

Some asymptotic equivalence results in the Le Cam sense

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Comparison of statistical models

Example (Le Cam and Yang (1990))

A physicist decides to estimate the half life of Carbon 14. He assumes that the life of a C^{14} has an exponential distribution of parameter θ , unknown. He takes a batch of n atoms and he begins to think about how to run the experiment. He has in mind two different ways to proceed :

- 1 Let P_θ be the law of $X_1 =$ numbers of atoms that decay before a certain time $\rightsquigarrow \mathcal{P}_1 : (P_\theta)_{\theta \in (0, \infty)}$.
- 2 Let Q_θ be the law of $X_2 =$ the first moment when the number of disintegrated atoms reaches a certain threshold $\rightsquigarrow \mathcal{P}_2 : (Q_\theta)_{\theta \in (0, \infty)}$.

Can one compare the experiments \mathcal{P}_1 and \mathcal{P}_2 ? How different can their statistical properties be?

The Le Cam Δ -distance

Definition

The **deficiency** $\delta(\mathcal{E}_1, \mathcal{E}_2)$ of \mathcal{E}_1 with respect to \mathcal{E}_2 is defined as

$$\delta(\mathcal{P}_1, \mathcal{P}_2) = \sup_L \inf_{\pi_1} \sup_{\pi_2} \sup_{\theta} |R(\mathcal{P}_1, \pi_1, L, \theta) - R(\mathcal{P}_2, \pi_2, L, \theta)|.$$

The so called **Δ -distance** between \mathcal{E}_1 and \mathcal{E}_2 is defined as:

$$\Delta(\mathcal{E}_1, \mathcal{E}_2) = \max(\delta(\mathcal{E}_1, \mathcal{E}_2), \delta(\mathcal{E}_2, \mathcal{E}_1)).$$

Two sequences of models $(\mathcal{E}_1^n)_{n \in \mathbb{N}}$ and $(\mathcal{E}_2^n)_{n \in \mathbb{N}}$ are **asymptotically equivalent** if $\Delta(\mathcal{E}_1^n, \mathcal{E}_2^n) \rightarrow 0$ as $n \rightarrow \infty$.

- **Interpretation:** Asymptotic equivalence means that any statistical inference procedure can be transferred from one experiment to the other in such a way that the asymptotic risk remains the same, at least for bounded loss functions.

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Additive processes

$$X_t = \int_0^t f(s)ds + \int_0^t \sigma(s)dW_s + \sum_{i=1}^{N_t} Y_i, \quad t \geq 0,$$

- $W = \{W_t\}_{t \geq 0}$ is a standard Brownian motion;
- $N = \{N_t\}_{t \geq 0}$ is an inhomogeneous Poisson process with intensity function $\lambda(\cdot)$, independent of W ;
- $(Y_i)_{i \geq 1}$ is a sequence of i.i.d. real random variables with distribution G (either concentrated on \mathbb{Z} or absolutely continuous with respect to Lebesgue), independent of W and N ;
- $f(\cdot)$ belongs to a certain non-parametric class \mathcal{F} ; $\lambda(\cdot)$ and G are unknown and $\sigma^2(\cdot)$ is known (to be discussed).

The problem we consider

We suppose to observe $\{X_t\}_{t \geq 0}$ at discrete times $0 = t_1 < \dots < t_n = T_n$ such that

$$\Delta_n = \max_{1 \leq i \leq n} \{|t_i - t_{i-1}|\} \downarrow 0 \text{ as } n \rightarrow \infty.$$

Problem: To estimate the drift function $f(\cdot)$ from the discrete data $(X_{t_i})_{i=1}^n$.

At least two natural questions arise:

- 1 How much information about the parameter $f(\cdot)$ do we lose by observing $(X_{t_i})_{i=1}^n$ instead of $\{X_t\}_{t \in [0, T_n]}$?
- 2 Can we construct an easier (read: mathematically more tractable), but equivalent, model from $(X_{t_i})_{i=1}^n$?

The case G concentrated on \mathbb{Z}

Theorem (M., 2014)

For n big enough:

$$\begin{aligned} \Delta(D_n, W) \leq & \sqrt{2 \sum_{i=1}^n \left(\frac{6}{\sigma_i} \varphi\left(\frac{1}{6\sigma_i}\right) + 4\phi\left(\frac{-1}{6\sigma_i}\right) \right)} \\ & + \sup_{f \in \mathcal{F}} \left(\sum_{i=1}^n \frac{(f(t_i) - f(\gamma_i))^2}{2\sigma^2(\eta_i)} \Delta_n + \int_0^{T_n} \frac{(f(t) - \bar{f}_n(t))^2}{\sigma^2(t)} dt \right) \\ & + 2 \sqrt{\sum_{i=1}^n \lambda_i^2}. \end{aligned}$$

Remark: If $\lambda \in L_\infty(\mathbb{R})$, then $\sqrt{\sum_{i=1}^n \lambda_i^2} = O(\sqrt{T_n \Delta_n})$.

Rate of convergence in the small variance case

\mathcal{F} : a class of α -Hölder, uniformly bounded functions on \mathbb{R} ,
 $\lambda(\cdot) \in L_\infty(\mathbb{R})$ and let T be fixed.

Theorem (M., 2014)

$$\begin{aligned}\Delta(D_n, W) &\rightarrow 0 \\ \Delta(C, D_n) &\rightarrow 0\end{aligned}\quad \text{as } n \rightarrow \infty,$$

under either of the following two sets of conditions:

- 1 Y_1 is discrete with support on \mathbb{Z} , $\alpha \geq \frac{1}{2}$; in this case the rate of convergence is $O(\sqrt{\Delta_n})$.
- 2 Y_1 admits a density with respect to the Lebesgue measure on \mathbb{R} , $\alpha \geq \frac{1}{4}$; in this case the rate of convergence is $O(\Delta_n^{\frac{1}{4}})$.

Compound Poisson processes

$$L_t = \sum_{i=1}^{N_t} Y_i, \quad t \geq 0,$$

- $N = \{N_t\}_{t \geq 0}$ is a Poisson process with mean λ ;
- $(Y_i)_{i \geq 1}$ is a sequence of i.i.d. real random variables with densities (with respect to Lebesgue) g , independent of N and concentrated on $[0, 1]$;
- $f(\cdot) := \lambda g(\cdot)$ belongs to a certain non-parametric class \mathcal{F} ;

We observe $\{L_t\}_{t \geq 0}$ at n equidistant discrete times

$$0 = t_1 < \cdots < t_n = T_n, \quad t_i = T_n \frac{i}{n}:$$

$$\Delta_n = \frac{T_n}{n} \downarrow 0 \text{ and } T_n \rightarrow \infty \text{ as } n \rightarrow \infty.$$

Problem: To estimate the Lévy density $f(\cdot)$ from the discrete data $(L_{t_i})_{i=1}^n$.

Definition of the experiments

- $P_{T_n}^f$: law of the process $\{L_t\}_{t \in [0, T_n]}$ on (D, \mathcal{D}) ,
- Q_i^f : law of the random variable $L_{t_i} - L_{t_{i-1}}$ on $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$,
- \mathbb{W}^f : law induced on (C, \mathcal{C}) by

$$dY_t = \sqrt{f(t)}dt + \frac{dW_t}{2\sqrt{T_n}}, \quad t \in [0, 1].$$

The statistical models we consider are:

- $\mathcal{P}_n = (D, \mathcal{D}_{T_n}, \{P_{T_n}^f : f \in \mathcal{F}\})$,
- $\mathcal{Q}_n = (\mathbb{R}^n, \mathcal{B}(\mathbb{R}^n), \{\otimes_{i=1}^n Q_i^f : f \in \mathcal{F}\})$,
- $\mathcal{W} = (C, \mathcal{C}, \{\mathbb{W}^f : f \in \mathcal{F}\})$.

Equivalence between discrete and continuous observations

Theorem (M. 2014)

For every choice of a sequence of integer $m = m_n$, we have an asymptotic equivalence with the following rates of convergence (provided that the stated sequences do converge to zero):

$$\Delta(\mathcal{Q}_n, \mathcal{W}) = O\left(\sqrt{T_n \Delta_n} + \frac{m \ln m}{\sqrt{n}} + \sqrt{T_n} m^{-\gamma}\right),$$

$$\Delta(\mathcal{P}_n, \mathcal{W}) = O\left(T_n^{-\frac{\gamma}{4+2\gamma}}\right),$$

$$\Delta(\mathcal{P}_n, \mathcal{Q}_n) = O\left(T_n^{-\frac{\gamma}{4+2\gamma}} + \sqrt{T_n \Delta_n} + \frac{m \ln m}{\sqrt{n}} + \sqrt{T_n} m^{-\gamma}\right).$$

Example: If $n = T_n^\alpha$ with $\alpha > 2$, then $m = T_n^{\frac{1+\alpha}{2(1+\gamma)}}$. In this case one finds that: $\Delta(\mathcal{Q}_n, \mathcal{W}) = O\left(\sqrt{T_n^{2-\alpha}} + T_n^{\frac{1-\alpha\gamma}{2(1+\gamma)}} \ln(T_n)\right)$.

Diffusion processes: small variance case

$$dy_t = f(y_t)dt + \varepsilon\sigma(y_t)dW_t, \quad t \in [0, T], \quad y_0 = 0.$$

We observe $\{y_t\}_{t \geq 0}$ at n equidistant discrete times $t_i = T \frac{i}{n}$.

Problem: To show that estimating $f(\cdot)$ from the discrete data $(y_{t_i})_{i=1}^n$ is equivalent to estimate $f(\cdot)$ from the Euler scheme:

$$Z_0 = 0, \quad Z_i = Z_{i-1} + \frac{f(Z_{i-1})}{n} + \varepsilon\sigma(Z_{i-1})\xi_i, \quad i = 1, \dots, n,$$

with independent standard normal variables ξ_i .

Motivation: Inference for discretely observed diffusion models is generally difficult (because of the intractability of the transitions densities). A way to bypass this problem is to consider statistical procedures based on the corresponding Euler scheme.

Main result

$$\begin{aligned} \mathcal{P}_y^{n,T} &= (C, \mathcal{C}_T, (P_f^{n,y}, f \in \mathcal{F})), & P_f^{n,y} &= \mathcal{L}(y) \\ \mathcal{Q}_y^n &= (\mathbb{R}^n, \mathcal{B}(\mathbb{R}^n), (Q_f^{n,y}, f \in \mathcal{F})), & Q_f^{n,y} &= \mathcal{L}((y_{t_i})_i), \\ \mathcal{Q}_Z^n &= (\mathbb{R}^n, \mathcal{B}(\mathbb{R}^n), (Q_f^{n,Z}, f \in \mathcal{F})), & Q_f^{n,Z} &= \mathcal{L}((Z_i)_i). \end{aligned}$$

Theorem

If $\varepsilon n \rightarrow \infty$ as $n \rightarrow \infty$ and $\varepsilon \rightarrow 0$, the experiments \mathcal{P}_y^T and \mathcal{Q}_Z^n are asymptotically equivalent. More precisely we have

$$\Delta(\mathcal{P}_y^T, \mathcal{Q}_Z^n) = O\left(\frac{1}{\varepsilon n} + (n^{-1} + \varepsilon)^{1/4}\right),$$

$$\Delta(\mathcal{P}_y^T, \mathcal{Q}_y^n) = O\left(\frac{1}{\varepsilon n}\right).$$

Perspectives

Extensions:

- A generalization for X_t taking values in \mathbb{R}^d .
- To generalize to the case ν infinite Lévy measure.

Future work:

- Asymptotic equivalence for stationary distribution.

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Thank you for your attention !