

Point process models and local asymptotics in statistics

III – Example

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9 Inference from jumps ≥ 1 of a stable increasing process

We continue the example of section 4, all notations as there: S is a stable increasing process of some index $0 < \alpha < 1$ and some weight parameter $\xi > 0$. We observe all jumps $\geq \varepsilon$ in the trajectory of S up to time t , with particular choice $\varepsilon := 1$:

$$X_t = \sum_{\substack{0 < s \leq t \\ \Delta S_s \geq 1}} \Delta S_s = \int_0^t \int_{[1, \infty)} z \mu(ds, dz) \quad , \quad t \geq 0$$

where $\mu(ds, dz)$ is Poisson random measure on $(0, \infty) \times [1, \infty)$ with intensity

$$\nu^{\alpha, \xi}(ds, dz) = \xi ds \alpha z^{-\alpha-1} 1_{\{z \geq 1\}} dz = \xi ds k_\alpha(z) dz$$

for some $0 < \alpha < 1$ and $\xi > 0$. Due to $\varepsilon = 1$, $k_\alpha(\cdot)$ is a probability density, and the counting process

$$N = (N_t)_{t \geq 0} \quad , \quad N_t := \mu((0, t] \times [1, \infty))$$

is Poisson with parameter ξ . Consider also the process

$$\bar{N} = (\bar{N}_t)_{t \geq 0} \quad , \quad \bar{N}_t := \int_0^t \int_{\{z \geq 1\}} \log(z) \mu(ds, dz) .$$

Aims : Show that LAN holds at every point (α, ξ) as $n \rightarrow \infty$,

characterize sequences of estimators for (α, ξ) which as $n \rightarrow \infty$ achieve the local asymptotic minimax bound (and thus are also regular and efficient in the sense of Hájek).

In this example, it is easy to find maximum likelihood estimators (MLE) :

the log-likelihood ratios are (section 4, special case $\varepsilon = 1$)

$$\log \left(\left[\prod_{0 < s \leq t} \frac{\tilde{\alpha} \tilde{\xi}}{\alpha \xi} (\Delta X_s)^{\alpha - \tilde{\alpha}} \right] \exp\{-t(\tilde{\xi} - \xi)\} \right) = \log\left(\frac{\tilde{\alpha} \tilde{\xi}}{\alpha \xi}\right) N_t + (\alpha - \tilde{\alpha}) \bar{N}_t - (\tilde{\xi} - \xi) t$$

so deriving with respect to $\tilde{\alpha}$ or to $\tilde{\xi}$ we obtain MLE's explicitly

$$\hat{\alpha}_t := \frac{N_t}{\bar{N}_t} \quad , \quad \hat{\xi}_t := \frac{N_t}{t} \quad , \quad \tau_1 \leq t < \infty .$$

Rescaling time and writing $\mathbb{F}^n := (\mathcal{F}_{tn})_{t \geq 0}$, the following are (local, at least) $(Q^{(\alpha, \xi)}, \mathbb{F}^n)$ -martingales:

$$\begin{aligned} \frac{1}{\sqrt{n}} \left(\bar{N}_{tn} - \frac{\xi}{\alpha} tn \right)_{t \geq 0} &= \frac{1}{\sqrt{n}} \int_0^{\bullet n} \int_{\{z \geq 1\}} \log(z) (\mu - \nu^{\alpha, \xi})(ds, dz) \\ \frac{1}{\sqrt{n}} (N_{tn} - \xi tn)_{t \geq 0} &= \frac{1}{\sqrt{n}} \int_0^{\bullet n} \int_{\{z \geq 1\}} (\mu - \nu^{\alpha, \xi})(ds, dz) . \end{aligned}$$

Also the difference of both is a (local, at least) $(Q^{(\alpha, \xi)}, \mathbb{F}^n)$ -martingale:

$$\frac{1}{\sqrt{n}} (N_{tn} - \alpha \bar{N}_{tn})_{t \geq 0} = \frac{1}{\sqrt{n}} \int_0^{\bullet n} \int_{\{z \geq 1\}} (1 - \alpha \log z) (\mu - \nu^{\alpha, \xi})(ds, dz) .$$

Below, B denotes 2-dimensional standard Brownian motion, and D is the canonical path space of cadlag functions $[0, \infty) \rightarrow \mathbb{R}^2$.

Lemma 1 : For all $0 < \alpha < 1$ and $\xi > 0$, we have weak convergence under $Q^{(\alpha, \xi)}$ (in D , as $n \rightarrow \infty$)

$$S(n, (\alpha, \xi)) := \frac{1}{\sqrt{n}} \begin{pmatrix} N_{tn} - \alpha \bar{N}_{tn} \\ N_{tn} - \xi tn \end{pmatrix}_{t \geq 0} \xrightarrow{w} \xi^{\frac{1}{2}} B .$$

Proof : First, integration by parts successively in $k \in \mathbb{N}_0$ grants

$$(+) \quad \int_{\{z \geq 1\}} \log^k(z) \alpha z^{-\alpha-1} dz = \frac{k!}{\alpha^k}$$

for all $0 < \alpha < 1$, $\xi > 0$. The components of $S(n, (\alpha, \xi))$ are locally square integrable martingales.

Using (+) we calculate angle brackets

$$\begin{aligned} \left\langle \frac{1}{\sqrt{n}}(N_{\bullet n} - \alpha \bar{N}_{\bullet n}), \frac{1}{\sqrt{n}}(N_{\bullet n} - \alpha \bar{N}_{\bullet n}) \right\rangle_t &= \frac{1}{n} \int_0^{tn} \int_{\{z \geq 1\}} (1 - \alpha \log z)^2 \nu^{\alpha, \xi}(ds, dz) = \xi t \\ \left\langle \frac{1}{\sqrt{n}}(N_{\bullet n} - \alpha \bar{N}_{\bullet n}), \frac{1}{\sqrt{n}}(N_{\bullet n} - \xi \bullet n) \right\rangle_t &= \frac{1}{n} \int_0^{tn} \int_{\{z \geq 1\}} (1 - \alpha \log z) \nu^{\alpha, \xi}(ds, dz) = 0 \\ \left\langle \frac{1}{\sqrt{n}}(N_{\bullet n} - \xi \bullet n), \frac{1}{\sqrt{n}}(N_{\bullet n} - \xi \bullet n) \right\rangle_t &= \frac{1}{n} \int_0^{tn} \int_{\{z \geq 1\}} \nu^{\alpha, \xi}(ds, dz) = \xi t \end{aligned}$$

whence

$$\langle S_n(\alpha, \xi) \rangle_t = \xi \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} t$$

for $0 \leq t < \infty$. Thus weak convergence in D under $Q^{(\alpha, \xi)}$ as $n \rightarrow \infty$ holds in virtue of the martingale convergence theorem (corollary VIII.3.24 in Jacod-Shiryaev 1987). \square

Since we deal with PRM, we could have formulated a 'elementary' proof, via classical central limit theory: independence assumptions in the definition of PRM show that martingale increments as above reduce to independent random variables.

From now on we write

$$\vartheta := \begin{pmatrix} \alpha \\ \xi \end{pmatrix} \in \Theta := (0, 1) \times (0, \infty) .$$

Fix a reference point $\vartheta \in \Theta$ and define local scale at ϑ by

$$\delta_n(\vartheta) := \frac{1}{\sqrt{n}} \begin{pmatrix} \alpha & 0 \\ 0 & \xi \end{pmatrix} , \quad \delta_n = \delta_n(\vartheta) \downarrow 0 \quad \text{as } n \rightarrow \infty .$$

Introduce local parameter $h = \begin{pmatrix} h_1 \\ h_2 \end{pmatrix}$ at ϑ , with h ranging over open sets

$$\Theta_{\vartheta, n} := \{h \in \mathbb{R}^2 : \vartheta + \delta_n h \in \Theta\} \quad \uparrow \quad \mathbb{R}^2 \quad \text{as } n \rightarrow \infty .$$

At a fixed reference point $\vartheta \in \Theta$, at stage n of the asymptotics:

- reparametrize neighbourhoods of ϑ , replacing $\begin{pmatrix} \tilde{\alpha} \\ \tilde{\xi} \end{pmatrix}$ in earlier notation by

$$\vartheta + \delta_n(\vartheta) h = \begin{pmatrix} \alpha(1 + \frac{h_1}{\sqrt{n}}) \\ \xi(1 + \frac{h_2}{\sqrt{n}}) \end{pmatrix}, \quad h \in \Theta_{\vartheta,n} = \dots \mathbb{R}^2 \dots$$

and view the local parameter h as new parametrization

- change time from t to tn , i.e. consider the filtration $\mathbb{F}^n := (\mathcal{F}_{tn})_{t \geq 0}$

and study the statistical model in shrinking neighbourhoods of the reference point ϑ .

We thus consider a sequence of filtered local models at ϑ

$$\mathcal{E}_n(\vartheta) := \left(\Omega, \mathbb{F}^n, \left\{ Q^{(\vartheta + \delta_n(\vartheta)h)} : h \in \Theta_{\vartheta,n} \right\} \right), \quad n \rightarrow \infty$$

where log-likelihood ratio processes take the form ($0 \leq t < \infty$)

$$(*) \quad \underbrace{\log L_{tn}^{(\vartheta + \delta_n h)/\vartheta}}_{= \log L_{tn}^{(\tilde{\alpha}, \tilde{\xi})/(\alpha, \xi)}} = \underbrace{\log\left(1 + \frac{h_1}{\sqrt{n}}\right)}_{= \log \frac{\tilde{\alpha}}{\alpha}} N_{tn} + \underbrace{\log\left(1 + \frac{h_2}{\sqrt{n}}\right)}_{= \log \frac{\tilde{\xi}}{\xi}} N_{tn} - \underbrace{h_1 \frac{\alpha}{\sqrt{n}} \bar{N}_{tn}}_{= \tilde{\alpha} - \alpha} - \underbrace{h_2 \frac{\xi}{\sqrt{n}} tn}_{= \tilde{\xi} - \xi}.$$

Using expansions

$$\log(1 + z) = z - \frac{1}{2}z^2 + o(z^2) \quad \text{as } z \rightarrow 0$$

in (*) and arranging terms

$$\begin{aligned} \log L_{tn}^{(\vartheta + \delta_n h)/\vartheta} &= h_1 \frac{1}{\sqrt{n}} (N_{tn} - \alpha \bar{N}_{tn}) + h_2 \frac{1}{\sqrt{n}} (N_{tn} - \xi tn) - \frac{1}{2} (h_1^2 + h_2^2) \frac{1}{n} N_{tn} + \dots \\ &= h_1 \frac{1}{\sqrt{n}} (N_{tn} - \alpha \bar{N}_{tn}) + h_2 \frac{1}{\sqrt{n}} (N_{tn} - \xi tn) - \frac{1}{2} (h_1^2 + h_2^2) \xi t + \dots \end{aligned}$$

up to remainder terms which are negligible under $Q^{(\vartheta)}$ as $n \rightarrow \infty$. Here a score martingale at ϑ appears

$$S(n, \vartheta)_t := \frac{1}{\sqrt{n}} \begin{pmatrix} N_{tn} - \alpha \bar{N}_{tn} \\ N_{tn} - \xi tn \end{pmatrix}, \quad t \geq 0$$

together with a process information at ϑ

$$J(n, \vartheta)_t := \langle S(n, \vartheta) \rangle_t = \xi \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} t$$

and we know about weak convergence of the score martingale under $Q^{(\vartheta)}$, by lemma 1.

Lemma 2 : ('2nd Le Cam lemma') At every reference point $\vartheta \in \Theta$, with local scale $\delta_n(\vartheta) = \frac{1}{\sqrt{n}} \begin{pmatrix} \alpha & 0 \\ 0 & \xi \end{pmatrix}$ and local parameter $h \in \dots \mathbb{R}^2 \dots$ as above, we have local asymptotic normality

$$\log L_{\bullet n}^{(\vartheta + \delta_n h)/\vartheta} = h^\top S(n, \vartheta) - \frac{1}{2} h^\top J(n, \vartheta) h + R(n, \vartheta)$$

where under $Q^{(\vartheta)}$

$$\left\{ \begin{array}{l} S(n, \vartheta) \longrightarrow \xi^{\frac{1}{2}} B \quad \text{weakly in } D \text{ as } n \rightarrow \infty, \\ J(n, \vartheta) = \left\langle \xi^{\frac{1}{2}} B \right\rangle \quad \text{for all } n, \\ \text{paths of } R(n, \vartheta) \text{ vanish uniformly on compact time intervals as } n \rightarrow \infty. \end{array} \right.$$

We have seen that maximum likelihood estimators (MLE) are given by

$$\widehat{\vartheta}_v := \begin{pmatrix} \widehat{\alpha}_v \\ \widehat{\xi}_v \end{pmatrix}, \quad \widehat{\alpha}_v = \frac{N_v}{\bar{N}_v}, \quad \widehat{\xi}_v = \frac{N_v}{v}.$$

Here $\bar{N}_v \sim \frac{\xi}{\alpha} v$ and $N_v \sim \xi v$ $Q^{(\alpha, \xi)}$ -almost surely as $v \rightarrow \infty$, whence consistency and

$$\begin{aligned} \frac{\sqrt{v}}{\alpha} (\widehat{\alpha}_v - \alpha) &= \frac{v}{\alpha \bar{N}_v} \frac{1}{\sqrt{v}} (N_v - \alpha \bar{N}_v) \sim \frac{1}{\xi} \frac{1}{\sqrt{v}} (N_v - \alpha \bar{N}_v) \\ \frac{\sqrt{v}}{\xi} (\widehat{\xi}_v - \xi) &= \frac{1}{\xi} \frac{1}{\sqrt{v}} (N_v - \xi v) \end{aligned}$$

as $v \rightarrow \infty$. In time scale $\bullet n$, this is the assertion

$$\delta_n^{-1}(\vartheta) \left(\widehat{\vartheta}_{tn} - \vartheta \right) = \frac{1}{\xi t} \left(\begin{array}{c} \frac{1}{\sqrt{n}} (N_{tn} - \alpha \bar{N}_{tn}) \\ \frac{1}{\sqrt{n}} (N_{tn} - \alpha \bar{N}_{tn}) \end{array} \right) + o_{Q^{(\vartheta)}}(1)$$

as $n \rightarrow \infty$, for every $0 < t < \infty$ fixed. We thus find that rescaled ML estimation errors behave as

$$Z(n, \vartheta)_t := J(n, \vartheta)_t^{-1} S(n, \vartheta)_t, \quad 0 < t < \infty, \quad n \rightarrow \infty$$

in the sequence of local models at ϑ .

Lemma 3 : At every $\vartheta \in \Theta$, as $n \rightarrow \infty$, rescaled ML estimation errors admit the representation

$$\delta_n^{-1}(\vartheta) \left(\widehat{\vartheta}_{tn} - \vartheta \right) = J(n, \vartheta)_t^{-1} S(n, \vartheta)_t + \widetilde{R}(n, \vartheta)_t, \quad 0 < t < \infty$$

where paths of $\widetilde{R}(n, \vartheta)$ vanish uniformly on compact time intervals $\subset (0, \infty)$, under $Q^{(\vartheta)}$, as $n \rightarrow \infty$.

Note that it does not make sense to consider $t = 0 \dots$

For inference about the unknown parameter $\vartheta \in \Theta$, Lemmata 2 and 3 allow to deal with

- deterministic observation schemes
- a broad class of random observation schemes.

Deterministic observation schemes:

at stage n of the asymptotics we observe up to time n , $n \rightarrow \infty$.

We discuss asymptotic optimality properties for estimators as $n \rightarrow \infty$.

Corollary 1 : The MLE sequence $(\hat{\vartheta}_n)_n$ is regular and efficient in the sense of Hájek.

Corollary 2 : Consider loss functions $\ell : \mathbb{R}^2 \rightarrow [0, \infty)$ continuous, subconvex and bounded. Then

a) for arbitrary sequences of \mathcal{F}_n -measurable estimators $(\tilde{\vartheta}_n)_n$ for ϑ

$$\lim_{c \uparrow \infty} \limsup_{n \rightarrow \infty} \sup_{|h| \leq c} E_{\vartheta + \delta_n(\vartheta)h} \left(\ell \left(\delta_n^{-1}(\vartheta) \left(\tilde{\vartheta}_n - (\vartheta + \delta_n(\vartheta)h) \right) \right) \right) \geq E \left(\ell \left(\xi^{-\frac{1}{2}} B_1 \right) \right) ;$$

b) the MLE sequence achieves this bound: for every $0 < c < \infty$,

$$\lim_{n \rightarrow \infty} \sup_{|h| \leq c} E_{\vartheta + \delta_n(\vartheta)h} \left(\ell \left(\delta_n^{-1}(\vartheta) \left(\hat{\vartheta}_n - (\vartheta + \delta_n(\vartheta)h) \right) \right) \right) = E \left(\ell \left(\xi^{-\frac{1}{2}} B_1 \right) \right) .$$

Random observation schemes: Let \mathcal{T} denote the class of all strictly increasing sequences $(T_n)_n$ of \mathbb{F} -stopping times with the following properties i) and ii):

i) for $\vartheta \in \Theta$, there is some constant $0 < c(\vartheta) < \infty$ such that

$$c(\vartheta) = \lim_{n \rightarrow \infty} \frac{1}{n} T_n \quad Q^{(\vartheta)}\text{-almost surely ;}$$

ii) for $\vartheta \in \Theta$, there is some compact $K(\vartheta)$ contained in $(0, \infty)$ and

a sequence $\sigma(n, \vartheta)$ of \mathbb{F}^n -stopping times taking values in $K(\vartheta)$, $n \geq 1$,

events $A_n(\vartheta) \in \mathcal{F}_{T_n}$, $n \geq 1$, such that $\liminf_{n \rightarrow \infty} A_n(\vartheta) = \Omega$ $Q^{(\vartheta)}$ -almost surely

such that $Q^{(\vartheta)}$ -almost surely

for every $n \geq 1$, T_n coincides with $\sigma(n, \vartheta) n$ in restriction to $A_n(\vartheta)$.

Then necessarily, also $\lim_{n \rightarrow \infty} \sigma(n, \vartheta) = c(\vartheta)$ exists $Q^{(\vartheta)}$ -almost surely.

Examples: consider increasing integrable additive functionals $A = (A_t)_{t \geq 0}$ of X and define

$$T_n := \inf\{t > 0 : A_t \geq n\} \quad , \quad n \geq 1 \quad , \quad c(\vartheta) := \left[\lim_{t \rightarrow \infty} \frac{1}{t} A_t \right]^{-1} \text{ under } Q^{(\vartheta)} \quad ;$$

in particular: $A_t := N_t$ with $c(\vartheta) = \frac{1}{\xi}$; $A_t := \bar{N}_t$ with $c(\vartheta) = \frac{\alpha}{\xi}$.

Corollary 3 : For random observation schemes of class \mathcal{T}

at stage n of the asymptotics we observe up to time T_n , $n \rightarrow \infty$

a) we have LAN with central sequence $J(n, \vartheta)_{\sigma(n, \vartheta)}^{-1} S(n, \vartheta)_{\sigma(n, \vartheta)}$ under $Q^{(\vartheta)}$;

b) the MLE sequence $\hat{\vartheta}_{T_n} = \begin{pmatrix} \hat{\alpha}_{T_n} \\ \hat{\xi}_{T_n} \end{pmatrix}$, $n \geq 1$ is regular and efficient in the sense of Hájek ;

c) the local asymptotic minimax bound

$$\lim_{c \uparrow \infty} \limsup_{n \rightarrow \infty} \sup_{|h| \leq c} E_{\vartheta + \delta_n(\vartheta)h} \left(\ell \left(\delta_n^{-1}(\vartheta) \left(\tilde{\vartheta}_{T_n} - (\vartheta + \delta_n(\vartheta)h) \right) \right) \right) \geq E \left(\ell \left([\xi c(\vartheta)]^{-\frac{1}{2}} B_1 \right) \right)$$

holds for any sequence of \mathcal{F}_{T_n} -measurable estimators $\tilde{\vartheta}_{T_n}$, $n \geq 1$, and for arbitrary loss functions $\ell : \mathbb{R}^2 \rightarrow [0, \infty)$ which are continuous, subconvex and bounded ;

d) the MLE sequence $\hat{\vartheta}_{T_n} = \begin{pmatrix} \hat{\alpha}_{T_n} \\ \hat{\xi}_{T_n} \end{pmatrix}$, $n \geq 1$, achieves this bound.