S(u) d\mathbb{L}'_p(u) - \int_0^\cdot S(u) \mathbb{L}'(u) d\Lambda_p(u) \\ -S(\cdot) \mathbb{L}'(\cdot) \end{pmatrix},$$

where $\mathbb{L}'_j(\cdot)$ is the j th component of the limiting process $\mathbb{L}'(\cdot)$ of Theorem 5.2 and $\mathbb{L}'(\cdot) = \mathbb{L}'_1(\cdot) + \cdots + \mathbb{L}'_p(\cdot)$.

Proof. This result is easily obtained from Theorem 5.2 and the functional δ -method (see e.g. van der Vaart & Wellner, 1996, for details on this method). Indeed, from the above, one can write:

$$\begin{pmatrix} F_1(\cdot) \\ \vdots \\ F_p(\cdot) \\ S(\cdot) \end{pmatrix} = \psi \begin{pmatrix} \Lambda_1(\cdot) \\ \vdots \\ \Lambda_p(\cdot) \end{pmatrix},$$

where $\psi(\cdot)$ is a function from $D^p[0, \tau]$ to $D^{p+1}[0, \tau]$ with coordinate functions defined, for $i = 1, \dots, p$, by:

$$F_i(\cdot) = \int_0^\cdot S(u^-) d\Lambda_i(u) = \psi_i \begin{pmatrix} \Lambda_1(\cdot) \\ \vdots \\ \Lambda_p(\cdot) \end{pmatrix},$$

and

$$S(\cdot) = \psi_{p+1} \begin{pmatrix} \Lambda_1(\cdot) \\ \vdots \\ \Lambda_p(\cdot) \end{pmatrix} = \prod_{u \in]0, \cdot]} (1 - d\Lambda(u)).$$

We know (see again van der Vaart & Wellner, 1996) that product-integral function

$$\begin{aligned} \phi(\cdot) : D[0, \tau] &\rightarrow D[0, \tau] \\ A &\mapsto \phi(A) = \prod_{u \in]0, \cdot]} (1 - dA(u)) \end{aligned}$$

is Hadamard differentiable on $BV_K[0, \tau]$, the subset of functions in $D[0, \tau]$ with total variation bounded by K . Its derivative is:

$$\phi'_A(\alpha)(\cdot) = - \int_0^\cdot \phi(A)(u^-) \frac{\phi(A)(\cdot)}{\phi(A)(u)} d\alpha(u)$$

and is equal to $-\phi(A)(\cdot)\alpha(\cdot)$ when A is continuous.

We also know that the function

$$\begin{aligned} \varphi(\cdot, \cdot) : D[0, \tau] \times BV_K[0, \tau] &\rightarrow D[0, \tau] \\ (A, B) &\mapsto \varphi(A, B) = \int_0^\cdot AdB \end{aligned}$$

is Hadamard differentiable on (A, B) where A is of bounded variation, with derivative:

$$\varphi'_{A,B}(\alpha, \beta)(\cdot) = \int_0^\cdot Ad\beta(u) + \int_0^\cdot \alpha dB(u).$$

Using for instance the chain rule (see Lemma 3.9.3 of van der Vaart & Wellner, 1996) and the composition

$$(\Lambda_1(\cdot), \dots, \Lambda_p(\cdot))^T \mapsto (\Lambda_i(\cdot), S(\cdot))^T \mapsto \int_0^\cdot S(u^-) d\Lambda_i(u),$$

one can prove that the coordinate functions $\psi_1(\cdot), \dots, \psi_p(\cdot)$ are differentiable and get their derivatives. The functional δ -method allows us to obtain from Theorem 5.2 the following weak convergence in $D^{p+1}[0, \tau]$:

$$\sqrt{n} \left(\psi(\tilde{\Lambda}) - \psi(\Lambda^*) \right) \rightarrow \psi'_{\Lambda^*}(\mathbb{L}'),$$

when $n \rightarrow +\infty$. Straightforward differential calculus and the continuity of $S(\cdot)$ give the expression of $\psi'_{\Lambda^*}(\mathbb{L}')$ detailed in the Theorem. \square

5.2 With explanatory variables

Now, let us come back to the semiparametric model of equation (1) with explanatory variable Z . Recall that we have, for $j = 1, \dots, p$:

$$dN_{\cdot j}(s) = dM_{\cdot j}(s) + \alpha Y(s) d\Lambda_{0j}(s) + \alpha n S_1^T(s) \beta_j ds.$$

Thus, an estimator of $\Lambda_{0j}(t)$ is given, for all $t \in [0, \tau]$, by

$$\hat{\Lambda}_{0j}(t) = \frac{1}{\hat{\alpha}} \int_0^t \frac{dN_{\cdot j}(s)}{Y(s)} - \hat{\beta}_j^T \int_0^t \frac{S_1(s)}{S_0(s)} ds,$$

where $\hat{\beta}_j$ is the estimator introduced in Section 3.1 and is such that $\mathcal{U}_j(\hat{\beta}_j, \alpha_j, \tau) = 0$.

Then we propose to estimate $\Lambda_j(\cdot|\mathbb{Z})$, for $j = 1, \dots, p$, by $\hat{\Lambda}_j(\cdot|\mathbb{Z})$ defined, for $t \geq 0$, by

$$\hat{\Lambda}_j(t|\mathbb{Z}) = \hat{\Lambda}_{0j}(t) + \hat{\beta}_j^T \int_0^t Z(s) ds = \frac{1}{\hat{\alpha}} \int_0^t \frac{dN_{\cdot j}(s)}{Y(s)} + \hat{\beta}_j^T \left(\int_0^t Z(s) ds - \int_0^t \frac{S_1(s)}{S_0(s)} ds \right),$$

where by abuse of notation $\int_0^t Z(s) ds$ denotes the vector of integrals of each coordinate of $Z(\cdot)$.

Before giving the large sample behaviour of these estimators in the following theorem, let us introduce other notations. For $j = 1, \dots, p$ let us define:

$$\begin{aligned}\mu_{1j}(\cdot) &= \alpha \int_0^\cdot \frac{s_0(s)\lambda_{0j}(s) + \beta_j^T s_1(s)}{s_0^2(s)} ds, \\ \mu_{2j}(\cdot) &= \frac{\alpha(1-\alpha)}{\theta(\tau)} \int_0^\cdot \frac{s_0(s)\lambda_{0j}(s) + \beta_j^T s_1(s)}{s_0(s)} ds, \\ \mu_{3j}(\cdot) &= \alpha \int_0^\cdot \frac{a(s)}{s_0(s)} ds \beta_j\end{aligned}$$

and the block-matrix

$$\Sigma_5(t) = \frac{1}{\alpha} \begin{pmatrix} 1 & 0 & 0 & \dots & 0 & K(t) & 0 & 0 & \dots & 0 & -\Lambda_1(t|\mathbb{Z}) \\ 0 & 1 & 0 & \dots & 0 & 0 & K(t) & 0 & \dots & 0 & -\Lambda_2(t|\mathbb{Z}) \\ \vdots & \ddots & \ddots & \ddots & \vdots & \vdots & \ddots & \ddots & \ddots & \vdots & \vdots \\ 0 & \dots & 0 & 1 & 0 & 0 & \dots & 0 & K(t) & 0 & -\Lambda_{p-1}(t|\mathbb{Z}) \\ 0 & \dots & 0 & 0 & 1 & 0 & \dots & 0 & 0 & K(t) & -\Lambda_p(t|\mathbb{Z}) \end{pmatrix}$$

where $K(t)$ is a $1 \times k$ vector defined by

$$K(t) = \left(\int_0^t Z(s) ds - \int_0^t \frac{s_1(s)}{s_0(s)} ds \right)^T A^{-1}(\tau)$$

Theorem 5.4 *Under Assumptions A1-A5, the process*

$$\sqrt{n} \left(\hat{\Lambda}_1(\cdot|\mathbb{Z}) - \Lambda_1(\cdot|\mathbb{Z}), \dots, \hat{\Lambda}_p(\cdot|\mathbb{Z}) - \Lambda_p(\cdot|\mathbb{Z}) \right)^T$$

converges weakly in $D^p[0, \tau]$, when $n \rightarrow +\infty$, to a mean zero gaussian process with covariance matrix $\Sigma_5(t)\Sigma_{\mathbb{W}'_\infty}(t)\Sigma_5^T(t)$, where:

$$\Sigma_{\mathbb{W}'_\infty}(t) = \frac{1}{\alpha} \begin{pmatrix} \mu_{11}(t) & 0 & 0 & \dots & 0 & \mu_{31}^T(t) & 0 & 0 & \dots & 0 & \mu_{21}(t) \\ 0 & \mu_{12}(t) & 0 & \dots & 0 & 0 & \mu_{32}^T(t) & 0 & \dots & 0 & \mu_{22}(t) \\ \vdots & \ddots & \ddots & \ddots & \vdots & \vdots & \ddots & \ddots & \ddots & \vdots & \vdots \\ 0 & \dots & 0 & \mu_{1(p-1)}(t) & 0 & 0 & \dots & 0 & \mu_{3(p-1)}^T(t) & 0 & \mu_{2(p-1)}(t) \\ 0 & \dots & 0 & 0 & \mu_{1p}(t) & 0 & \dots & 0 & 0 & \mu_{3p}^T(t) & \mu_{2p}(t) \\ \mu_{31}(t) & 0 & 0 & \dots & 0 & \Theta_1(\tau) & 0 & 0 & \dots & 0 & \xi_1(\tau) \\ 0 & \mu_{32}(t) & 0 & \dots & 0 & 0 & \Theta_2(\tau) & 0 & \dots & 0 & \xi_2(\tau) \\ \vdots & \ddots & \ddots & \ddots & \vdots & \vdots & \ddots & \ddots & \ddots & \vdots & \vdots \\ 0 & \dots & 0 & \mu_{3(p-1)}(t) & 0 & 0 & \dots & 0 & \Theta_{p-1}(\tau) & 0 & \xi_{p-1}(\tau) \\ 0 & \dots & 0 & 0 & \mu_{3p}(t) & 0 & \dots & 0 & 0 & \Theta_p(\tau) & \xi_p(\tau) \\ \mu_{21}(t) & \dots & \dots & \dots & \mu_{2p}(t) & \xi_1^T(\tau) & \dots & \dots & \dots & \xi_p^T(\tau) & \xi_\alpha(\tau) \end{pmatrix}$$

Proof. By the definition of $\Lambda_j(\cdot|\mathbb{Z})$ and $\hat{\Lambda}_j(\cdot|\mathbb{Z})$, one can write, for all $t > 0$ and $j = 1, \dots, p$:

$$\sqrt{n} \left(\hat{\Lambda}_j(\cdot|\mathbb{Z}) - \Lambda_j(\cdot|\mathbb{Z}) \right) = \sqrt{n} \left[\left(\frac{1}{\hat{\alpha}} \int_0^t \frac{dN_{\cdot j}(s)}{Y(s)} - \hat{\beta}_j^T \int_0^t \frac{S_1(s)}{S_0(s)} ds - \Lambda_{0j}(t) \right) + (\hat{\beta}_j - \beta_j)^T \int_0^t Z(s) ds \right]$$

But it is easy to check that our assumptions and preliminary results yield

$$\begin{aligned} & \sqrt{n} \left(\frac{1}{\hat{\alpha}} \int_0^t \frac{dN_{\cdot j}(s)}{Y(s)} - \hat{\beta}_j^T \int_0^t \frac{S_1(s)}{S_0(s)} ds - \Lambda_{0j}(\cdot) \right) \\ &= \frac{\sqrt{n}}{\hat{\alpha}} \int_0^t \frac{dM_{\cdot j}(s)}{Y(s)} - \frac{\sqrt{n}(\hat{\alpha} - \alpha)}{\alpha} \left(\beta_j^T \int_0^t \frac{s_1(s)}{s_0(s)} ds + \Lambda_{0j}(\cdot) \right) - \sqrt{n}(\hat{\beta}_j - \beta_j)^T \int_0^t \frac{s_1(s)}{s_0(s)} ds + o_P(1). \end{aligned}$$

These two last equations and (7) enable us to write:

$$\begin{aligned} & \sqrt{n} \left(\hat{\Lambda}_j(\cdot|\mathbb{Z}) - \Lambda_j(\cdot|\mathbb{Z}) \right) = \\ & \frac{\sqrt{n}}{\hat{\alpha}} \int_0^t \frac{dM_{\cdot j}(s)}{Y(s)} - \frac{\sqrt{n}(\hat{\alpha} - \alpha)}{\alpha} \Lambda_j(\cdot|\mathbb{Z}) + \frac{1}{\alpha} \left(A^{-1}(\tau) \frac{\mathcal{U}_j(\beta_j, \alpha_j, \tau)}{\sqrt{n}} \right)^T \left(\int_0^t Z(s) ds - \int_0^t \frac{s_1(s)}{s_0(s)} ds \right) + o_P(1). \end{aligned}$$

Hence we have, :

$$\sqrt{n} \begin{pmatrix} \hat{\Lambda}_1(\cdot|\mathbb{Z}) - \Lambda_1(\cdot|\mathbb{Z}) \\ \vdots \\ \hat{\Lambda}_p(\cdot|\mathbb{Z}) - \Lambda_p(\cdot|\mathbb{Z}) \end{pmatrix} = \Sigma_5(\cdot) \mathbb{W}'_n(\cdot) + o_P(1),$$

where

$$\mathbb{W}'_n(\cdot) = \left(\sqrt{n} \int_0^t \frac{dM_{\cdot 1}(s)}{Y(s)}, \dots, \sqrt{n} \int_0^t \frac{dM_{\cdot p}(s)}{Y(s)}, \frac{\mathcal{U}_1^T(\beta_1, \alpha_1, \tau)}{\sqrt{n}}, \dots, \frac{\mathcal{U}_p^T(\beta_p, \alpha_p, \tau)}{\sqrt{n}}, \frac{1}{\sqrt{n}} \sum_{j=1}^{p+1} \frac{\alpha_j^*}{\theta(\tau)} M_{\cdot j}(\tau) \right)^T$$

But a straightforward application of Rebollo's Theorem proves that the process

$$\mathbb{W}_n(\cdot) = \left(\sqrt{n} \int_0^t \frac{dM_{\cdot 1}(s)}{Y(s)}, \dots, \sqrt{n} \int_0^t \frac{dM_{\cdot p}(s)}{Y(s)}, \frac{\mathcal{U}_1(\beta_1, \alpha_1, \cdot)}{\sqrt{n}}, \dots, \frac{\mathcal{U}_p(\beta_p, \alpha_p, \cdot)}{\sqrt{n}}, \frac{1}{\sqrt{n}} \sum_{j=1}^{p+1} \frac{\alpha_j^*}{\theta(\tau)} M_{\cdot j}(\cdot) \right)^T$$

converges weakly in $D^{p(k+1)+1}[0, \tau]$ to a mean-zero multivariate gaussian martingale $\mathbb{W}_\infty(\cdot)$.

It is easy to check that the covariance matrix $\Sigma_{\mathbb{W}_\infty}(\cdot)$ of this limiting process is similar to $\Sigma_{\mathbb{W}'_\infty}(\cdot)$ where τ is everywhere replaced by t . This ends the proof. \square

Estimators $\hat{\Theta}_1(\tau), \dots, \hat{\Theta}_p(\tau), \hat{\xi}_1(\tau), \dots, \hat{\xi}_p(\tau)$ and $\hat{\xi}_\alpha(\tau)$ of respectively $\Theta_1(\tau), \dots, \Theta_p(\tau), \xi_1(\tau), \dots, \xi_p(\tau)$ and $\xi_\alpha(\tau)$ have been introduced in Section 4.4. Moreover, one can estimate $\mu_{1j}(t), \mu_{2j}(t), \mu_{3j}(t)$, for $j = 1, \dots, p$ and $t \in [0, \tau]$, with

$$\begin{aligned} \hat{\mu}_{1j}(t) &= n\hat{\alpha} \int_0^t \frac{dN_{\cdot j}}{S_0^2(s)}, \\ \hat{\mu}_{2j}(t) &= \frac{\hat{\alpha}(1 - \hat{\alpha})}{\hat{\theta}(\tau)} \int_0^t \frac{dN_{\cdot j}(s)}{S_0(s)}, \\ \hat{\mu}_{3j}(t) &= \hat{\alpha} \hat{A}(t) \hat{\beta}_j \end{aligned}$$

and an estimator of $K(t)$ is given by:

$$\hat{K}(t) = \left(\int_0^t Z(s)ds - \int_0^t \frac{S_1(s)}{S_0(s)} ds \right)^T \hat{A}^{-1}(\tau).$$

Using these estimators one can get consistent estimators of the matrices $\Sigma_5(t)$ and $\Sigma_{\mathbb{W}'_\infty}(t)$.

Finally, it has to be noted that, as in Section 5.1.3, it is also possible to get estimators of the survival function and the cumulative incidence functions as well as to get their large sample behaviour (like in Theorem 5.3) . But this is omitted here since it is very similar to what has been done in Section 5.1.3.

6 Numerical study

6.1 A simulated example with covariates

In this section we give an example where we have two competing risks with a single covariate Z . We assume that Z is 1 or 2 with equal probabilities. Conditional on Z , we suppose that the hazard rate functions of T_1 and T_2 are respectively given by $\lambda_1(t|Z) = t/2 + 2Z$ and $\lambda_2(t|Z) = 2t/9 + 3Z$, therefore we have $\beta_1 = 2$ and $\beta_2 = 3$. The censoring time C is exponentially distributed with mean 1 whereas the rate of missingness α is equal to 0.5. As a consequence, on the whole simulated data the rate of censored data is about 12%, the rates of observed failures from cause 1 and 2 are respectively about 15% and 28%, and the rate of missingness is about 45%.

n	$\hat{\beta}_1$	$\tilde{\beta}_1$	$\hat{\beta}_2$	$\tilde{\beta}_2$
100	2.116 [1.583]	2.117 [1.438]	3.024 [1.923]	3.004 [1.610]
200	2.055 [1.111]	2.023 [1.000]	3.083 [1.367]	3.039 [1.146]
400	2.021 [0.768]	2.001 [0.687]	3.043 [0.919]	3.011 [0.784]
1000	1.998 [0.500]	2.001 [0.454]	2.989 [0.584]	2.993 [0.502]

Table 1: Comparison of means and standard errors (within brackets) of $N = 1000$ estimates of $\hat{\beta}_i$ and $\tilde{\beta}_i$ for $i = 1, 2$.

In Table 1 we compare the performances of estimators $(\hat{\beta}_i)_{i=1,2}$ based on transitions $0 \rightarrow i$ with T -optimal estimators $(\tilde{\beta}_i)_{i=1,2}$ that use observations coming from the three informative transitions. We computed the mean and standard errors of 1000 estimates of β_1 and β_2 . We can see in Table 1 that from the bias point of view the T -optimal estimators are generally better (except for β_1 when $n = 100$) whereas the standard errors of T -optimal

estimates are always smaller than the standard errors of estimates based on transitions 1 and 2.

6.2 A reliability example without covariates

This example deals with the hard drives data sample that may be found in Flehinger *et al.* (2002). These authors consider a scenario in which a company manufacturing hard drives for computers tries to analyze causes of failures of a certain sub-assembly. Some of these causes, such as "defective head", are related to components, but others (e.g., "particle contamination") are not; in this example, there are three major causes of failures which, without going into details, are denoted as causes 1, 2 and 3. We assume that these causes act independently and in series. 10,000 drives were manufactured and then information about failures was collected in a database during 4 years. The number of failures observed in this period was 172. Some of the failures were masked and a selected number of those were analyzed to complete resolution in the defect isolation laboratory. The only observed masked groups were $\{1, 2, 3\}$ and $\{1, 3\}$. Considering causes 1 and 3 as a single failure cause we obtain data from a competing risks model with two failure modes. Mode 1 (corresponding to causes 1, 3 or masked group $\{1, 3\}$ of the original data set) and mode 2 (that corresponds to cause 2 in the original data set). The failure cause is missing when none of the three original cause of failure is known (corresponding to the masking group $\{1, 2, 3\}$ of the original data set). Finally, we obtain a data set with 119 failures of type 1, 19 failures of type 2 and 34 failures for which the failure cause is unavailable. The lifetimes of the 9828 drives still functioning at the end of the study are censored by the 4 years of the study duration. Because no information is available after 4 years we fix τ to 4. The probability α that the two failure causes are missing is estimated by $\hat{\alpha} = 0.802$. Figure 2 shows, for each failure cause, estimates of cumulative hazard rate functions with and without using the transition $0 \rightarrow 3$ and the corresponding 95% pointwise confidence intervals for each estimate. We can see that there is a little gain to use transition $0 \rightarrow 3$. We can see also that the modified Nelson-Aalen estimators that we propose are slightly more regular (smaller size jumps) than the corresponding Nelson-Aalen estimators, in exchange of which our estimators can be non legitimate (they can be locally decreasing). However this drawback disappears as the sample size increases because of uniform convergence of our estimators. This is also true for the two causes reliability estimates that are given on Figure 3 with pointwise 95% confidence intervals.

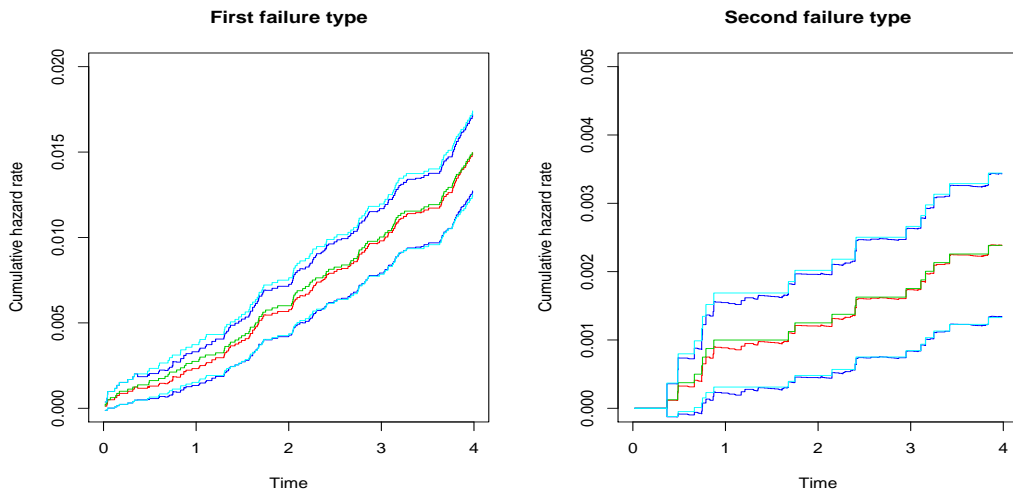


Figure 2: Cumulative hazard rate functions estimated without using the transition $0 \rightarrow 3$ (dotted lines) with 95% pointwise confidence intervals (long-dashed lines) and optimized estimation of the cumulative hazard functions (solid lines) with 95% pointwise confidence intervals (dashed lines) for the two failure causes.

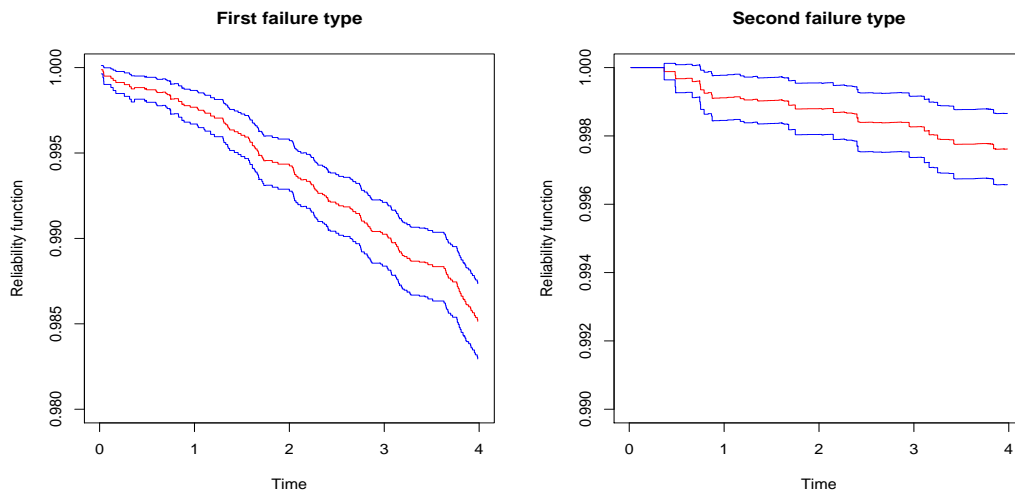


Figure 3: Estimated reliability functions (solid lines) with 95% pointwise confidence intervals (dashed lines) for the two failure causes.

7 Conclusions

In this paper we consider a semiparametric competing risks model that accounts covariates and the fact that information on failure cause can be missing completely at random. In this paper the missingness mechanism is very simple because it is independent of everything (time, failure causes, covariates, etc.). However, because of nonparametric assumptions for baseline hazard rate function of every type of failure cause, this model is quite adaptable. It is certainly possible to extend this model in several directions: dependent risks, missingness mechanism dependent on failure cause, etc. This model can also be extended to the case of masked cause of failure for which many sophisticated parametric models and inference methods have been developed over the two past decades. The estimation method that consists in seeing data as realizations of a nonhomogeneous markov process is inspired by McKeague and Subramanian (1998) while the estimators of the regression parameters of each transition is inspired from the Lin and Ying (1994) method. In addition we propose a linear transformation of these estimators which is shown to be asymptotically optimal in the sense of variance reduction.

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