

# LAN property for ergodic jump-diffusion processes with discrete observations

Eulalia Nualart  
(Universitat Pompeu Fabra, Barcelona)

joint work with Arturo Kohatsu-Higa (Ritsumeikan University, Japan)  
& Ngoc Khue Tran (University of Paris 13)

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# Parametric statistical model

- Consider a **real-valued Markov process**  $X^\theta = (X_t^\theta, t \geq 0)$  defined on a complete probability space  $(\Omega, \mathcal{F}, \mathbb{P})$  and adapted to the natural filtration  $\{\mathcal{F}_t\}_{t \geq 0}$  of a standard Brownian motion  $B = (B_t, t \geq 0)$ .
- Let  $\mathbb{P}^\theta$  be the probability measure induced by  $X^\theta$ .
- The unknown parameter  $\theta$  belongs to  $\Theta$  a closed rectangle of  $\mathbb{R}^k$ .
- Consider a **high frequency observation** of  $X^\theta$  denoted  $X^n = (X_{t_0}, X_{t_1}, \dots, X_{t_n})$ , where  $t_k = k\Delta_n$ :
  - Distance between observations  $\Delta_n \rightarrow 0$ , as  $n \rightarrow \infty$ .
  - Horizon  $n\Delta_n \rightarrow \infty$ , as  $n \rightarrow \infty$ .
- Let  $\mathbb{P}_n^\theta$  the probability measure on induced by  $X^n$  under  $\theta$ .
- Assume that  $X^n$  admits a density  $p_n(x; \theta)$ .
- Let  $p^\theta(t-s, x, y)$  the transition density of  $X_t^\theta$  at  $y$  conditionally on  $X_s^\theta = x$ .

# The LAN property

The parametric statistical model  $\{\mathbb{P}_n^\theta, \theta \in \Theta\}$  is said to have the **local asymptotic normality (LAN)** property at  $\theta$  if there exist

- 1 a  $k$ -dimensional vector  $\varphi_n(\theta)$  with strictly positive entries tending to zero as  $n \rightarrow \infty$
- 2 a  $k \times k$  symmetric positive definite matrix  $\Gamma(\theta)$

such that for any  $u \in \mathbb{R}^k$ , as  $n \rightarrow \infty$ ,

$$\log \frac{d\mathbb{P}_n^{\theta + \varphi_n(\theta)u}}{d\mathbb{P}_n^\theta}(X^n) \xrightarrow{\mathcal{L}(\mathbb{P}^\theta)} u^T \mathcal{N}(0, \Gamma(\theta)) - \frac{1}{2} u^T \Gamma(\theta) u.$$

$\mathcal{N}(0, \Gamma(\theta))$  : centered  $\mathbb{R}^k$ -valued Gaussian variable with covariance  $\Gamma(\theta)$ .  
 $\Gamma(\theta)$  : **asymptotic Fisher information matrix**.

**References** : Le Cam'60, Hájek'70.

**Extension to  $\Gamma(\theta)$  random (mixed normal, LAMN)** : Jeganathan'82-83

## Remarks

- Observe that the LAN property is equivalent to

$$\begin{aligned}\log \frac{dP_n^{\theta + \varphi_n(\theta)u}}{dP_n^\theta}(X^n) &= \log \frac{p_n(X^n; \theta + \varphi_n(\theta)u)}{p_n(X^n; \theta)} \\ &= u^\top \varphi_n(\theta) \nabla_\theta \log p_n(X^n; \theta) - \frac{1}{2} u^\top \Gamma(\theta) u + o_{P^\theta}(1),\end{aligned}$$

where  $\varphi_n(\theta) \nabla_\theta \log p_n(X^n; \theta)$  converges in  $P^\theta$ -law to  $\mathcal{N}(0, \Gamma(\theta))$ .

- Assume  $k = 1$ . By the Markov property

$$\log \frac{p_n(X^n; \theta + \varphi_n(\theta)u)}{p_n(X^n; \theta)} = \sum_{k=0}^{n-1} \varphi_n(\theta)u \int_0^1 \partial_\theta \log p^{\theta(\ell)}(\Delta_n, X_{t_k}, X_{t_{k+1}}) d\ell$$

where  $\theta(\ell) := \theta + \ell \varphi_n(\theta)u$ .

# Expression of the log-likelihood via Malliavin calculus

## Theorem (Malliavin, Gobet'01)

Suppose that  $X_t^\theta \in \mathbb{D}^{1,2}$  for all  $t \geq 0$ , and there exists a stochastic process  $u \in \text{Dom}(\delta)$  such that

$$\int_{t_i}^{t_{i+1}} D_t X_{t_i}^\theta u(t) dt = \partial_\theta X_{t_i}^\theta, \quad \forall i = 0, \dots, n-1,$$

Then,  $P^\theta$ -a.s.,

$$\partial_\theta \log p^\theta(\Delta_n, X_{t_k}, X_{t_{k+1}}) = E_{X_{t_k}}^\theta \left[ \delta(u) \mid X_{t_{k+1}}^\theta = X_{t_{k+1}} \right].$$

**Proof** If  $\varphi$  is a test function, using the chain rule and the duality relation,

$$\begin{aligned} E_{X_{t_k}}^\theta \left[ \partial_\theta \varphi(X_{t_{k+1}}^\theta) \right] &= E_{X_{t_k}}^\theta \left[ \varphi'(X_{t_{k+1}}^\theta) \cdot \partial_\theta X_{t_{k+1}}^\theta \right] = E_{X_{t_k}}^\theta \left( \langle D(\varphi(X_{t_{k+1}}^\theta)), u \rangle_2 \right) \\ &= E_{X_{t_k}}^\theta \left( \varphi(X_{t_{k+1}}^\theta) \delta(u) \right). \end{aligned}$$

On the other hand,

$$E_{X_{t_k}}^\theta \left[ \partial_\theta \varphi(X_{t_{k+1}}^\theta) \right] = E_{X_{t_k}}^\theta \left( \varphi(X_{t_{k+1}}^\theta) \partial_\theta \log p^\theta(\Delta_n, X_{t_k}, X_{t_{k+1}}^\theta) \right).$$

## Consequences of the LAN property

Assume that  $\{P_n^\theta, \theta \in \Theta\}$  satisfies the LAN property.

- A sequence of estimators  $(\theta_n)_{n \geq 1}$  is called **regular** if for all  $u \in \mathbb{R}^k$ ,

$$\varphi_n(\theta)^{-1} (\theta_n - (\theta + \varphi_n(\theta)u)) \xrightarrow{\mathcal{L}(P_n^{\theta + \varphi_n(\theta)u})} V(\theta), \quad \text{as } n \rightarrow \infty,$$

for some  $\mathbb{R}^k$ -valued random variable  $V(\theta)$ .

- **Conditional convolution theorem** : Let  $(\theta_n)_{n \geq 1}$  a sequence of regular estimators of  $\theta$ . Then

$$\mathcal{L}(V(\theta)) = \mathcal{N}(0, \Gamma(\theta)^{-1}) \star G_{\Gamma(\theta)},$$

where  $G_{\Gamma(\theta)}$  is independent of  $\mathcal{N}$ .

- A sequence of estimators  $(\theta_n)_{n \geq 1}$  is called **asymptotically efficient** if

$$\varphi_n^{-1}(\theta) (\theta_n - \theta) \xrightarrow{\mathcal{L}(P_n^\theta)} \mathcal{N}(0, \Gamma(\theta)^{-1}), \quad \text{as } n \rightarrow \infty.$$

- **Minimax theorem** :  $\Gamma(\theta)^{-1}$  is a lower bound for the asymptotic covariance of any sequence of unbiased estimators.

# LAN property for diffusion processes

- 1 Gobet'01 derives the LAMN property in the non-ergodic case :

$$X_t^\theta = X_0 + \int_0^t b(\theta, s, X_s^\theta) ds + \int_0^t \sigma(\theta, s, X_s^\theta) dB_s, \quad t \in [0, 1].$$

- 2 Gobet'02 shows the LAN property in the ergodic case :

$$X_t^{\theta, \beta} = X_0 + \int_0^t b(\theta, X_s^{\theta, \beta}) ds + \int_0^t \sigma(\beta, X_s^{\theta, \beta}) dB_s, \quad t \geq 0.$$

- 3 Delattre and al.'11 have established the LAMN property :

$$X_t^\lambda = X_0 + \int_0^t b(s, X_s^\lambda) ds + \int_0^t a(s, X_s^\lambda) dB_s + \sum_{k: T_k \leq t} c(X_{T_k}^\lambda, \lambda_k),$$

for  $t \in [0, 1]$ , where the jump times  $T_1, T_2, \dots, T_K$  are given.

- 4 Kawai'13, LAN for Ornstein-Uhlenbeck Processes with Jumps

# The density estimates

- These papers use upper and lower **Gaussian type estimates** of the transition densities of the diffusion processes.
- Some computations show that in simpler one dimensional situations (**Gaussian type jumps**) the **upper density estimate** is of the type

$$\frac{C}{\sqrt{t}} \exp \left( -c|y - x| \sqrt{|\ln \frac{|y - x|}{t}|} \right),$$

and the **lower density estimates** are of the type

$$Ce^{-\lambda t} \exp \left( -c|y - x| \sqrt{|\ln \frac{|y - x|}{t}|} \right),$$

with a different estimate over the diagonal.

- This shows that the upper and lower bounds are of different characteristic and Gobet's argument cannot be implemented.

# LAN property for a linear model with jumps

$$X_t = x + \theta t + \sigma B_t + N_t - \lambda t.$$

## Theorem

For all  $z = (u, v, w) \in \mathbb{R}^3$ , as  $n \rightarrow \infty$ ,

$$\log \frac{p(X^n; (\theta_n, \sigma_n, \lambda_n))}{p(X^n; (\theta, \sigma, \lambda))} \xrightarrow{\mathcal{L}(P_x^{\theta, \sigma, \lambda})} z^T \mathcal{N}(0, \Gamma(\theta, \sigma, \lambda)) - \frac{1}{2} z^T \Gamma(\theta, \sigma, \lambda) z,$$

where  $\mathcal{N}(0, \Gamma(\theta, \sigma, \lambda))$  is a centered  $\mathbb{R}^3$ -valued Gaussian vector with covariance matrix

$$\Gamma(\theta, \sigma, \lambda) = \frac{1}{\sigma^2} \begin{pmatrix} 1 & 0 & -1 \\ 0 & 2 & 0 \\ -1 & 0 & 1 + \frac{\sigma^2}{\lambda} \end{pmatrix},$$

and we set  $\theta_n := \theta + \frac{u}{\sqrt{n\Delta_n}}$ ,  $\sigma_n := \sigma + \frac{v}{\sqrt{n}}$ ,  $\lambda_n := \lambda + \frac{w}{\sqrt{n\Delta_n}}$ .

# Sketch of the proof

- 1 Markov's property, the integration by parts formula of the Malliavin calculus and Girsanov's theorem, allows to obtain an expansion of the log-likelihood of the form

$$\log \frac{\rho(X^n; (\theta_n, \sigma_n, \lambda_n))}{\rho(X^n; (\theta, \sigma, \lambda))} = \sum_{k=0}^{n-1} (\xi_{k,n} + H_{k,n} + \eta_{k,n} + M_{k,n} + \beta_{k,n} - R_{k,n}).$$

- 2 Apply a **central limit theorem for triangular arrays** of random variables to  $\xi_{k,n} + \eta_{k,n} + \beta_{k,n}$  to show the convergence in law.
- 3 **Negligible terms** : the key argument consists in **conditioning on the number of jumps**  $J_j := \{N_{t_{k+1}} - N_{t_k} = j\}$  within the conditional expectation which expresses the transition density and outside it.
- 4 Show a large deviation type inequality.

# Sketch of the proof

Large deviation principle : Set

$$M_{1,p}^{\bar{\theta}, \bar{\sigma}, \bar{\lambda}} := \sum_{j=0}^{\infty} j^p \mathbb{E}_{X_{t_k}}^{\theta, \sigma, \lambda} \left[ \mathbf{1}_{J_j} \mathbb{E}_{X_{t_k}}^{\bar{\theta}, \bar{\sigma}, \bar{\lambda}} \left[ \mathbf{1}_{J_j^c} \left| X_{t_{k+1}}^{\bar{\theta}, \bar{\sigma}, \bar{\lambda}} = X_{t_k} \right| \right] \right],$$

$$M_{2,p}^{\bar{\theta}, \bar{\sigma}, \bar{\lambda}} := \sum_{j=0}^{\infty} \mathbb{E}_{X_{t_k}}^{\theta, \sigma, \lambda} \left[ \mathbf{1}_{J_j} \mathbb{E}_{X_{t_k}}^{\bar{\theta}, \bar{\sigma}, \bar{\lambda}} \left[ \mathbf{1}_{J_j^c} (N_{t_{k+1}} - N_{t_k})^p \left| X_{t_{k+1}}^{\bar{\theta}, \bar{\sigma}, \bar{\lambda}} = X_{t_k} \right| \right] \right].$$

**Lemma** Assume that  $|\theta - \bar{\theta}| \leq \frac{C}{\sqrt{n\Delta_n}}$  and  $|\lambda - \bar{\lambda}| \leq \frac{C}{\sqrt{n\Delta_n}}$ . Then for all  $\alpha \in (0, \frac{1}{2})$ , and  $n$  large enough,

$$M_{1,p}^{\bar{\theta}, \bar{\sigma}, \bar{\lambda}} + M_{2,p}^{\bar{\theta}, \bar{\sigma}, \bar{\lambda}} \leq C_1 e^{-\frac{1}{C_2 \Delta_n^{1-2\alpha}}}.$$

**Idea of the proof** : Separate the cases  $\mathbf{1}_{\{|B_{t_{k+1}} - B_{t_k}| \leq \Delta_n^\alpha\}}$  and  $\mathbf{1}_{\{|B_{t_{k+1}} - B_{t_k}| > \Delta_n^\alpha\}}$ .

## An ergodic diffusion process with jumps

$$dX_t^\theta = b(\theta, X_t^\theta)dt + \sigma(X_t^\theta)dB_t + \int_{\mathbb{R}_0} c(X_{t-}^\theta, z) (N(dt, dz) - \nu(dz)dt)$$

- Usual Lipschitz, ellipticity, ergodicity and regularity assumptions.
- $N(dt, dz)$  is a Poisson random measure with intensity measure  $\nu(dz)dt$ , where  $\lambda = \int_{\mathbb{R}_0} \nu(dz) < \infty$  independent of  $B$  such that
- There exist constants  $q > 1$ ,  $\rho_1, \rho_2 > 0$  and  $0 < \nu, \gamma < \frac{1}{2}$  such that as  $n \rightarrow \infty$ ,

$$\sqrt{n} \left( n\Delta_n \left( \int_{\{|z| \geq \rho_2 \Delta_n^{-\gamma}\}} \nu(dz) + \int_{\{|z| \leq \rho_1 \Delta_n^\nu\}} \nu(dz) \right) \right)^{\frac{1}{q}} \rightarrow 0.$$

- There exists  $n_0 \geq 1$  such that for all  $\theta \in \Theta$ , there exists  $C > 0$  such that

$$\sup_{n \geq n_0} \max_{k \in \{0, \dots, n\}} \mathbb{E}_x^\theta \left[ e^{C\Delta_n^{1-2\gamma} X_{t_k}^2} \right] < \infty.$$

# LAN property

## Theorem

For all  $\theta \in \Theta$  and  $u \in \mathbb{R}$ , as  $n \rightarrow \infty$ ,

$$\log \frac{p(X^n; \theta_n)}{p(X^n; \theta)} \xrightarrow{\mathcal{L}(\mathbb{R}_X^\theta)} u\mathcal{N}(0, \Gamma(\theta)) - \frac{u^2}{2}\Gamma(\theta),$$

where  $\theta_n = \theta + \frac{u}{\sqrt{n}\Delta_n}$ , and  $\mathcal{N}(0, \Gamma(\theta))$  is a centered Gaussian random variable with variance

$$\Gamma(\theta) = \int_{\mathbb{R}} \left( \frac{\partial_\theta b(\theta, x)}{\sigma(x)} \right)^2 \pi_\theta(dx).$$

## Another diffusion process with jumps

$$dX_t^{\theta, \beta} = b(\theta, X_t^{\theta, \beta})dt + \sigma(\beta, X_t^{\theta, \beta})dB_t + dZ_t - \lambda \int_{\mathbb{R}_0} z\mu(dz)dt$$

- $Z_t$  is a **compound Poisson process** independent of  $B$  rate  $\lambda > 0$  and jump size distribution  $\mu(dz) = \sum_{i=1}^{\infty} p_{a_i} \delta_{a_i}(dz)$ ,  $a_i \in \mathbb{R}_0$ ,  $0 \leq p_{a_i} \leq 1$ ,  $\sum_{i=1}^{\infty} p_{a_i} = 1$ , and for any  $p > 1$ ,  $\sum_{a_i} p_{a_i}^{\frac{1}{p}} < \infty$ .
- For any  $\omega, \omega' \in \Omega$

$$|(Z_{t_{k+1}} - Z_{t_k})(\omega) - (Z_{t_{k+1}} - Z_{t_k})(\omega')| \begin{cases} = 0, & \text{or} \\ \geq C\Delta_n^v. \end{cases}$$

Furthermore, for all  $q > 1$  and  $p \in \{2, 4\}$ ,

$$\sum_r r^p P_{X_{t_k}^{\theta, \beta}}(Z_{t_{k+1}} - Z_{t_k} = r)^{\frac{1}{q}} < \infty, \quad \sum_r P_{X_{t_k}^{\theta, \beta}}(Z_{t_{k+1}} - Z_{t_k} = r)^{\frac{1}{q}} < \infty.$$

**Example :** Assume that the jump sizes are positive and for some constant  $c > 0$ ,  $\int_0^{\infty} e^{cz} \mu(dz) \leq 2$ . Then by the result of Willmot and Lin, for any  $r > 0$ , and  $n$  large enough  $P(Z_{t_{k+1}} - Z_{t_k} \geq r) \leq 2e^{-cr}$ .

# LAN property

## Theorem

For all  $(\theta, \beta) \in \Theta \times \Sigma$  and  $w = (u, v) \in \mathbb{R}^2$ , as  $n \rightarrow \infty$ ,

$$\log \frac{p(X^n; (\theta_n, \beta_n))}{p(X^n; (\theta, \beta))} \xrightarrow{\mathcal{L}(P_x^{\theta, \beta})} w^T \mathcal{N}(0, \Gamma(\theta, \beta)) - \frac{1}{2} w^T \Gamma(\theta, \beta) w,$$

where  $\theta_n = \theta + \frac{u}{\sqrt{n\Delta_n}}$ ,  $\beta_n = \beta + \frac{v}{\sqrt{n}}$ , and  $\mathcal{N}(0, \Gamma(\theta, \beta))$  is a centered  $\mathbb{R}^2$ -valued Gaussian random variable with covariance matrix

$$\Gamma(\theta, \beta) = \begin{pmatrix} \int_{\mathbb{R}} \left( \frac{\partial_{\theta} b(\theta, x)}{\sigma(\beta, x)} \right)^2 \pi_{\theta, \beta}(dx) & 0 \\ 0 & 2 \int_{\mathbb{R}} \left( \frac{\partial_{\beta} \sigma(\beta, x)}{\sigma(\beta, x)} \right)^2 \pi_{\theta, \beta}(dx) \end{pmatrix}.$$

# Work in progress

- 1 The case of **infinite jumps** requires a convergence argument.
- 2 The case where the **drift is unbounded** and we have a **general Poisson random measure** :

$$dX_t = b(\theta, X_t)dt + \sigma(\beta, X_t)dB_t + \int_{\mathbb{R}_0} c(X_{t-}, z) (N(dt, dz) - \nu(dz)dt).$$

# References

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