

On asymptotic inference about intensity parameters of a counting process

Kacha Dzhaparidze

Centre for Mathematics and Computer Science
Kruislaan 413, 1098 SJ Amsterdam,
The Netherlands

SUMMARY

The Cox regression model may be viewed as a special case (see (1.3)) of the general model described in this paper via the pair (\bar{A}_t, Ψ_t) of predictable characteristics of an r -variate counting process $N_t = (N_t^1, \dots, N_t^r)$, associated with its compensator $A_t = (A_t^1, \dots, A_t^r)$ as follows: $\bar{A}_t = A_t^1 + \dots + A_t^r$ and $\Psi_t = dA_t/dA_t$. It is supposed that the latter characteristic involves the real valued parameter β , i.e. $\Psi_t = \Psi_t(\beta)$, to be estimated by means of a given sample path of $\{N_t, 0 \leq t \leq 1\}$. Treating this problem in its asymptotic setting, we consider our experiment (2.1) as n -th in a sequence of experiments, and let \bar{A}_t meet Condition I of asymptotic stability. Under this and certain additional conditions introduced on demand, we study asymptotic properties of the estimator $\hat{\beta}$ for β defined by (1.4), which is in fact the Cox estimator extended to our situation. In particular, we characterize the consistency and asymptotic normality of $\hat{\beta}$ by estimating the probability of large deviations, and then showing the convergence in all moments of the distribution of $\hat{\beta}$ to a normal law. Finally, it is shown that $\hat{\beta}$ is the best within a class of (regular) estimators in the sense that neither of them can have an asymptotic distribution that is less spread out than that of $\hat{\beta}$.

RESUME

Le modèle de régression de Cox peut être considéré comme un cas spécial (voir (1.3)) du modèle général décrit dans cet article via les caractéristiques prévisibles (\bar{A}_t, Ψ_t) d'une processus de comptage r -dimensionnel $N_t = (N_t^1, \dots, N_t^r)$ avec sa compensatrice $A_t = (A_t^1, \dots, A_t^r)$ comme suit: $\bar{A}_t = A_t^1 + \dots + A_t^r$ et $\Psi_t = dA_t/d\bar{A}_t$. Il est supposé que la dernière caractéristique dépend d'un paramètre réel β , c'est à dire $\Psi_t = \Psi_t(\beta)$, qui doit être estimé à la base d'une trajectoire de $\{N_t, 0 \leq t \leq 1\}$. En traitant ce problème dans une cadre asymptotique, nous considérons notre expériment (2.1) comme la n -ième dans une série d'expériences, et nous supposons que \bar{A}_t satisfait la condition I de stabilité asymptotique. Sous cette hypothèse et certaines autres conditions introduites aux points différents plus tard nous étudions les propriétés asymptotiques de l'estimateur $\hat{\beta}$ de β défini par (1.4), qui est en fait l'estimateur de Cox étendue à notre situation. Particulièrement nous caractérisons la convergence et la normalité asymptotique de $\hat{\beta}$ par l'estimation de la probabilité des grandes déviations et puis par démonstration la convergence des tous les moments de la loi de $\hat{\beta}$ vers une loi normale. Finalement nous montrons que $\hat{\beta}$ est le meilleur dans une classe d'estimateur réguliers au sens qu'aucun de ceux possède une distribution asymptotique plus dispersée que celle de $\hat{\beta}$.

1. INTRODUCTION

1. Statistical inference on counting processes attracts considerable attention in the literature of recent years; see Bibliography where a number of related references is enclosed which may serve as a source for many further references. Typically, the approach taken in these works is inspired by the developments of the theory of stochastic processes related to the notion of martingales, see, e.g. Shirayev (1981), as well as by the developments of the asymptotic theory of statistical decisions, see, e.g. Le Cam (1969) or Ibragimov/Has'minskii (1981); also Greenwood/Shirayev (1985).

Within the framework of the theory of stochastic processes, these processes are defined on a complete probability space (Ω, \mathcal{F}, P) equipped with a nondecreasing family $\{\mathcal{F}_t, t \geq 0\}$ of right-continuous sub- σ -algebras of \mathcal{F} augmented by sets from \mathcal{F} of zero probability. For the sake of simplicity, we discuss only the case in which $t \in [0, 1]$.

Let $N = (N_t, \mathcal{F}_t, P)$ be r -variate counting process which by definition consists of components $N_t^i, i = 1, \dots, r$ having stepwise sample paths: $N_0^i = 0, N_t^i - N_{t-}^i = \Delta N_t^i = 0$ or $1, \Delta N_t^i \Delta N_t^j = 0$ if $i \neq j$ (no two component processes jumping at the same time), and $N_t^i < \infty$ P -a.s. With N one may associate an r -variate predictable increasing process $A = \{A_t, \mathcal{F}_t, P\}$ such that $N - A \equiv M = \{M_t, \mathcal{F}_t, P\}$ is an r -variate local square integrable martingale with the quadratic characteristic $\langle M \rangle_t = \text{diag} A_t - [A]$ (see Lemma 3.1).

If, in addition, the filtration is of special form $\mathcal{F}_t = \sigma\{\omega: N_s, s \leq t\}$ then the probability measure P is completely defined by the compensator A (in the sense of Liptser/Shirayev (1978), Section 18.3). Hence in this the statistical model for the observed phenomena may be completely specified in terms of the compensator A , or, for convenience, in terms of the so-called (P, \mathcal{F}_t) -predictable characteristics (\bar{A}_t, Ψ_t) of N_t , associated with A , by the following relations $\Psi_t = dA_t/d\bar{A}_t$ and $\bar{A}_t = \mathbb{1}_r^T A_t$ (here $\mathbb{1}_r = \text{col}(1, \dots, 1)$, and T indicates the transposition). Obviously, the first of these characteristics is the compensator of $\bar{N}_t = N_t^1 + \dots + N_t^r$, while the r -variate nonnegative predictable process $\Psi = \{\Psi_t, \mathcal{F}_t, P\}$ consists of components $\Psi_t^i, i = 1, \dots, r, \Psi_t^i$ being, roughly speaking, the probability of having a jump of N_t^i at time t , given \mathcal{F}_{t-} and given that \bar{N}_t jumps at time t ; Brémaud (1981), pp. 34 and 236.

2. In applications the latter characteristic is usually parametrized: it is restricted to a certain parametric

family $\Psi \in \{\Psi(\beta), \beta \in \mathfrak{B}\}$ of nonnegative \mathfrak{F}_t -predictable processes for each admissible value of the parameter $\beta \in \mathfrak{B}$.

In such a case β is "the parameter of interest" - inference about β is required by means of a given sample path of $\{\mathbf{N}_t, 0 \leq t \leq 1\}$ drawn according to the pair $(\bar{A}_t, \Psi_t(\beta))$ of the characteristics of \mathbf{N} for an unknown β and, typically, for the characteristic \bar{A}_t specified only up to the restrictions of a general nature (to be introduced below). Actually, \bar{A}_t itself may depend on the parameter of interest β , as well as on certain nuisance quantities, as it is illustrated by the following

Example 1.1. Let $\{P_{\alpha, \beta}, \alpha \in \mathcal{A}, \beta \in \mathfrak{B}\}$ be a family of the probability measures, where \mathcal{A} is a set of deterministic nonnegative and nondecreasing functions $\alpha = \alpha_t, 0 \leq t \leq 1$, and \mathfrak{B} an open set of R^1 . For each $\alpha \in \mathcal{A}$ and $\beta \in \mathfrak{B}$ let $\mathbf{N} = (\mathbf{N}_t, \mathfrak{F}_t, P_{\alpha, \beta})$ be an r -variate counting process of the Poisson type (Liptser/Shiryayev (1978), p. 249) defined on the stochastic basis $(\Omega, \mathfrak{F}, \{\mathfrak{F}_t, 0 \leq t \leq 1\}, P_{\alpha, \beta})$, with the compensator of form

$$\mathbf{A}_t = \mathbf{A}_t(\alpha, \beta) = \int_0^t \Phi_s(\beta) d\alpha_s, \quad 0 \leq t \leq 1 \quad (1.1)$$

where $\Phi(\beta)$ is an r -variate nonnegative \mathfrak{F}_t -predictable process for each $\beta \in \mathfrak{B}$. Obviously, the pair of the $(P_{\alpha, \beta}, \mathfrak{F}_t)$ -predictable characteristics of the process \mathbf{N} is given by the following relations

$$\Psi_t(\beta) = \Phi_t(\beta) / \bar{\Phi}_t(\beta) \quad \text{with} \quad \bar{\Phi}_t(\beta) = \mathbf{1}_t^T \Phi_t(\beta), \quad \text{and} \quad \bar{A}_t(\alpha, \beta) = \int_0^t \bar{\Phi}_s(\beta) d\alpha_s \quad (1.2)$$

The most popular special case of the Cox regression model for censored survival data specifies these characteristics as follows:

$$\Psi_t^i(\beta) = Y_t^i e^{\beta Z_t^i} / \sum_{i=1}^r Y_t^i e^{\beta Z_t^i}, \quad \bar{A}_t(\alpha, \beta) = \int_0^t \sum_{i=1}^r Y_s^i e^{\beta Z_s^i} d\alpha_s \quad (1.3)$$

with certain \mathfrak{F}_t -predictable processes Y_t^i and Z_t^i , free from β ; see, e.g., Andersen/Gill (1982) (or, for a bit more general model, Prentice/Self (1983)). These authors and later Begun et al. (1983) have shown that under wide conditions the particular estimator $\hat{\beta}$ for β , defined by the relation

$$\sup_{\beta \in \mathfrak{B}} \int_0^1 \ln^T \Psi_s(\beta) d\mathbf{N}_s = \int_0^1 \ln^T \Psi_s(\hat{\beta}) d\mathbf{N}_s, \quad \ln \Psi = \text{col}\{\ln \Psi^i, i = 1, \dots, r\} \quad (1.4)$$

possesses the desired asymptotic properties (to be specified in the next section)

Obviously, if $\Psi_s(\beta)$ is a sufficiently smooth function of β , then the estimator $\hat{\beta}$ of β is well defined by condition (1.4) also for the general set up discussed at the beginning of this subsection (and not only for the special Cox model; see (1.3)). Naturally, one can expect that under circumstances similar to those of the papers mentioned above, the estimator $\hat{\beta}$ preserves its desired properties. In the present paper this conjecture is confirmed, furthermore, a refined characterization of these properties is given (cp. Efron (1977)).

Note that unlike Andersen/Gill (1982) here only the case of the real valued parameter β is discussed, and the abstract parameter α in (1.3) (or (1.2)) is considered as the nuisance quantity.

2. ASYMTOTIC INFERENCE

1. Following the usual device of the asymptotic theory (Le Cam (1969), Ibragimov/Has'minskii (1978)) suppose that observed is an outcome of the experiment.

$$\mathfrak{E}_n = (\Omega^n, \mathfrak{F}^n, \{\mathfrak{F}_t^n, 0 \leq t \leq 1\}, \{P^n\})$$

(with a certain family of probability measures $\{P^n\}$), which is actually n -th in the sequence of experiments $\mathfrak{E}_1, \mathfrak{E}_2, \dots$. Fix P^n at the right-hand side of (2.1), and define on that stochastic basis an r_n -variate counting process $\mathbb{N}^n = \{\mathbb{N}_t^n, \mathfrak{F}_t^n, P^n\}$ where $r_n, n = 1, 2, \dots$ is a nondecreasing sequence of integers. As above, with the compensator $\mathbb{A}^n = \{\mathbb{A}_t^n, \mathfrak{F}_t^n, P^n\}$ of \mathbb{N}^n relate the pair (\bar{A}_t^n, Ψ_t^n) of the (P^n, \mathfrak{F}_t^n) -predictable characteristics, and let Ψ_t^n depend on $\beta \in \mathfrak{B}$.

The class of all admissible pairs $(\bar{A}_t^n, \Psi_t^n(\beta))$ of the (P^n, \mathfrak{F}_t^n) -predictable characteristics of \mathbb{N}^n determines the family of the probability measures $\{P^n\}$ in (2.1). The following basic condition restricts this class up to an asymptotic stability requirement on the sequence $F_t^n \equiv \bar{A}_t^n / k_n = \int_0^t \mathbb{A}_s^n / k_n$ with an unboundedly increasing sequence of numbers $k_n, n = 1, 2, \dots$

Condition I. For each admissible pair $(\bar{A}_t^n, \Psi_t^n(\beta))$ of the (P^n, \mathfrak{F}_t^n) -predictable characteristics there exists a continuous deterministic function of bounded variation F_t such that $F_t^n \rightarrow F_t$ in P^n probability as $n \rightarrow \infty$, each $t, 0 \leq t \leq 1$.

Remark 2.1.

In fact, by lemma 1 of Mcleish (1978), p. 146 the continuity of F_t implies $\sup_{0 \leq t \leq 1} |F_t^n - F_t| \rightarrow 0$ in P^n probability as $n \rightarrow \infty$

Define now the estimator $\hat{\beta}_n$ for β by condition (1.4) with $\mathbb{N} = \mathbb{N}^n$ and $\Psi = \Psi^n$. On deriving asymptotic (as $n \rightarrow \infty$) properties of $\hat{\beta}_n$, we require some regularity conditions on $\Psi^n(\beta)$; see Conditions II-IV in Section 4.

Condition II requires differentiability (in a certain sense) of $\sqrt{\Psi^n(\beta)} = \text{col}\{\sqrt{\Psi^{in}}, i=1, \dots, r_n\}$ and existence of a positive number ν - the limit of $\int_0^1 |(\partial/\partial\beta)\sqrt{\Psi^n(\beta)}|^2 dF^n$ in P^n probability. Condition III (of the Lindeberg type), together with Condition II, leads to the conclusion of Corollary 4.1 needed for deriving asymptotic normality $N(0, 1/4\nu)$ of the estimator $\hat{\beta}_n$.

As for Condition IV, it permits us (via Lemma 4.1) to apply a generalized version of Theorem 5.1 (Ibragimov/Has'minskii (1981), Section 1.5: Inequalities for Probabilities of Large Deviations) due to Sieders (1985), the conclusion of which can be informally described as follows: Let an estimator $\hat{\beta}_n$ for β be defined by maximizing with respect to β a certain functional of observations (e.g., the likelihood function). If this functional satisfies certain conditions, similar to the conditions imposed on the likelihood function in the above mentioned Theorem 5.1, then the estimator $\hat{\beta}_n$ is not only consistent (in P^n probability), but also the following holds: for sufficiently large values of n the P^n -probability that $2\sqrt{k_n\nu}(\hat{\beta}_n - \beta)$ exceeds in absolute value a (sufficiently large) number H is less than $C_0 \exp -c_0 H^2$, with some positive constants c_0 and C_0 .

Hence, this way we get the first main result of Section 4 - the refinement of consistency of the estimator $\hat{\beta}_n$ (Proposition 4.1).

The second main result concerns the refinement of asymptotic normality of $\hat{\beta}_n$ based on a generalization of Theorem 10.1 (Ibragimov/Has'minskii (1981), p. 103): if the generalized version of Theorem 5.1 holds (Sieders (1985)), as well as Corollary 4.1 and Lemma 4.2, then all moments of $2\sqrt{k_n\nu}(\hat{\beta}_n - \beta)$ converge to the corresponding moments of the standard normal distribution (Proposition 4.2).

2. On discussing optimality properties of the estimator $\hat{\beta}_n$ in Section 5, we restrict our considerations to the processes of the Poisson type; see Example 1.1 in which all the introduced quantities are indexed now by n , except the parameters α and β , of course.

In the first place we show the LAN property of the family $\{P_{\alpha, \beta}^n, \alpha \in \mathfrak{A}, \beta \in \mathfrak{B}\}$ of the probability measures defined on $(\Omega^n, \mathfrak{F}^n)$; see Definition 4.1. Along with $P^n = P_{\alpha, \beta}^n$, let the probability measure $\bar{P}^n = P_{\alpha, \beta}^n / \int d\alpha$ be defined on $(\Omega^n, \mathfrak{F}^n)$, where $\beta^n = \beta + b/\sqrt{k_n} \in \mathfrak{B}$, $b \in R^1$ and $\alpha^n \in \mathfrak{A}$ is defined by the relation $\sqrt{d\alpha^n/d\alpha} = 1 + a_t/\sqrt{k_n}$, $a_t \in L^2(dF)$ with $F_t = F_t(\alpha, \beta)$ of Condition V1.2. Then $\bar{P}^n \ll P^n$, and $d\bar{P}^n/dP^n$ is given by (5.1). The above mentioned LAN property is stated in Proposition 5.1 which tells us that under the Conditions

V-VII the logarithm of dP^n/dP^n is in fact asymptotically quadratic with the asymptotically normal linear term $\delta_{\alpha,\beta}^n(a,b)$, and the quadratic term $-\frac{1}{2}g_{\alpha,\beta}(a,b)$ where $g_{\alpha,\beta}(a,b)$ is the limit in P^n probability of the quadratic characteristic of $\delta_{\alpha,\beta}^n(a,b)$.

Condition V.I requires continuous differentiability of $\sqrt{\Phi^n(\beta)}$ (in certain sense), and Condition V.2, together with Condition VI, determines the form of $g_{\alpha,\beta}(a,b)$. Condition VII (of the Lindeberg type) ensures the asymptotic normality of the linear term $\delta_{\alpha,\beta}^n(a,b)$.

Having the LAN, one can take advantage of its fairly general implications due to Le Cam and Hájek (see, e.g., Ibragimov/Has'minskii (1981), Ch. II and III, or Millar (1983)). Specifically, our conclusions about asymptotic optimality properties of the estimator $\hat{\beta}_n$ are based on the application of Hájek's convolution theorem to the situation under consideration (see Theorem 5.1).

For these purposes, define first the class of regular estimators $\{\beta_R^n\}$ for β . Under the conditions ensuring the LAN property of the family $\{P_{\alpha,\beta}^n, \alpha \in \mathcal{A}, \beta \in \mathcal{B}\}$, at "point" $\alpha \in \mathcal{A}, \beta \in \mathcal{B}$ (Proposition 5.1), the estimator β_R^n is called regular (at the point $\alpha \in \mathcal{A}, \beta \in \mathcal{B}$) if for some nondegenerate distribution function G_R^0 the following weak convergence takes place:

$$\mathcal{L}\{\sqrt{k_n}(\beta_R^n - \beta) | P^n\} \Rightarrow G_R^0 \quad (2.2)$$

uniformly for each $|b| < c$ whatever $c > 0$, and each bounded $a \in L^2(dF)(\underline{\alpha}^n, \underline{\beta}^n$ and \underline{P}^n being defined as above).

Now, Hájek's convolution theorem (Begun et al. (1983)) tells us that G_R^0 at the right-hand side of (2.2) can be represented as the convolution of a certain normal law with another distribution law, G_R^1 say. By Proposition 5.2, in our special case $G_R^0 = N(0, 1/4\nu) * G_R^1$ where $N(0, 1/4\nu)$ coincides with the asymptotic distribution of $\sqrt{k_n}(\hat{\beta}_n - \beta)$; see the previous subsection.

Since convolution "spreads out mass", no regular estimator β_R^n can have an asymptotic distribution that is less spread out than $N(0, 1/4\nu)$. Thus, in this sense the estimator $\hat{\beta}_n$ (which is regular under the conditions of the previous subsection; see Theorem 5.1) is best within the class $\{\beta_R^n\}$.

The proof of the results just mentioned uses the fact that the neighborhood about α that shrinks at rate $k_n^{-\frac{1}{2}}$ in the directions $\{a\}$, defined above, is "sufficiently fat" to include the function $(\partial/\partial\beta)\sqrt{\phi_r(\beta)}/\sqrt{\phi_r(\beta)}$ where $\phi_r(\beta)$ is the bounded limit in $P_{\alpha,\beta}^n$ probability of $\bar{\Phi}_r^n(\beta)/k_n$ (Condition VI). Simply, the variety $\{a\}$ includes $(\partial/\partial\beta)\sqrt{\phi_r(\beta)}/\sqrt{\phi_r(\beta)}$; see Proposition 5.2.

3. This inclusion typically fails in situations in which $\{a\}$ is a low dimensional subspace of $L^2(dF)$, namely, in the frequently encountered situations in which "the cumulative hazard function" α_r is also parametrized up to a certain number of nuisance parameters, and hence $\{a\}$ is taken as a linear subspace, $A = A(\alpha)$ say, spanned by the logarithmic derivatives of the density of α_r with respect to the nuisance parameters; see, e.g., Efron (1977), Jarupskin (1983), Borgan (1984), Hjort (1984). According to these works the following conclusions can be drawn about the maximum likelihood estimator β_{ML}^n for β , defined by maximizing the likelihood function (see (5.1)) simultaneously with respect to the parameter of interest β and the nuisance parameters.

Under certain regularity conditions $\mathcal{L}\{\sqrt{k_n}(\beta_{ML}^n - \beta^n) | P^n\} \Rightarrow N(0, \mathcal{G}_{\alpha,\beta}^-)$ with $\mathcal{G}_{\alpha,\beta}^-$ defined as in (5.3), and this means that no $R^1 \times A$ -regular estimator β_{RA}^n can have an asymptotic distribution less spread than that of β_{ML}^n . In fact, the estimator β_{RA}^n is called $R^1 \times A$ -regular if for some nondegenerate distribution function G_{RA}^0 $\mathcal{L}\{\sqrt{k_n}(\beta_{RA}^n - \beta^n) | P^n\} \Rightarrow G_{RA}^0$ for each $b \in R^1, a \in A$, whereas Proposition 5.2 tells us that G_{RA}^0 may be represented as the convolution (5.3). In particular, β_{ML}^n is less dispersed than the estimator $\hat{\beta}_n$, for comparing their variances we have $\mathcal{G}^{-1} \leq (4\nu)^{-1}$ with equality iff $(\partial/\partial\beta)\sqrt{\phi_r(\beta)}/\sqrt{\phi_r(\beta)} \in A$ (see Remark 5.3).

It is important, however, that there is a subclass of estimators for β within which no estimator has a less spread asymptotic distribution than $\hat{\beta}_n$ defined by (1.4). This is the subclass $\{\beta_R^n\} \subset \{\beta_{RA}^n\}$ of regular estimators defined as in the previous subsection by the condition: whatever the (bounded) direction $a \in L^2(dF)$ of

approach to α there is some nondegenerate distribution function G_R^0 such that (2.2) takes place. Of course, β_{ML}^a is not regular in this sense, as for $a \in A$ a bias appears in its limiting distribution. While the estimator $\hat{\beta}_n$ is regular, and it is the best among $\{\beta_R^a\}$ since by Proposition 5.3 G_R^0 may be always represented as the convolution $G_R^0 = N(0, 1/4\nu) * G_R^1$ (Theorem 5.1).

3. THE LIKELIHOOD RATIO

1. Let $(\Omega, \mathcal{F}_t, P)$ be a complete probability space with a filtration $\{\mathcal{F}_t, 0 \leq t \leq 1\}$ satisfying the usual conditions.

Let $\mathbf{N} = \{\mathbf{N}_t, \mathcal{F}_t, P; 0 \leq t \leq 1\}$ be a multivariate (r -variate) counting process: $\mathbf{N} = \text{col}\{N^1, \dots, N^r\}$. Consider its Doob-Meyer decomposition $\mathbf{N} = \mathbf{M} + \mathbf{A}$ where $\mathbf{M} = \{\mathbf{M}_t, \mathcal{F}_t, P; 0 \leq t \leq 1\}$ is a local square integrable martingale, and $\mathbf{A} = \{\mathbf{A}_t, \mathcal{F}_t, P; 0 \leq t \leq 1\}$ a predictable compensator.

Lemma 3.1. The quadratic variation and quadratic characteristic of \mathbf{M} are given by the following relations:

- 1) $[\mathbf{M}] = \text{diag} \mathbf{N} - [\mathbf{A}] - [\mathbf{M}, \mathbf{A}] - [\mathbf{A}, \mathbf{M}]$
- 2) $\langle \mathbf{M} \rangle = \text{diag} \mathbf{A} - [\mathbf{A}]$

Proof. By definition $[\mathbf{N}] = \text{diag} \mathbf{N}$, and this gives 1). To get 2) take the compensator of both sides of 1).

Remark 3.1. Denote $\bar{N} = N^1 + \dots + N^r, \bar{N} = \bar{M} + \bar{A}$. From 2) follows

$$\langle \bar{M} \rangle_t = \bar{A}_t - [\bar{A}]_t = \int_0^t (1 - \Delta \bar{A}) d\bar{A}, \quad \Delta \langle \bar{M} \rangle = (1 - \Delta \bar{A}) \Delta \bar{A},$$

hence $0 \leq \Delta \bar{A} \leq 1$. For simplicity assume $\Delta \bar{A} < 1$ (in fact one can easily dispense with this restriction; see e.g. Kabanov et al. (1975) or (1980)).

Remark 3.2. Consider $V_t = I_r - \Delta \mathbf{A}_t \otimes \mathbb{1}_r$ and $V_t^{-1} = I_r + (1 - \Delta \bar{A}_t)^{-1} \Delta \mathbf{A}_t \otimes \mathbb{1}_r$ with $\mathbb{1}_r = \text{col}(1, \dots, 1)$ and $I_r = \text{diag} \mathbb{1}_r$. Then $\langle \mathbf{M} \rangle_t = \int_0^t V \text{diag} d\mathbf{A}$ and $\text{diag} \mathbf{A}_t = \int_0^t V^{-1} d\langle \mathbf{M} \rangle$.

Lemma 3.2. Let $\mathcal{Q}_t = \int_0^t V^{-1} d\mathbf{A} = \int_0^t (1 - \Delta \bar{A})^{-1} d\mathbf{A}$ and $\mathcal{R}_t = \int_0^t V^{-1} d\mathbf{M} = \mathbf{M}_t + [\mathcal{Q}, \bar{M}_t]$. Then

- 1) $[\mathcal{R}]_t = \text{diag} \mathbf{N}_t + \int_0^t (1 - \Delta \bar{N}) d[\mathcal{Q}]$,
- 2) $\langle \mathcal{R} \rangle = \text{diag} \mathbf{A} + [\mathcal{Q}, \mathbf{A}]$.

Proof. As $\Delta \mathbf{N} \otimes \mathbb{1}_r^2 = \text{diag} \Delta \mathbf{N}, (1 - \Delta \bar{N})^2 = (1 - \Delta \bar{N})$ and $\Delta \mathbf{N}(1 - \Delta \bar{N}) = 0$, 1) follows from

$$\Delta [\mathcal{R}] = \Delta \mathbf{M} + \Delta \mathcal{Q} \Delta \bar{M} = \Delta \mathbf{N} - \Delta \mathcal{Q} (1 - \Delta \bar{N}). \quad (3.1)$$

To get 2) take the compensators of both sides of 1).

2. Suppose that a probability measure \underline{P} in addition to the probability measure P is given on a measurable space (Ω, \mathcal{F}) with a filtration of special form $\underline{\mathcal{F}}_t = \sigma\{\mathbf{N}_s, s \leq t\}, 0 \leq t \leq 1$. Along with $\mathbf{N} = (\mathbf{N}_t, \mathcal{F}_t, P)$, consider the counting process $\underline{\mathbf{N}} = (\mathbf{N}_t, \underline{\mathcal{F}}_t, \underline{P})$ with compensator $\underline{\mathbf{A}} = (\mathbf{A}_t, \underline{\mathcal{F}}_t, \underline{P})$.

Theorem 3.1. (Kabanov et al. (1980)). 1) For absolute continuity of \underline{P} with respect to $P (\underline{P} \ll P)$ the following

conditions are necessary and sufficient: \underline{P} -a.s.

I $\Delta \bar{A} = 1$ implies $\Delta \bar{A} = 1$.

II. The components \underline{A}^i and $A^i, i=1, \dots, r$ of $\underline{\mathbf{A}}$ and \mathbf{A} are related as $\underline{A}_t^i = \int_0^t \lambda^i dA^i$ where $col\{\lambda^1, \dots, \lambda^r\} = \underline{\Lambda} = \{\Lambda_r, \mathfrak{F}_t\}$ is a nonnegative predictable process such that the associate Hellinger process is bounded: $\mathfrak{H}_t = \int_0^t \sum_{i=1}^r (\sqrt{d\underline{A}^i} - \sqrt{dA^i})^2 + \sum_{\substack{s \leq t \\ 0 < \Delta A_s < 1}} (\sqrt{1 - \Delta \bar{A}_s} - \sqrt{1 - \Delta A_s})^2 < \infty$.

2) Assume $\underline{P} \ll P$, and denote z_t a right-continuous modification of the martingale $E(d\underline{P}/dP|\mathfrak{F}_t), 0 \leq t \leq 1$. Then $z_t = \exp\{m_t + \sum_{s \leq t} \Phi_1(\Delta m_s)\}$ where $m_t = \int_0^t (\Lambda - \mathbb{1}_r)^T d\mathfrak{N}$ and $\Phi_1(x) = \ln(1+x) - x$.

Remark 3.3. By (3.1) and $(\Lambda - \mathbb{1}_r)^T \Delta \mathfrak{E} = 1 - \frac{1 - \Delta \bar{A}}{1 - \Delta A}$, $\Phi_1(\Delta m) = \Phi_1^T(\Lambda - \mathbb{1}_r) \Delta \mathfrak{N} + (1 - \Delta \bar{N}) \Phi_1(\frac{1 - \Delta \bar{A}}{1 - \Delta A} - 1)$.

Hence $z_t = \exp\{\int_0^t \ln^T \Lambda d\mathfrak{N} - \bar{A}_t^c + \bar{A}_t^c + \sum_{s \leq t} (1 - \Delta \bar{N}_s) \ln \frac{1 - \Delta \bar{A}_s}{1 - \Delta A_s}\}$ (cp. Liptser/Shiryayev (1978), p. 312).

Remark 3.4. Process $z = (z_t, \mathfrak{F}_t, P)$, being a nonnegative supermartingale with $E(z|P) = 1$ as well as a local martingale, is a solution of the Doleans-Dade equation $z_t = 1 + \int_0^t z_s - dm_s, 0 \leq t \leq 1$ (Liptser/Shiryayev (1978), p. 288).

3. Let $\{\Omega^n, \mathfrak{F}_t^n, (\mathfrak{F}_t^n, 0 \leq t \leq 1), P^n\}, n=1, 2, \dots$ be a sequence of stochastic bases of the same type as above. Let $\mathfrak{N}^n = (\mathfrak{N}_t^n, \mathfrak{F}_t^n, P^n)$ be an r_n -variate counting process with the Doob-Meyer decomposition $\mathfrak{N}^n = \mathfrak{M}^n + \mathbf{A}^n$, where $r_n, n=1, 2, \dots$ is a nondecreasing sequence of integers.

Define also $\mathfrak{N}_t^n = \int_0^t (V^n)^{-1} d\mathfrak{M}^n$ where $V^n = I_{r_n} - \Delta \mathbf{A}^n \otimes \mathbb{1}_{r_n}$. Assume that the compensator \mathbf{A}^n satisfies Condition I of Section 2.

Lemma 3.3. Under Condition I for each $t, 0 \leq t \leq 1$ $k_n^{-1} \langle \mathfrak{N}^n \rangle_t \rightarrow F_t$ in P^n probability as $n \rightarrow \infty$.

Proof. By 2) of Lemma 3.2 $k_n^{-1} \langle \mathfrak{N}^n \rangle_t = F_t^n + k_n^{-1} \sum_{s \leq t} (1 - \Delta \bar{A}_s^n)^{-1} (\Delta \bar{A}_s^n)^2$, where the second term satisfies the inequality

$$\begin{aligned} & \frac{1}{k_n} \sum_{\substack{s \leq t \\ 0 < \Delta A_s^n < \frac{1}{2}}} (1 - \Delta \bar{A}_s^n)^{-1} (\Delta \bar{A}_s^n)^2 + \frac{1}{k_n} \sum_{\substack{s \leq t \\ \frac{1}{2} < \Delta A_s^n < 1}} (1 - \Delta \bar{A}_s^n)^{-1} (\Delta \bar{A}_s^n)^2 \\ & \leq \frac{2}{k_n} [\bar{A}^n]_t + \frac{1}{k_n} \sum_{\substack{s \leq t \\ \frac{1}{2} < \Delta A_s^n < 1}} (1 - \Delta \bar{A}_s^n)^{-1} \end{aligned}$$

and therefore tends to 0 in P^n probability, as $k_n^{-1} [\bar{A}^n]_t \leq k_n^{-1} \bar{A}_t^{nd} \rightarrow 0$ and the number of jumps of $\bar{A}_s^n, s \leq t$, exceeding $\frac{1}{2}$ is finite.

The last argument is used also in (3.2) and (3.4) below.

Theorem 3.2. Let $W^1 = (W_t^1, \mathfrak{F}_t)$ be a continuous Gaussian martingale with the quadratic variation $\langle W^1 \rangle_t = F_t$. Then, under Condition I, $k_n^{-\frac{1}{2}} \mathfrak{N}^n \xrightarrow{D} W$ as $n \rightarrow \infty$ in $D[0, 1]$.

Proof follows from Liptser/Shiryayev (1980), Corollary 2. In fact, the condition (12) of this corollary is met (Lemma 3.3). As for the Lindeberg condition (L_2) of the corollary, for $k_n^{-\frac{1}{2}} \mathfrak{N}_t^n = k_n^{-\frac{1}{2}} \int_0^t (1 - \Delta \bar{A}_s^n)^{-1} d\bar{M}_s^n$ it is

satisfied as for each ϵ , $0 < \epsilon < \frac{1}{2}$

$$k_n^{-1} \int_0^t I(\Delta \bar{A}_s^n > 1 - \epsilon)(1 - \Delta \bar{A}_s^n)^{-2} d\langle \bar{M} \rangle_s = k_n^{-1} \int_0^t I(\Delta \bar{A}_s^n > 1 - \epsilon)(1 - \Delta \bar{A}_s^n)^{-1} d\bar{A}_s^n \leq k_n^{-1} \sum_{\substack{s \leq t \\ 1 - \epsilon < \Delta \bar{A}_s^n < 1}} (1 - \Delta \bar{A}_s^n)^{-1} \rightarrow 0 \quad (3.2)$$

in P^n probability as $n \rightarrow \infty$.

Lemma 3.4. Let $\mathbf{H}^n = \{\mathbf{H}_t^n, \mathfrak{F}_t^n, P^n\}$, $n = 1, 2, \dots$ be a sequence of r_n -vector valued predictable processes such that there is a function σ_t^2 satisfying $\int_0^t \sigma^2 dF > 0$ for which (each t , $0 \leq t \leq 1$)

$$\int_0^t \mathbf{H}^{nT} \text{diag} d\mathbf{A}^n \rightarrow \int_0^t \sigma^2 dF \quad (3.3)$$

in P^n probability as $n \rightarrow \infty$. Then $\langle \int_0^t \mathbf{H}^{nT} d\mathfrak{N}^n \rangle \rightarrow \int_0^t \sigma^2 dF$ in P^n probability as $n \rightarrow \infty$.

Proof. In view of the continuity of F

$$\int_0^t \mathbf{H}^{nT} \text{diag} d\mathbf{A}^{nd} \mathbf{H}^n = \sum_{s \leq t} \mathbf{H}_s^{nT} \text{diag} \Delta \mathbf{A}^n \mathbf{H}_s^n \rightarrow 0$$

in P^n probability as $n \rightarrow \infty$, and this implies

$$\begin{aligned} \int_0^t \mathbf{H}^{nT} d[\mathfrak{N}^n, \mathbf{A}^n] \mathbf{H}^n &= \sum_{s \leq t} (1 - \Delta \bar{A}_s^n)^{-1} (\mathbf{H}_s^{nT} \Delta \mathbf{A}_s^n)^2 \leq \\ &\leq \sum_{\substack{s \leq t \\ 0 < \Delta \bar{A}_s^n < \frac{1}{2}}} \mathbf{H}_s^{nT} \text{diag} \Delta \mathbf{A}_s^n \mathbf{H}_s^n + \sum_{\substack{s \leq t \\ \frac{1}{2} < \Delta \bar{A}_s^n < 1}} (1 - \Delta \bar{A}_s^n)^{-1} \mathbf{H}_s^{nT} \text{diag} \Delta \mathbf{A}_s^n \mathbf{H}_s^n \rightarrow 0 \end{aligned} \quad (3.4)$$

in P^n probability as $n \rightarrow \infty$, by $\mathfrak{N}_t^n = \int_0^t (1 - \Delta \bar{A}_s^n)^{-1} d\mathbf{A}^n$ and the Schwartz inequality. Now, the desired result follows from (3.3), (3.4) and 2) of Lemma 3.2.

Theorem 3.3. Along with (3.3) let the following Lindeberg condition be satisfied: for each t , $0 \leq t \leq 1$ and $\epsilon > 0$ (here $\mathbf{H}^n = \text{col}\{H^{in}, i = 1, \dots, r_n\}$)

$$\int_0^t \sum_{i=1}^{r_n} I(|H^{in}| > \epsilon)(H^{in})^2 dA^{in} \rightarrow 0 \quad (3.5)$$

in P^n probability as $n \rightarrow \infty$. Let $W = (W_t, \mathfrak{F}_t)$ be a continuous Gaussian martingale with the quadratic variation $\langle W \rangle_t = \int_0^t \sigma^2 dF$. Then $\int_0^t \mathbf{H}^{nT} d\mathfrak{N}^n \xrightarrow{D} W_t$ as $n \rightarrow \infty$ in $D([0, 1])$.

Proof is immediate consequence of Liptser/Shiryayev (1980), Corollary 2, for its conditions (12) and (L_2) are verified by Lemma 3.4 and, respectively, (3.4) and (3.5).

4. Suppose that a probability measure \underline{P}^n in addition to P^n is given on a measurable space $\{\Omega^n, \mathfrak{F}^n\}$ in the sequence of stochastic bases of the preceding subsection. Suppose in addition that the filtration $\{\mathfrak{F}_t^n, 0 \leq t \leq 1\}$ is minimal: $\mathfrak{F}_t^n = \sigma\{\mathbf{N}_s^n : s \leq t\}$ where $\mathbf{N}^n = (\mathbf{N}_t^n, \mathfrak{F}_t^n, P^n)$ is an r_n -variate counting process with the compensator $\mathbf{A}^n = (\mathbf{A}_t^n, \mathfrak{F}_t^n, P^n)$. Let $\underline{\mathbf{N}}^n = (\underline{\mathbf{N}}_t^n, \mathfrak{F}_t^n, \underline{P}^n)$ be another counting process with the compensator $\underline{\mathbf{A}}^n = (\underline{\mathbf{A}}_t^n, \mathfrak{F}_t^n, \underline{P}^n)$.

For each n assume $\underline{P}^n \ll P^n$ and, in accordance with II of Theorem 3.1, define the Hellinger process

$$\mathfrak{H}_t^n = \int_0^t \mathbf{U}^{nT} \text{diag} d\mathbf{A}^n \mathbf{U}^n + \sum_{\substack{s \leq t \\ 0 < \Delta \bar{A}_s^n < 1}} (\sqrt{1 - \Delta \bar{A}_s^n} - \sqrt{1 - \Delta \bar{A}_s^n})^2$$

where $\mathbf{U}^n = \text{col}\{U^{in} = \sqrt{dA^{in}/dA^{in}} - 1, i=1, \dots, r_n\}$. Obviously, $\Lambda^n = \text{col}\{\lambda^{in} = (U^{in} + 1)^2, i=1, \dots, r_n\}$.

Theorem 3.4. Let there be a function σ_t^2 satisfying $\int_0^1 \sigma^2 dF > 0$ such that for each $t, 0 \leq t \leq 1$ $\mathfrak{C}_t^n \rightarrow \int_0^1 \sigma^2 dF$ in P^n probability as $n \rightarrow \infty$. Let $\mathbf{U}^n, n=1, 2, \dots$ satisfy the Lindeberg condition (3.5). Then $\ln z_1^n = m_1^n + \sum_{s \leq 1} \Phi_1(\Delta m_s^n)$ (with $m_1^n = \int_0^1 (\Lambda^n - \mathbb{1}_n)^T d\mathfrak{M}^n$) is asymptotically normal:

$$\mathfrak{L}\{\ln z_1^n | P^n\} \Rightarrow N\left(-2 \int_0^1 \sigma^2 dF, 4 \int_0^1 \sigma^2 dF\right). \quad (3.6)$$

Proof of this theorem follows the same line as that of Gill (1979) Proposition 5.3.1, and therefore it will be shortly sketched in the following two remarks.

Remark 3.5. Since \mathbf{U}^n satisfies the conditions of Theorem 3.3, $m_1^n = 2 \int_0^1 \mathbf{U}^{nT} d\mathfrak{M}^n + \int_0^1 \mathbf{U}^{nT} \text{diag} d\mathfrak{M}^n \mathbf{U}^n$ is asymptotically normal with zero mean and variance $4 \int_0^1 \sigma^2 dF$, that is the limit in P^n probability of $4 < \int_0^1 \mathbf{U}^{nT} d\mathfrak{M}^n >$.

Remark 3.6. As

$$\frac{1}{2} \sum_{s \leq 1} \Phi_1(\Delta m_s^n) = \int_0^1 \Phi_2^T(\mathbf{U}^n) d\mathfrak{N}^n + \sum_{s \leq 1} (1 - \Delta \bar{N}^n) \Phi_2\left(1 - \sqrt{\frac{1 - \Delta \bar{A}^n}{1 - \Delta \bar{A}^n}}\right) - \int_0^1 \mathbf{U}^{nT} \text{diag} d\mathbf{A}^n \mathbf{U}^n$$

where the first two terms tend to zero, while the third term tends to $-\int_0^1 \sigma^2 dF$ in P^n probability, the desired limiting value is obtained for the mean in (3.6). Here $\Phi_2(x)$ for $x = \text{col}(x^1, \dots, x^r)$ denotes $\text{col}\{\ln(1+x^i) - x^i + \frac{1}{2}x^{i2}, i=1, \dots, r\}$.

In the sequel we deal with a situation in which the following condition is satisfied: There is a sequence of bounded r_n -variate predictable processes $\mathfrak{S}^n = \{\mathfrak{S}_t^n, \mathfrak{S}_t^n, P^n\}, n=1, 2, \dots$ such that

$$\int_0^1 (\mathbf{U}^n - k_n^{-\frac{1}{2}} \mathfrak{S}^n)^T \text{diag} d\mathbf{A}^n (\mathbf{U}^n - k_n^{-\frac{1}{2}} \mathfrak{S}^n) \rightarrow 0 \quad (3.7)$$

in P^n probability as $n \rightarrow \infty$.

Corollary 3.1. If $k_n^{-\frac{1}{2}} \mathfrak{S}^n, n=1, 2, \dots$ satisfies (3.3), (3.5) and (3.7) (with $\mathbb{M}^n = k_n^{-\frac{1}{2}} \mathfrak{S}^n$), then $z_1^n = \exp\left\{\frac{2}{\sqrt{k_n}} \int_0^1 \mathfrak{S}^{nT} d\mathfrak{M}^n - 2 \int_0^1 \sigma^2 dF + \eta_n\right\}$ where $\eta_n \rightarrow 0$ in P^n probability as $n \rightarrow \infty$ and $\mathfrak{L}\{k_n^{-\frac{1}{2}} \int_0^1 \mathfrak{S}^{nT} d\mathfrak{M}^n\} \Rightarrow N\left(0, \int_0^1 \sigma^2 dF\right)$.

4. CONSISTENCY AND ASYMPTOTIC NORMALITY

1. Consider the situation described in Subsection 2.1, and suppose that the r_n -vector valued process $\sqrt{\Psi^n(\beta)}$ is continuously differentiable (in β) in the following sense:

Condition II. There is a sequence of continuous in β r_n -vector valued predictable processes

$$\mathbf{L}^n(\beta) \left(\equiv \frac{\partial}{\partial \beta} \sqrt{\Psi^n(\beta)} \right) = \{ \mathbf{L}^n(\beta), \mathfrak{F}_t^n, P^n \} \quad n=1,2,\dots$$

such that if $(\bar{A}_t^n, \Psi_t^n(\beta))$ is the pair of the (P^n, \mathfrak{F}_t^n) -predictable characteristics, then

II 1. For each real valued b such that $\bar{\beta}^n = \beta + b/\sqrt{k_n} \in \mathfrak{B}$, eventually,

$$\int_0^1 |\sqrt{\Psi^n(\bar{\beta}^n)} - \sqrt{\Psi^n(\beta)} - \frac{b}{\sqrt{k_n}} \mathbf{L}^n(\beta)|^2 d\bar{A}^n \rightarrow 0$$

in P^n probability as $n \rightarrow \infty$.

II 2. For some deterministic function $\sigma_t^2(\beta)$ such that $\nu_t(\beta) = \int_0^t \sigma^2(\beta) dF > 0$, $0 \leq t \leq 1$

$$\nu_t^n(\beta) = \int_0^t |\mathbf{L}^n(\beta)|^2 dF^n \rightarrow \nu_t(\beta)$$

in P^n probability as $n \rightarrow \infty$.

We shall show that the estimator $\hat{\beta}_n$, defined by (1.4) with $\Psi = \Psi^n$ and $\mathfrak{N} = \mathfrak{N}^n$ is consistent and asymptotically normal $N(0, 1/4\nu)$, $\nu = \nu_1(\beta)$. For this we need some additional conditions stipulated in the next subsection.

2. Define $\frac{\partial}{\partial \beta} \ln \Psi^n(\beta) = 2(\text{diag } \Psi^n(\beta))^{1/2} \frac{\partial}{\partial \beta} \sqrt{\Psi^n(\beta)}$ and

$$\frac{\partial}{\partial \beta} \ln \Psi^n(\beta) = 2(\text{diag } \Psi^n(\beta))^{-1/2} \frac{\partial}{\partial \beta} \sqrt{\Psi^n(\beta)}.$$

Obviously,

$$\int_0^t \left\{ \frac{\partial}{\partial \beta} \ln \Psi^n(\beta) \right\}^T d\mathbf{A}^n = \int_0^t \mathfrak{N}_t^n \frac{\partial}{\partial \beta} \Psi^n(\beta) d\bar{A}^n = 0. \quad (4.1)$$

Hence,

$$\int_0^t \left\{ \frac{\partial}{\partial \beta} \ln \Psi^n(\beta) \right\}^T d\mathfrak{N}^n = \int_0^t \left\{ \frac{\partial}{\partial \beta} \ln \Psi^n(\beta) \right\}^T d\mathfrak{N}^n \quad (4.2)$$

and

$$\frac{1}{k_n} \int_0^t \left\{ \frac{\partial}{\partial \beta} \ln \Psi^n(\beta) \right\}^T \text{diag } d\mathbf{A}^n \left\{ \frac{\partial}{\partial \beta} \ln \Psi^n(\beta) \right\} = 4 \int_0^t |\mathbf{L}^n(\beta)|^2 dF^n \rightarrow 4\nu_t(\beta) \quad (4.3)$$

in P^n probability as $n \rightarrow \infty$ (see II.2)).

Now we apply Theorem 3.3. to derive asymptotic normality of the intergral in (4.2), taking account of (4.1) and (4.3).

Corollary 4.1. Along with Conditions II, let the following Lindeberg condition hold ($\mathbf{L}^n = \text{col}\{L^{in}, i=1, \dots, r_n\}$):

Condition III. If $(\bar{A}_t^n, \Psi_t^n(\beta))$ is the pair of the (P^n, \mathfrak{F}_t^n) -predictable characteristics, then for each $\epsilon > 0$

$$\frac{1}{k_n} \int_0^1 \sum_{i=1}^{r_n} I(k_n^{-1/2} |L^{in}(\beta)| > \epsilon) |L^{in}(\beta)|^2 d\bar{A}^n \rightarrow 0$$

in P^n probability as $n \rightarrow \infty$ Then

$$\mathcal{E}\left(\frac{1}{k_n} \int_0^1 \left\{ \frac{\partial}{\partial \beta} \ln \Psi^n(\beta) \right\}^T d\mathbb{N}^n | P^n\right) \Rightarrow N(0, 4\nu)$$

Condition IV. If $(\bar{A}_t^n, \Psi_t^n(\beta))$ is the pair of the (P^n, \mathfrak{F}_t^n) -predictable characteristics, then

$$\int_0^1 |\sqrt{\Psi^n(\beta_n^2)} - \sqrt{\Psi^n(\beta_n^1)}|^2 d\bar{A}^n,$$

where

$$\beta_n^i = \beta + b_i/2\sqrt{k_n\nu}, \quad b_i \in B_n = \mathfrak{B} - \beta/2\sqrt{k_n\nu}, \quad i=1,2,$$

obeys the following bounds: there are constants $C_1 > 0$ and $C_2 > C_1$ (independent of n) such that for sufficiently large values of n and each $b_i \in B_n$, $i=1,2$

$$P^n \text{ a.s. } C_1(b_2 - b_1)^2 \leq \int_0^1 |\sqrt{\Psi^n(\beta_n^2)} - \sqrt{\Psi^n(\beta_n^1)}|^2 d\bar{A}^n \leq C_2(b_2 - b_1)^2$$

Lemma 4.1. Let Condition IV hold. Define $Y^n(b) = \exp \int_0^1 (\ln \Psi_s^n(\beta_n) - \ln \Psi_s^n(\beta)) d\mathbb{N}^n$, $b \in B_n$. Then there are constants $c_1 > 0$ and $c_2 > 0$ such that for each $b \in B_n$ and $b_i \in B_n$, $i=1,2$

- (i) $E\{\sqrt{Y^n(b)} | P^n\} \leq e^{-c_1 b^2}$,
- (ii) $E\{|\sqrt{Y^n(b_2)} - \sqrt{Y^n(b_1)}|^2 | P^n\} \leq c_2 |b_2 - b_1|^2$

Proof.

- (i). In accordance with the remarks 3.3 and 3.4

$$E\{\sqrt{Y^n(b)} \exp(\frac{1}{2} \int_0^1 |\sqrt{\Psi_s^n(\beta_n)} - \sqrt{\Psi_s^n(\beta)}|^2 d\bar{A}^{nc} + \sum_{s \leq 1} (1 - \Delta \bar{N}_s^n) \ln(1 + \frac{1}{2} \frac{\Delta \bar{A}_s^n}{1 - \Delta \bar{A}_s^n} |\sqrt{\Psi_s^n(\beta_n)} - \sqrt{\Psi_s^n(\beta)}|^2)) | P^n\} = 1.$$

Thus

$$1 \geq \exp \frac{1}{2} C_1 b^2 E\{\sqrt{Y^n(b)} \exp - \frac{1}{2} \sum_{s \leq 1} |\sqrt{\Psi_s^n(\beta_n)} - \sqrt{\Psi_s^n(\beta)}|^2 \Delta A_s^n | P^n\} \geq E\{\sqrt{Y^n(b)} | P^n\} \exp c_1 b^2.$$

- (ii) As

$$E\{Y^n(b) | P^n\} = E\{\exp \int_0^1 (\ln \Psi_s^n(\beta_n) - \ln \Psi_s^n(\beta)) d\mathbb{N}^n | P^n\} = 1, \quad (4.4)$$

and

$$E\{\sqrt{Y^n(b_1)Y^n(b_2)} \exp(\frac{1}{2} \int_0^1 |\sqrt{\Psi_s^n(\beta_n^2)} - \sqrt{\Psi_s^n(\beta_n^1)}|^2 d\bar{A}^{nc} + \sum_{s \leq 1} (1 - \Delta \bar{N}_s^n) \ln(1 + \frac{1}{2} \frac{\Delta \bar{A}_s^n}{1 - \Delta \bar{A}_s^n} |\sqrt{\Psi_s^n(\beta_n^2)} - \sqrt{\Psi_s^n(\beta_n^1)}|^2)) | P^n\} = 1,$$

we have

$$\begin{aligned} 1 &\leq 2 \exp \frac{1}{2} C_2 (b_2 - b_1)^2 E\{\sqrt{Y^n(b_1)Y^n(b_2)} \exp \frac{1}{2} \sum_{s \leq 1} \frac{\Delta \bar{A}_s^n}{1 - \Delta \bar{A}_s^n} |\sqrt{\Psi_s^n(\beta_n^2)} - \sqrt{\Psi_s^n(\beta_n^1)}|^2 | P^n\} \\ &\leq 2 \exp \frac{1}{2} C_2 (b_2 - b_1)^2 E\{\sqrt{Y^n(b_1)Y^n(b_2)} \exp(\sum_{\substack{s \leq 1 \\ 0 < \Delta \bar{A}_s^n < \frac{1}{2}}} |\sqrt{\Psi_s^n(\beta_n^2)} - \sqrt{\Psi_s^n(\beta_n^1)}|^2 \Delta A_s^n) | P^n\} \end{aligned}$$

$$+ \frac{1}{2} \sum_{\substack{s \leq 1 \\ \frac{1}{2} < \Delta A_s^1 < 1}} \frac{\Delta A_s^1}{1 - \Delta A_s^1} |\sqrt{\Psi_s^1(\beta_n^1)} - \sqrt{\Psi_s^1(\beta_n^2)}|^2 |P^n| \leq E\{\sqrt{Y^n(b_1)Y^n(b_2)} | P^n\} e^{\frac{1}{2}c_2(b_2 - b_1)^2}$$

(cp. the proof of Lemma 3.3), and

$$\begin{aligned} E\{|\sqrt{Y^n(b_2)} - \sqrt{Y^n(b_1)}|^2 | P^n\} &\leq 2(1 - E\{\sqrt{Y^n(b_2)Y^n(b_1)} | P^n\}) \leq \\ &\leq 2(1 - e^{-\frac{1}{2}c_2(b_2 - b_1)^2}) \leq c_2(b_2 - b_1)^2. \end{aligned}$$

Lemma 4.1 and the equation (4.4) allow us to apply the result of Sieders (1985) mentioned in Subsection 2.1.

Proposition 4.1. Under the conditions stipulated above there are certain positive constants C_0 and c_0 such that the estimator $\hat{\beta}_n$ is consistent: $\hat{\beta}_n \rightarrow \beta$ in P^n probability, and for sufficiently large values of n and H

$$P^n\{|2\sqrt{k_n v}(\hat{\beta}_n - \beta)| > H\} \leq C_0 e^{-c_0 H^2}$$

Repeating the arguments leading to Corollary 3.5, and taking into account Corollary 4.1 we arrive at the assertion of the following lemma.

Lemma 4.2. Under the conditions stipulated above finite dimensional distributions of $Y^n(b)$ tend to finite dimensional distributions of $e^{bt - \frac{1}{2}b^2}$, $\mathcal{L}(\xi) = N(0, 1)$.

In view of the assertions of the Lemmas 4.1 and 4.2, we can make use of Theorem I.10.1 and III.1.2 of Ibragimov/Has'minskii (1981). The result can be formulated as

Proposition 4.2. Under the conditions stipulated above, for each $\delta > 0$ as $n \rightarrow \infty$

$$\begin{aligned} P^n\{|2\sqrt{k_n v}(\hat{\beta}_n - \beta) - \frac{1}{2\sqrt{k_n v}} \int_0^1 \left\{ \frac{\partial}{\partial \beta} \ln \Psi^n(\beta) \right\}^T d\mathbb{N}^n | > \delta\} \rightarrow 0 \\ \mathcal{L}\{2\sqrt{k_n v}(\hat{\beta}_n - \beta) | P^n\} \Rightarrow N(0, 1) \end{aligned}$$

and

$$E\{|2\sqrt{k_n v}(\hat{\beta}_n - \beta)|^k | P^n\} \rightarrow \frac{2^k/2}{\sqrt{\pi}} \Gamma\left(\frac{k+1}{2}\right).$$

5. ASYMPTOTIC OPTIMALITY

1. As in Subsection 2.2, suppose that the process \mathbb{N}^n is of the Poisson type with the compensator (1.1) where $\Phi = \Phi^n$ satisfies the conditions stipulated below.

Condition V. There is a sequence of r_n -vector valued \mathfrak{F}_t^n -predictable processes, continuously dependent on β , say $(\partial/\partial\beta)\sqrt{\Phi^n(\beta)}$, $n=1, 2, \dots$, such that for each $\alpha \in \mathcal{Q}$ and $\beta \in \mathfrak{B}$ the following holds:

V.1. For each b such that $\beta^n = \beta + b/\sqrt{k_n} \in \mathfrak{B}$ eventually,

$$\int_0^1 |\sqrt{\Phi^n(\beta^n)} - \sqrt{\Phi^n(\beta)} - \frac{b}{\sqrt{k_n}} \frac{\partial}{\partial \beta} \sqrt{\Phi^n(\beta)}|^2 d\alpha \rightarrow 0$$

in $P_{\alpha, \beta}^n$ probability as $n \rightarrow \infty$;

V.2. For some deterministic function $\rho_t^2(\beta)$ such that $w_t(\alpha, \beta) = \int_0^t \rho_s^2(\beta) d\alpha_s > 0$, and for each t , $0 \leq t \leq 1$, $\alpha \in \mathcal{A}$, $\beta \in \mathfrak{B}$

$$\mathfrak{W}_t^n(\alpha, \beta) = \frac{1}{k_n} \int_0^t \left| \frac{\partial}{\partial \beta} \sqrt{\Phi_s^n(\beta)} \right|^2 d\alpha_s \rightarrow w_t(\alpha, \beta)$$

in $P_{\alpha, \beta}^n$ probability as $n \rightarrow \infty$.

Condition VI. There is a positive bounded deterministic function $\phi_t(\beta)$ (uniformly in t and β $m < \phi_t(\beta) < M$ where $0 < m < M < \infty$) having continuous bounded derivative in β , such that for each $\alpha \in \mathcal{A}$, $\beta \in \mathfrak{B}$ and $0 \leq t \leq 1$

VI.1. $F_t^n(\alpha, \beta) = \int_0^t \frac{1}{k_n} \bar{\Phi}_s^n(\beta) d\alpha_s \rightarrow F_t(\alpha, \beta)$ in $P_{\alpha, \beta}^n$ probability as $n \rightarrow \infty$ where $F_t = F_t(\alpha, \beta) = \int_0^t \phi_s(\beta) d\alpha_s > 0$ (cp. Condition I).

VI.2. For $(\partial/\partial\beta)\bar{\Phi}^n = \mathbb{1}_{r_n}^T (\partial/\partial\beta)\Phi^n = 2\mathbb{1}_{r_n}^T \{diag \Phi^n\}^{1/2} (\partial/\partial\beta) \sqrt{\Phi^n}$

$$\int_0^t \frac{\partial}{\partial \beta} \bar{\Phi}_s^n(\beta) d\alpha_s \rightarrow \int_0^t \frac{\partial}{\partial \beta} \phi_s(\beta) d\alpha_s < \infty$$

in $P_{\alpha, \beta}^n$ probability as $n \rightarrow \infty$.

Remark 5.1. By the Conditions II.2, V.2, VI.1, VI.2 and (4.3)

$$\mathfrak{V}_t(\alpha, \beta) = \mathfrak{W}_t(\alpha, \beta) - \int_0^t \left| \frac{\partial}{\partial \beta} \sqrt{\Phi_s^n} \right|^2 d\alpha_s \rightarrow w_t(\alpha, \beta) - \int_0^t \left| \frac{\partial}{\partial \beta} \sqrt{\phi_s} \right|^2 d\alpha_s = v_t(\alpha, \beta)$$

in $P_{\alpha, \beta}^n$ probability as $n \rightarrow \infty$.

2. Let the probability measures P^n and \underline{P}^n be defined on $(\Omega^n, \mathfrak{F}^n)$ as in Subsection 2.2. Then (see remark 3.3)

$$\frac{dP^n}{d\underline{P}^n} = \exp\left\{ \int_0^1 (\ln \Phi_s^n(\beta^n) - \ln \Phi_s^n(\beta)) dN_s^n + 2 \int_0^1 \ln \frac{d\alpha_s^n}{d\underline{\alpha}_s^n} dN_s^n - \int_0^1 \bar{\Phi}_s^n(\beta^n) d\underline{\alpha}_s^n + \int_0^1 \bar{\Phi}_s^n(\beta) d\underline{\alpha}_s^n \right\} \quad (5.1)$$

We shall now apply Corollary 3.1 to show the LAN of the $\{P_{\alpha, \beta}^n, \alpha \in \mathcal{A}, \beta \in \mathfrak{B}\}$ in the sense of

Definition 5.1. This family is called Locally Asymptotically Normal (LAN) at the "point" $\alpha \in \mathcal{A}$, $\beta \in \mathfrak{B}$ if for each $b \in \mathcal{R}^1$ and each bounded $a \in L^2(dF)$ such that $\underline{\alpha}^n \in \mathcal{A}$, $\underline{\beta}^n \in \mathfrak{B}$ eventually, there is a sequence of asymptotically normal variables $\delta_{\alpha, \beta}^n(a, b)$, $n = 1, 2, \dots$:

$$\mathbb{E}\{\delta_{\alpha, \beta}^n(a, b) | P_{\alpha, \beta}^n\} \Rightarrow N(0, g_{\alpha, \beta}(a, b))$$

as $n \rightarrow \infty$ with $g_{\alpha, \beta}(a, b) > 0$ for which $d\underline{P}^n/dP^n = \exp\{\delta_{\alpha, \beta}^n(a, b) - \frac{1}{2} g_{\alpha, \beta}(a, b) + \eta_{\alpha, \beta}^n(a, b)\}$ where $\eta_{\alpha, \beta}^n(a, b) \rightarrow 0$ in $P_{\alpha, \beta}^n$ probability as $n \rightarrow \infty$.

Note first that if

$$\mathbb{U}_i^n = col\left\{ \sqrt{\Phi_i^n(\beta^n) / \Phi_i^n(\beta)} \sqrt{d\underline{\alpha}_i^n / d\underline{\alpha}_i} - 1, i = 1, \dots, r_n \right\},$$

then (3.7) is satisfied by $\mathbb{S}_i^n = \mathbb{S}_{i, \beta}^n(a, b) = \frac{1}{2} b (\partial/\partial\beta) \ln \Phi_i^n(\beta) + a_i \mathbb{1}_{r_n}$, for which

$$\frac{1}{k_n} \int_0^1 \mathbb{S}^{nT} diag d\mathbf{A}^n \mathbb{S}^n \rightarrow b^2 w_t(\alpha, \beta) + 2b \int_0^t \frac{(\partial/\partial\beta) \sqrt{\Phi_s(\beta)}}{\sqrt{\Phi_s(\beta)}} a_s dF_s(\alpha, \beta) + \int_0^1 a_s^2 dF_s(\alpha, \beta) \quad (5.2)$$

in P^n probability as $n \rightarrow \infty$, by the Conditions V and VI. Finally, let the following Lindeberg condition hold:

Condition VII. For each $\alpha \in \mathfrak{A}$, $\beta \in \mathfrak{B}$ and $\epsilon > 0$

$$\frac{1}{k_n} \int \sum_{i=1}^{r_n} I(k_n^{-1/2} \frac{\partial}{\partial \beta} \sqrt{\Phi_s^{(n)}(\beta)} | > \epsilon) | \frac{\partial}{\partial \beta} \sqrt{\Phi_s^{(n)}(\beta)}|^2 d\alpha_s \rightarrow 0$$

in $P_{\alpha, \beta}^n$ as $n \rightarrow \infty$.

Proposition 5.1. Under the Conditions V-VII the family $\{P_{\alpha, \beta}^n, \alpha \in \mathfrak{A}, \beta \in \mathfrak{B}\}$ is LAN at the "pair" for $\delta_{\alpha, \beta}^n(a, b) = \frac{1}{\sqrt{k_n}} \int \mathfrak{S}_{\beta}^n(a, b)^T d(\mathbb{N}^n - \mathbf{A}^n(\alpha, \beta))$ and $g_{\alpha, \beta}(a, b)$ that equals to 4 times the righ (5.2) evaluated at $t=1$.

3. Suppose that the underling model confines "the directions" a to a linear subspace $\mathbf{A} \in L$ $\{\beta_{RA}^n\}$ be a class of $R^1 \times \mathbf{A}$ -regular estimators for β , which includes a subclass of regu $\{\beta_R^n\} \subset \{\beta_{RA}^n\}$ (see Subsection 2.3). Then, by Hájek's convolution theorem (Begun et al. (1983), we have

Proposition 5.2. Let the Condition V-VII hold. Then

$$(i) \quad \mathcal{L}\{\sqrt{k_n}(\beta_{RA}^n - \beta^n) | P^n\} \Rightarrow G_{RA}^0 = N(0, \mathfrak{g}_{\alpha, \beta}^{-1}) * G_{RA}^1$$

as $n \rightarrow \infty$ with some distribution law G_{RA}^1 , where $\mathfrak{g}_{\alpha, \beta} = 4\{w_1(\alpha, \beta) - \int_0^1 \pi_s^2(\alpha, \beta) dF_s(\alpha, \beta)\}$, $\pi_s(\alpha, \beta)$ jection of $(\partial/\partial\beta) \sqrt{\Phi_t(\beta)} / \sqrt{\Phi_t(\beta)}$ into \mathbf{A} , that is, it satisfies the equation

$$\int_0^1 \left\{ \frac{(\partial/\partial\beta) \sqrt{\Phi_s(\beta)}}{\sqrt{\Phi_s(\beta)}} - \pi_s(\alpha, \beta) \right\} a_s dF_s(\alpha, \beta) = 0$$

for each $a_s \in \mathbf{A}$.

$$(ii) \quad \mathcal{L}\{\sqrt{k_n}(\beta_R^n - \beta^n) | P^n\} \Rightarrow G_R^0 = N(0, 1/4v_1(\alpha, \beta)) * G_R^1$$

as $n \rightarrow \infty$ with some distribution law G_R^1 (see Remark 5.1), uniformly for each $|b| < c$ whatever c bounded $a \in L^2(dF)$

Remark 5.2. For the "least favorable" direction $a_t = -b\pi_t(\beta)$ the quantity $g_{\alpha, \beta}(a, b)$ coincides w being Fisher's information for β (Begun et al. (1983), Section 3).

Remark 5.3. Evidently, $\mathfrak{g}_{\alpha, \beta} \geq 4v_1(\alpha, \beta)$ with equality iff $(\partial/\partial\beta) \sqrt{\Phi_t(\beta)} / \sqrt{\Phi_t(\beta)} \in \mathbf{A}$ (see Remark

Having the limiting distribution of $\sqrt{k_n}(\hat{\beta}_n - \beta)$ under P^n (Proposition 4.2), one can apply tiguity arguments (allowed by Proposition (5.2)) to arrive at the formula (5.4) for $\beta_R^n = \hat{\beta}_n$ degenerates at 0. These considerations can be summarized as the following statement on the opti ties of the estimator $\hat{\beta}_n$.

Theorem 5.1. Under the conditions stipulated above, the estimator $\hat{\beta}_n$ is $\mathcal{L}\{\sqrt{k_n}(\hat{\beta}_n - \beta^n) | P^n\} \Rightarrow N(0, 1/4v_1(\alpha, \beta))$ for each $b \in R^1$ and each bounded $a \in L^2(dF)$ determin P^n as in Subsection 2.2.

The estimator $\hat{\beta}_n$ is the best among $\{\beta_R^n\}$ in the sense that no regular estimator can have the bution less spread then $\hat{\beta}_n$. Besides, iff $(\partial/\partial\beta) \sqrt{\Phi_t(\beta)} / \sqrt{\Phi_t(\beta)} \in \mathbf{A}$, then it is the best among $\{f$ the same sense.

BIBLIOGRAPHY

- Andersen, P. K. and Gill, R.D. (1982) Cox's regression model for counting processes: a large sample study. *Ann. Statist.* **10** 1100-1120.
- Begun, J.M., Hall, W.J., Huang, W.M. and Wellner, J.A. (1983) Information and asymptotic efficiency in parametric and non-parametric models, *Ann. Statist.* **11** 432-452.
- Borgan, Ø. (1984) Maximum likelihood estimation in parametric counting process models, with applications to censored failure time data. *Scand. J. Statist.* **11** 1-16.
- Brémaud, P. (1981) Point Processes and Queues. Martingale Dynamics. Springer-Verlag. New York.
- Efron, B. (1977) The efficiency of Cox's likelihood function for censored data *J. Amer. Statist. Assoc.* **72** 557-565.
- Gill, R.D. (1979) Censoring and Stochastic Integrals. Mathematisch Centrum Amsterdam.
- Greenwood, P.E. and Shiryayev, A.N. (1985) Continuity and the Statistical Invariance Principle. Stochastic Monographs. Vol. 1, Gordon and Breach, New York.
- Hjort, N.L. (1984) Bayes estimators and asymptotic efficiency in parametric counting process models. Research report. Norw. Comp. Centre, Oslo (submitted to *Scand. J. Statist.*).
- Ibragimov, I.A. and Has'minskii A.N. (1981) Statistical Estimation. Asymptotic Theory. Springer-Verlag. New York.
- Jarupskin, B.D.S. (1983) Maximum likelihood and related estimation methods in point processes and point process systems. Ph. D. Dept. Statist. University of California. Berkeley.
- Kabanov, Yu. M., Lipcer, R.S. and Shiryayev A.N. (1976) Criteria of absolute continuity of measures corresponding to multivariate point processes. Proc. Third Japan-USSR Sympos. Probability Theory (Tashkent, 1975), Lecture Notes in Math., vol. 550, Springer-Verlag, New York.
- Kabanov, Yu. M., Lipcer, R. S. and Shiryayev A.N. (1980) Absolute continuity and singularity of locally absolute continuous probability distributions. II *Math. USSR Sbornik.* **36** 31-58.
- Kabanov, Yu. M., Liptser R. Sh. and Shiryayev A.N. (1980) Some limit theorems for simple point processes (a martingale approach). *Stochastics.* **3** 203-216.
- Le Cam, L. (1969) Theorie Asymptotic de la Decision Statistique. Les Presses de l'Universite de Montreal. Montreal.
- Liptser, R.S. and Shiryayev A.N. (1978) Statistics of Random Processes II. Applications. Springer-Verlag. New York.
- Liptser, R. Sh. and Shiryayev A.N. (1980) A functional central limit theorem for samimartingales. *Theory Probab. Appl.* **25** 667-688.
- McLeish D.L. (1978) An extended martingale principle. *Ann. Probab.* **6** 144-150.
- Prentice, R.L. and Self, S.G. (1983) Asymptotic distribution theory for Cox-type regression models with general relative risk form. *Ann. Statist.* **11** 804-813.
- Shiryayev, A.N. (1981) Martingales: Recent Developments, Results and Applications. *Int. Statist. Review.* **49** 199-233.
- Sieders A. (1985) An extension of a Theorem by Ibragimov and Has'minskii. Research report, TH Delft.