

# Sharp large deviations for the fractional Ornstein-Uhlenbeck process

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# Outline

- 1 Introduction
  - On the Cramer-Chernov theorem
  - On the Bahadur-Rao theorem
- 2 Main results
  - Gaussian quadratic forms
  - Large deviation principle
  - Sharp large deviation principle
- 3 Statistical applications
  - Autoregressive process
  - Ornstein-Uhlenbeck process
  - Fractional Ornstein-Uhlenbeck process



# The Gaussian example

Let  $(X_n)$  be a sequence of iid  $\mathcal{N}(0, \sigma^2)$  random variables. If

$$S_n = \sum_{k=1}^n X_k$$

we clearly have  $S_n \sim \mathcal{N}(0, \sigma^2 n)$ . Consequently, for all  $c > 0$

$$\mathbb{P}(S_n \geq nc) = \frac{\sigma}{c\sqrt{2\pi n}} \exp\left(-\frac{c^2 n}{2\sigma^2}\right) \left[1 + o(1)\right].$$

Therefore,

$$\lim_{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}(S_n \geq nc) = -\frac{c^2}{2\sigma^2}.$$

**Question.** What about the non-Gaussian case ?



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Let  $(X_n)$  be a sequence of iid random variables with mean  $m$ .  
The **Fenchel-Legendre** dual of the log-Laplace  $L$  of  $(X_n)$  is

$$I(c) = \sup_{t \in \mathbb{R}} \{ct - L(t)\}.$$

### Theorem (Cramer-Chernov)

The sequence  $(S_n/n)$  satisfies an **LDP** with rate function  $I$

- **Upper bound:** for any closed set  $F \subset \mathbb{R}$

$$\limsup_{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}\left(\frac{S_n}{n} \in F\right) \leq - \inf_F I,$$

- **Lower bound:** for any open set  $G \subset \mathbb{R}$

$$\liminf_{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}\left(\frac{S_n}{n} \in G\right) \geq - \inf_G I.$$



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# On the Cramer-Chernov theorem

The rate function  $I$  is convex with  $I(m) = 0$ . For all  $c > m$ ,

$$\lim_{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}(S_n \geq nc) = -I(c).$$

- **Gaussian:** If  $X_n \sim \mathcal{N}(0, \sigma^2)$  with  $\sigma^2 > 0$ ,

$$I(c) = \frac{c^2}{2\sigma^2}.$$

- **Exponential:** If  $X_n \sim \mathcal{E}(\lambda)$  with  $\lambda > 0$ ,

$$I(c) = \begin{cases} \lambda c - 1 - \log(\lambda c) & \text{if } c > 0, \\ +\infty & \text{otherwise.} \end{cases}$$



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# On the Bahadur-Rao theorem

## Theorem (Bahadur-Rao)

Assume that  $L$  is finite on all  $\mathbb{R}$  and that the law of  $(X_n)$  is absolutely continuous. Then, for all  $c > m$ ,

$$\mathbb{P}(S_n \geq nc) = \frac{\exp(-nl(c))}{\sigma_c t_c \sqrt{2\pi n}} [1 + o(1)]$$

where  $t_c$  is given by  $L'(t_c) = c$  and  $\sigma_c^2 = L''(t_c)$ .

**Remark.** The core of the proof is the Berry-Esséen theorem.



## Theorem (Bahadur-Rao)

$(S_n/n)$  satisfies an **SLDP** associated with  $L$ . For all  $c > m$ , it exists  $(d_{c,k})$  such that for any  $p \geq 1$  and  $n$  large enough

$$\mathbb{P}(S_n \geq nc) = \frac{\exp(-nI(c))}{\sigma_c t_c \sqrt{2\pi n}} \left[ 1 + \sum_{k=1}^p \frac{d_{c,k}}{n^k} + \mathcal{O}\left(\frac{1}{n^{p+1}}\right) \right].$$

**Remark.** The coefficients  $(d_{c,k})$  may be explicitly calculated as functions of the derivatives  $l_k = L^{(k)}(t_c)$ . For example,

$$d_{c,1} = \frac{1}{\sigma_c^2} \left( \frac{l_4}{8\sigma_c^2} - \frac{5l_3^2}{24\sigma_c^4} - \frac{l_3}{2t_c\sigma_c^2} - \frac{1}{t_c^2} \right).$$



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# Gaussian quadratic forms

Let  $(X_n)$  be a centered stationary real Gaussian process with spectral density  $g \in \mathbb{L}^\infty(\mathbb{T})$

$$\mathbb{E}[X_n X_k] = \frac{1}{2\pi} \int_{\mathbb{T}} \exp(i(n-k)x) g(x) dx.$$

We are interested in the behavior of

$$W_n = \frac{1}{n} \mathbf{X}^{(n)t} M_n \mathbf{X}^{(n)}$$

where  $(M_n)$  is a sequence of Hermitian matrices of order  $n$  and

$$\mathbf{X}^{(n)} = \begin{pmatrix} X_1 \\ \vdots \\ X_n \end{pmatrix}.$$



# Toeplitz and Cochran

Let  $T_n(g)$  be the covariance matrix of  $X^{(n)}$ . Via Cochran,

$$W_n = \frac{1}{n} \sum_{k=1}^n \lambda_k^n Z_k^n$$

- $\lambda_1^n, \dots, \lambda_n^n$  are the eigenvalues of  $T_n(g)^{1/2} M_n T_n(g)^{1/2}$
- $Z_1^n, \dots, Z_n^n$  are iid with  $\chi^2(1)$  distribution

The normalized cumulant generating function of  $W_n$  is given by

$$L_n(t) = \frac{1}{n} \log \mathbb{E} \left[ \exp(ntW_n) \right] = -\frac{1}{2n} \sum_{k=1}^n \log(1 - 2t\lambda_k^n)$$

as soon as  $t$  belongs to  $\Delta_n = \{t \in \mathbb{R} / 2t\lambda_k^n \leq 1\}$ .



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**LDP assumption.** There exists  $\varphi \in \mathbb{L}^\infty(\mathbb{T})$  not identically zero such that, if  $m_\varphi = \text{essinf } \varphi$  and  $M_\varphi = \text{esssup } \varphi$ ,

$$(H_1) \quad m_\varphi \leq \lambda_k^n \leq M_\varphi$$

and, for all  $h \in \mathbb{C}([m_\varphi, M_\varphi])$ ,

$$(H_1) \quad \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{k=1}^n h(\lambda_k^n) = \frac{1}{2\pi} \int_{\mathbb{T}} h(\varphi(x)) dx.$$

Under  $(H_1)$ , the asymptotic cumulant generating function is

$$L(t) = -\frac{1}{4\pi} \int_{\mathbb{T}} \log(1 - 2t\varphi(x)) dx$$

where  $t$  belongs to  $\Delta = \{t \in \mathbb{R} / 2 \max(m_\varphi t, M_\varphi t) < 1\}$ .





# Large deviation principle

The **Fenchel-Legendre** dual of  $L$  is given by

$$I(c) = \sup_{t \in \mathbb{R}} \left\{ ct + \frac{1}{4\pi} \int_{\mathbb{T}} \log(1 - 2t\varphi(x)) dx \right\}.$$

**Theorem (Bercu-Gamboa-Lavielle)**

If  $(H_1)$  holds, the sequence  $(W_n)$  satisfies an **LDP** with rate function  $I$ . In particular, for all  $c > \mu$

$$\lim_{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}(W_n \geq c) = -I(c).$$

with  $\mu = \frac{1}{2\pi} \int_{\mathbb{T}} \varphi(x) dx.$



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# Sharp large deviation results

**SLDP assumption.** There exists  $H$  such that, for all  $t \in \Delta$

$$(H_2) \quad L_n(t) = L(t) + \frac{1}{n}H(t) + o\left(\frac{1}{n}\right)$$

where the remainder is uniform in  $t$ .

## Theorem (Bercu-Gamboa-Lavielle)

Assume that  $(H_1)$  and  $(H_2)$  hold. Then, for all  $c > \mu$

$$\mathbb{P}(W_n \geq c) = \frac{\exp(-nl(c) + H(t_c))}{\sigma_c t_c \sqrt{2\pi n}} \left[1 + o(1)\right]$$

where  $t_c$  is given by  $L'(t_c) = c$  and  $\sigma_c^2 = L''(t_c)$ .



# Sharp large deviation results

**SLDP assumption.** For  $p \geq 1$ , there exists  $H \in \mathcal{C}^{2p+3}(\mathbb{R})$  such that, for all  $t \in \Delta$  and for any  $0 \leq k \leq 2p + 3$

$$(H_2(p)) \quad L_n^{(k)}(t) = L^{(k)}(t) + \frac{1}{n} H^{(k)}(t) + \mathcal{O}\left(\frac{1}{n^{p+2}}\right)$$

where the remainder is uniform in  $t$ .

**Remark.** Assumption  $(H_2(p))$  is not really restrictive. It is fulfilled in many statistical applications.



## Theorem (Bercu-Gamboa-Lavielle)

For  $p \geq 1$ , assume that  $(H_1)$  and  $(H_2(p))$  hold. Then,  $(W_n)$  satisfies an **SLDP** of order  $p$  associated with  $L$  and  $H$ . For all  $c > \mu$ , it exists  $(d_{c,k})$  such that for  $n$  large enough

$$\begin{aligned} & \mathbb{P}(W_n \geq c) \\ &= \frac{\exp(-nl(c) + H(tc))}{\sigma_c t_c \sqrt{2\pi n}} \left[ 1 + \sum_{k=1}^p \frac{d_{c,k}}{n^k} + \mathcal{O}\left(\frac{1}{n^{p+1}}\right) \right]. \end{aligned}$$

**Remark.** The coefficients  $(d_{c,k})$  may be given as functions of the derivatives  $l_k = L^{(k)}(t_c)$  and  $h_k = H^{(k)}(t_c)$ . For example,

$$d_{c,1} = \frac{1}{\sigma_c^2} \left( -\frac{h_2}{2} - \frac{h_1^2}{2} + \frac{l_4}{8\sigma_c^2} + \frac{l_3 h_1}{2\sigma_c^2} - \frac{5l_3^2}{24\sigma_c^4} + \frac{h_1}{t_c} - \frac{l_3}{2t_c \sigma_c^2} - \frac{1}{t_c^2} \right).$$



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# Stable autoregressive process

Consider the stable autoregressive process

$$X_{n+1} = \theta X_n + \varepsilon_{n+1}, \quad |\theta| < 1$$

where  $(\varepsilon_n)$  is iid  $\mathcal{N}(0, \sigma^2)$ ,  $\sigma^2 > 0$ . If  $X_0$  is independent of  $(\varepsilon_n)$  with  $\mathcal{N}(0, \sigma^2/(1 - \theta^2))$  distribution,  $(X_n)$  is a centered stationary Gaussian process with spectral density given, for all  $x \in \mathbb{T}$ , by

$$g(x) = \frac{\sigma^2}{1 + \theta^2 - 2\theta \cos x}.$$



Let  $\hat{\theta}_n$  be the **least squares** estimator of the parameter  $\theta$

$$\hat{\theta}_n = \frac{\sum_{k=1}^n X_k X_{k-1}}{\sum_{k=1}^n X_{k-1}^2}.$$

We have  $\hat{\theta}_n \rightarrow \theta$  a.s. and  $\sqrt{n}(\hat{\theta}_n - \theta) \xrightarrow{\mathcal{L}} \mathcal{N}(0, 1 - \theta^2)$ . One can also estimate  $\theta$  by the **Yule-Walker** estimator

$$\tilde{\theta}_n = \frac{\sum_{k=1}^n X_k X_{k-1}}{\sum_{k=0}^n X_k^2}.$$





$$a = \frac{\theta - \sqrt{\theta^2 + 8}}{4} \quad \text{and} \quad b = \frac{\theta + \sqrt{\theta^2 + 8}}{4}.$$

### Theorem (Bercu-Gamboa-Rouault)

- $(\hat{\theta}_n)$  satisfies an **LDP** with rate function

$$J(c) = \begin{cases} \frac{1}{2} \log \left( \frac{1 + \theta^2 - 2\theta c}{1 - c^2} \right) & \text{if } c \in [a, b], \\ \log |\theta - 2c| & \text{otherwise.} \end{cases}$$

- $(\tilde{\theta}_n)$  satisfies an **LDP** with rate function

$$I(c) = \begin{cases} \frac{1}{2} \log \left( \frac{1 + \theta^2 - 2\theta c}{1 - c^2} \right) & \text{if } c \in ]-1, 1[, \\ +\infty & \text{otherwise.} \end{cases}$$



$$a = \frac{\theta - \sqrt{\theta^2 + 8}}{4} \quad \text{and} \quad b = \frac{\theta + \sqrt{\theta^2 + 8}}{4}.$$

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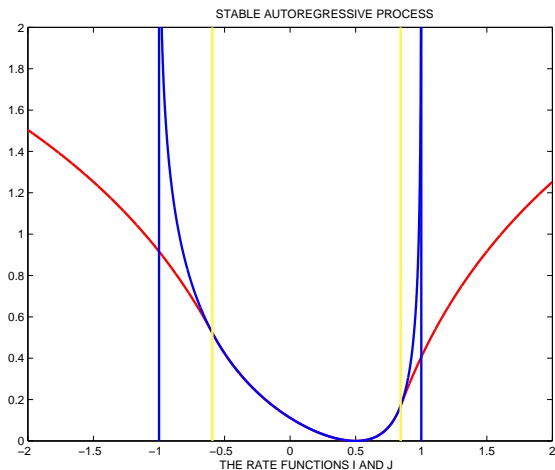
$$J(c) = \begin{cases} \frac{1}{2} \log \left( \frac{1 + \theta^2 - 2\theta c}{1 - c^2} \right) & \text{if } c \in [a, b], \\ \log |\theta - 2c| & \text{otherwise.} \end{cases}$$

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# Least squares and Yule-Walker



# Yule-Walker

## Theorem (Bercu-Gamboa-Lavielle)

The sequence  $(\tilde{\theta}_n)$  satisfies an **SLDP**. For all  $c \in \mathbb{R}$  with  $c > \theta$  and  $|c| < 1$ , it exists a sequence  $(d_{c,k})$  such that for any  $p \geq 1$  and  $n$  large enough

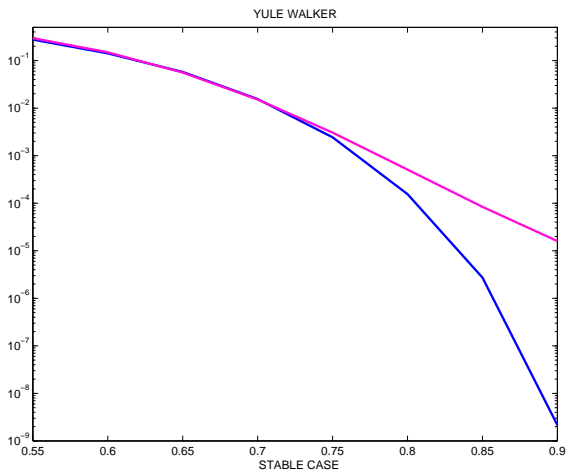
$$\mathbb{P}(\tilde{\theta}_n \geq c) = \frac{\exp(-nl(c) + H(c))}{\sigma_c t_c \sqrt{2\pi n}} \left[ 1 + \sum_{k=1}^p \frac{d_{c,k}}{n^k} + \mathcal{O}\left(\frac{1}{n^{p+1}}\right) \right]$$

$$t_c = \frac{c(1 + \theta^2) - \theta(1 - c^2)}{1 - c^2}, \quad \sigma_c^2 = \frac{1 - c^2}{(1 + \theta^2 - 2\theta c)^2},$$

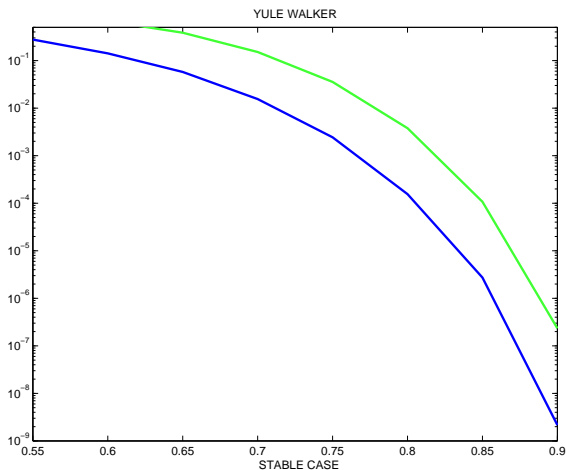
$$H(c) = -\frac{1}{2} \log \left( \frac{(1 - c\theta)^4}{(1 - \theta)^2(1 + \theta^2 - 2\theta c)(1 - c^2)^2} \right).$$



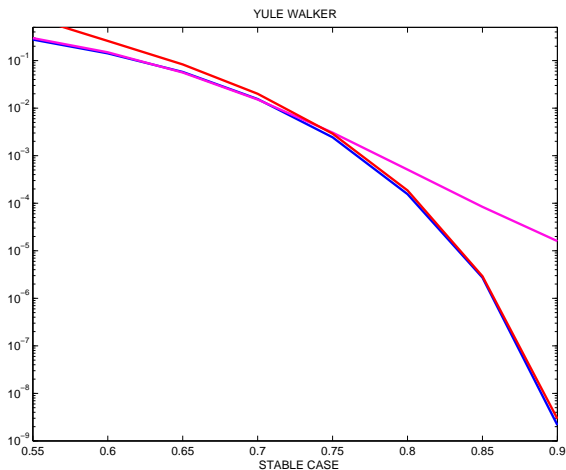
# Yule-Walker



# Yule-Walker



# Yule-Walker



# Explosive autoregressive process

Consider the explosive autoregressive process

$$\mathbf{X}_{n+1} = \theta \mathbf{X}_n + \varepsilon_{n+1}, \quad |\theta| > 1$$

where  $(\varepsilon_n)$  is iid  $\mathcal{N}(0, \sigma^2)$ ,  $\sigma^2 > 0$ . The **Yule-Walker** estimator satisfies  $\tilde{\theta}_n \rightarrow 1/\theta$  a.s. together with

$$|\theta|^n \left( \tilde{\theta}_n - \frac{1}{\theta} \right) \xrightarrow{\mathcal{L}} \frac{(\theta^2 - 1)}{\theta^2} \mathcal{C}$$

where  $\mathcal{C}$  stands for the Cauchy distribution.





# Explosive autoregressive process

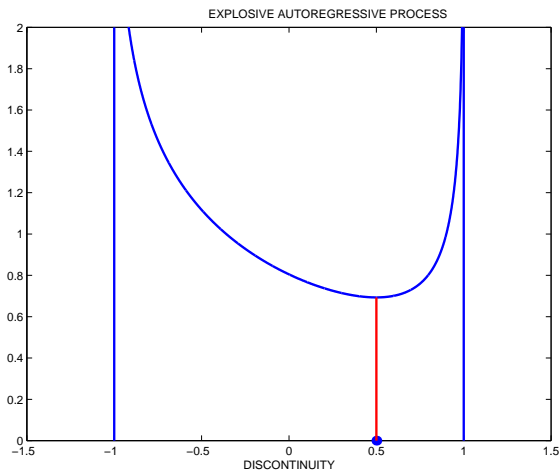
## Theorem (Bercu)

The sequence  $(\tilde{\theta}_n)$  satisfies an **LDP** with rate function

$$I(c) = \begin{cases} \frac{1}{2} \log \left( \frac{1 + \theta^2 - 2\theta c}{1 - c^2} \right) & \text{if } c \in ]-1, 1[, c \neq 1/\theta, \\ 0 & \text{if } c = 1/\theta, \\ +\infty & \text{otherwise.} \end{cases}$$



# Discontinuity



# Yule-Walker

## Theorem (Bercu)

The sequence  $(\tilde{\theta}_n)$  satisfies an **SLDP**. For all  $c \in \mathbb{R}$  with  $c > 1/\theta$  and  $|c| < 1$ , it exists a sequence  $(d_{c,k})$  such that for any  $p \geq 1$  and  $n$  large enough

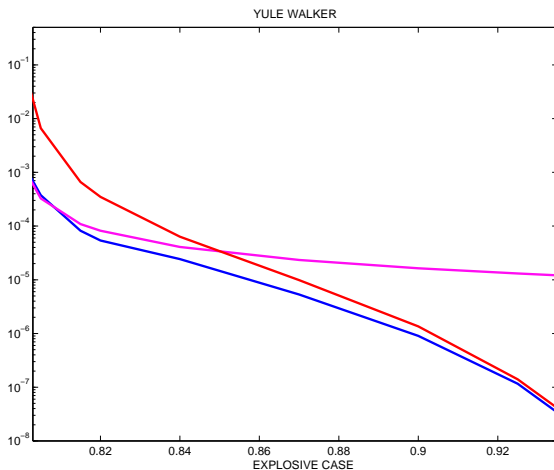
$$\mathbb{P}(\tilde{\theta}_n \geq c) = \frac{\exp(-nl(c) + H(c))}{\sigma_c t_c \sqrt{2\pi n}} \left[ 1 + \sum_{k=1}^p \frac{d_{c,k}}{n^k} + \mathcal{O}\left(\frac{1}{n^{p+1}}\right) \right]$$

$$t_c = \frac{(\theta c - 1)(\theta - c)}{1 - c^2}, \quad \sigma_c^2 = \frac{1 - c^2}{(1 + \theta^2 - 2\theta c)^2},$$

$$H(c) = -\frac{1}{2} \log \left( \frac{(\theta c - 1)^2}{(1 + \theta^2 - 2\theta c)(1 - c^2)} \right).$$



# Yule-Walker



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# Stable Ornstein-Uhlenbeck process

Consider the stable Ornstein-Uhlenbeck process

$$dX_t = \theta X_t dt + dB_t, \quad \theta < 0$$

with initial state  $X_0 = 0$ , where  $(B_t)$  is a standard Brownian motion. We are interested in **SLDP** for **the energy**

$$S_T = \int_0^T X_t^2 dt$$

and **the maximum likelihood** estimator of  $\theta$

$$\hat{\theta}_T = \frac{\int_0^T X_t dX_t}{\int_0^T X_t^2 dt} = \frac{X_T^2 - T}{2 \int_0^T X_t^2 dt}.$$



# Strong laws and Central Limit Theorems

## Theorem

We have the **SLLN**  $S_T/T \rightarrow -1/2\theta$  a.s. Moreover, we have the **CLT**

$$\frac{1}{\sqrt{T}} \left( S_T + \frac{T}{2\theta} \right) \xrightarrow{\mathcal{L}} \mathcal{N} \left( 0, -\frac{1}{2\theta^3} \right).$$

## Theorem

We have the **SLLN**  $\hat{\theta}_T \rightarrow \theta$  a.s. Moreover, we have the **CLT**

$$\sqrt{T}(\hat{\theta}_T - \theta) \xrightarrow{\mathcal{L}} \mathcal{N}(0, -2\theta).$$



# Stable Ornstein-Uhlenbeck process

## Theorem (Bryc-Dembo)

The sequence  $(S_T/T)$  satisfies an **LDP** with rate function

$$I(c) = \begin{cases} \frac{(2\theta c + 1)^2}{8c} & \text{if } c > 0, \\ +\infty & \text{otherwise.} \end{cases}$$

## Theorem (Florens-Pham)

The sequence  $(\hat{\theta}_T)$  satisfies an **LDP** with rate function

$$I(c) = \begin{cases} -\frac{(c - \theta)^2}{4c} & \text{if } c < \theta/3, \\ 2c - \theta & \text{otherwise.} \end{cases}$$





# Stable Ornstein-Uhlenbeck process

## Theorem (Bercu-Rouault)

The sequence  $(S_T/T)$  satisfies an **SLDP**. For all  $c > -1/2\theta$ , it exists a sequence  $(b_{c,k})$  such that, for any  $p \geq 1$  and  $T$  large enough

$$\mathbb{P}(S_T \geq cT) = \frac{\exp(-Tl(c) + H(c))}{\sigma_c t_c \sqrt{2\pi T}} \left[ 1 + \sum_{k=1}^p \frac{b_{c,k}}{T^k} + \mathcal{O}\left(\frac{1}{T^{p+1}}\right) \right]$$

$$t_c = \frac{4\theta^2 c^2 - 1}{8c^2}, \quad H(c) = -\frac{1}{2} \log\left(\frac{1}{2}(1 - 2\theta c)\right)$$

$$\sigma_c^2 = 4c^3.$$



# Stable Ornstein-Uhlenbeck process

## Theorem (Bercu-Rouault)

The sequence  $(\hat{\theta}_T)$  satisfies an **SLDP**. For all  $\theta < c < \theta/3$ , it exists a sequence  $(d_{c,k})$  such that, for any  $p \geq 1$  and  $T$  large enough

$$\mathbb{P}(\hat{\theta}_T \geq c) = \frac{\exp(-Tl(c) + H(c))}{\sigma_c t_c \sqrt{2\pi T}} \left[ 1 + \sum_{k=1}^p \frac{d_{c,k}}{T^k} + \mathcal{O}\left(\frac{1}{T^{p+1}}\right) \right]$$

$$t_c = \frac{c^2 - \theta^2}{2c}, \quad H(c) = -\frac{1}{2} \log \left( \frac{(c + \theta)(3c - \theta)}{4c^2} \right)$$

$\sigma_c^2 = -1/2c$ . Similar expansion holds for  $c > \theta/3$  with  $c \neq 0$ .



# Stable Ornstein-Uhlenbeck process

## Theorem (Bercu-Rouault)

- For  $c = 0$ , it exists a sequence  $(b_k)$  such that, for any  $p \geq 1$  and  $T$  large enough

$$\mathbb{P}(\hat{\theta}_T \geq 0) = \frac{\exp(\theta T)}{\sqrt{\pi T} \sqrt{-\theta}} \left[ 1 + \sum_{k=1}^p \frac{b_k}{T^k} + \mathcal{O}\left(\frac{1}{T^{p+1}}\right) \right].$$

- For  $c = \theta/3$ , it exists a sequence  $(d_k)$  such that, for any  $p \geq 1$  and  $T$  large enough

$$\mathbb{P}(\hat{\theta}_T \geq c) = \frac{\exp(-Tl(c))}{4\pi T^{1/4} \tau_\theta} \left[ 1 + \sum_{k=1}^{2p} \frac{d_k}{(\sqrt{T})^k} + \mathcal{O}\left(\frac{1}{T^p \sqrt{T}}\right) \right]$$

where  $\tau_\theta = (-\theta/3)^{1/4} / \Gamma(1/4)$ .



# Outline

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# Fractional Ornstein-Uhlenbeck process

Consider the fractional Ornstein-Uhlenbeck process

$$dX_t = \theta X_t dt + dB_t^H, \quad \theta < 0$$

where  $(B_t^H)$  is a **fractional Brownian motion** with **Hurst parameter**  $0 < H < 1$ ,  $(B_t^H)$  is a Gaussian process with continuous paths such that  $B_0^H = 0$ ,  $\mathbb{E}[B_t^H] = 0$  and

$$\mathbb{E}[B_t^H B_s^H] = \frac{1}{2} (t^{2H} + s^{2H} - |t - s|^{2H}).$$

The weighting function

$$w(t, s) = w_H^{-1} s^{-H+1/2} (t - s)^{-H+1/2}$$

plays a crucial role for stochastic calculus associated with  $(B_t^H)$ .



# A Gaussian martingale

For all  $t > 0$  and  $H > 1/2$ , let

$$M_t = \int_0^t w(t, s) dB_s^H.$$

Then,  $(M_t)$  is a Gaussian martingale with quadratic variation

$$\langle M \rangle_t = \frac{t^{2-2H}}{\lambda_H}$$

$$\lambda_H = \frac{8H(1-H)\Gamma(1-2H)\Gamma(H+1/2)}{\Gamma(1/2-H)}$$

where  $\Gamma$  stands for the classical gamma function.



For all  $t > 0$ , let

$$Y_t = \int_0^t w(t, s) dX_s$$
$$Q_t = \frac{\ell_H}{2} \left( t^{2H-1} Y_t + \int_0^t s^{2H-1} dY_s \right)$$

where  $\ell_H = \lambda_H / (2(1 - H))$ . **The energy** is given by

$$S_T = \int_0^T Q_t^2 d\langle M \rangle_t$$

while **the maximum likelihood** estimator of  $\theta$  is

$$\hat{\theta}_T = \frac{\int_0^T Q_t dY_t}{\int_0^T Q_t^2 d\langle M \rangle_t}.$$



# Strong laws and Central Limit Theorems

## Theorem

We have the **SLLN**  $S_T/T \rightarrow -1/2\theta$  a.s. Moreover, we have the **CLT**

$$\frac{1}{\sqrt{T}} \left( S_T + \frac{T}{2\theta} \right) \xrightarrow{\mathcal{L}} \mathcal{N} \left( 0, -\frac{1}{2\theta^3} \right).$$

## Theorem

We have the **SLLN**  $\hat{\theta}_T \rightarrow \theta$  a.s. Moreover, we have the **CLT**

$$\sqrt{T}(\hat{\theta}_T - \theta) \xrightarrow{\mathcal{L}} \mathcal{N}(0, -2\theta).$$





# The energy

## Theorem (Bercu-Coutin-Savy)

The sequence  $(S_T/T)$  satisfies an **LDP** with rate function

$$I(c) = \begin{cases} \frac{(2\theta c + 1)^2}{8c} & \text{if } 0 < c \leq -\frac{1}{2\theta\delta_H}, \\ \frac{c\theta^2}{2}(1 - \delta_H^2) + \frac{\theta}{2}(1 - \delta_H) & \text{if } c \geq -\frac{1}{2\theta\delta_H}, \\ +\infty & \text{otherwise.} \end{cases}$$

where  $\delta_H = (1 - \sin(\pi H))/(1 + \sin(\pi H))$ .

**Remark.** In the particular case  $H = 1/2$ ,  $\delta_H = 0$  and the **LDP** for  $(S_T/T)$  is exactly the one established by Bryc and Dembo.

## Theorem (Bercu-Coutin-Savy)

The sequence  $(S_T/T)$  satisfies an **SLDP**. For all  $c > -1/(2\theta)$  with  $c < -1/(2\theta\delta_H)$ , it exists a sequence  $(b_{c,k}^H)$  such that, for any  $p > 0$  and  $T$  large enough,

$$\mathbb{P}(S_T \geq cT) = \frac{\exp(-Tl(c) + J(c) + K_H(c))}{\sigma_c t_c \sqrt{2\pi T}} \left[ 1 + \sum_{k=1}^p \frac{b_{c,k}^H}{T^k} + \mathcal{O}\left(\frac{1}{T^{p+1}}\right) \right]$$

where  $\sigma_c^2 = 4c^3$ ,

$$t_c = \frac{4\theta^2 c^2 - 1}{8c^2}, \quad J(c) = -\frac{1}{2} \log\left(\frac{1 - 2\theta c}{2}\right),$$

$$K_H(c) = -\frac{1}{2} \log\left(\frac{(1 + \sin(\pi H))(1 + 2\theta c \delta_H)}{2 \sin(\pi H)}\right).$$



## Theorem (Bercu-Coutin-Savy)

For all  $c > -1/(2\theta\delta_H)$ , it exists a sequence  $(d_{c,k}^H)$  such that, for any  $p > 0$  and  $T$  large enough,

$$\mathbb{P}(\mathbf{S}_T \geq cT) = \frac{\exp(-Tl(c) + P_H(c) + Q_H(c))}{\sigma_H t_H \sqrt{2\pi T}} \left[ 1 + \sum_{k=1}^p \frac{d_{c,k}^H}{T^k} + \mathcal{O}\left(\frac{1}{T^{p+1}}\right) \right]$$

where  $\sigma_H^2 = -1/2\theta^3\delta_H^3$ ,

$$t_H = \frac{\theta^2(1 - \delta_H^2)}{2}, \quad P_H(c) = -\frac{1}{2} \log\left(\frac{-(1 + 2\theta c\delta_H)}{4\delta_H \sin(\pi H)}\right),$$

$$Q_H(c) = \frac{(2H - 1)^2 \sin(\pi H)(1 + 2\theta c\delta_H)}{2(1 - (\sin(\pi H))^2)}.$$



## Theorem (Bercu-Coutin-Savy)

For  $c = -1/(2\theta\delta_H)$ , it exists a sequence  $(d_k^H)$  such that, for any  $p > 0$  and  $T$  large enough

$$\mathbb{P}(\mathbf{S}_T \geq cT) = \frac{\exp(-Tl(c) + K_H)\Gamma(1/4)}{2\pi\sigma_H t_H T^{1/4}}$$

$$\left[ 1 + \sum_{k=1}^{2p} \frac{d_k^H}{(\sqrt{T})^k} + \mathcal{O}\left(\frac{1}{T^p\sqrt{T}}\right) \right]$$

where

$$K_H = \frac{1}{2} \log(\delta_H \sin(\pi H)) + \frac{1}{4} \log(-\theta\delta_H).$$

## the maximum likelihood estimator

## Theorem (Bercu-Coutin-Savy)

The sequence  $(\hat{\theta}_T)$  satisfies an **LDP** with rate function

$$I(c) = \begin{cases} -\frac{(c - \theta)^2}{4c} & \text{if } c < \theta/3, \\ 2c - \theta & \text{otherwise.} \end{cases}$$

**Remark.** One can observe that  $(\hat{\theta}_T)$  shares the same LDP than the one established by Florens-Landais and Pham for  $H = 1/2$ .



## Theorem (Bercu-Coutin-Savy)

The sequence  $(\hat{\theta}_T)$  satisfies an **SLDP**. For all  $\theta < c < \theta/3$ , it exists a sequence  $(b_{c,k}^H)$  such that, for any  $p > 0$  and  $T$  large enough,

$$\mathbb{P}(\hat{\theta}_T \geq c) = \frac{\exp(-Tl(c) + J(c) + K_H(c))}{\sigma_c t_c \sqrt{2\pi T}} \left[ 1 + \sum_{k=1}^p \frac{b_{c,k}^H}{T^k} + \mathcal{O}\left(\frac{1}{T^{p+1}}\right) \right]$$

where  $\sigma_c^2 = -1/2c$ ,  $p_H = (1 - \sin(\pi H))/\sin(\pi H)$ ,

$$t_c = \frac{c^2 - \theta^2}{2c}, \quad J(c) = -\frac{1}{2} \log \left( \frac{(c + \theta)(3c - \theta)}{4c^2} \right),$$

$$K_H(c) = -\frac{1}{2} \log \left( 1 + p_H \frac{(c - \theta)^2}{4c^2} \right).$$



## Theorem (Bercu-Coutin-Savy)

For all  $c > \theta/3$  with  $c \neq 0$ , it exists a sequence  $(d_{c,k}^H)$  such that, for any  $p > 0$  and  $T$  large enough,

$$\mathbb{P}(\hat{\theta}_T \geq c) = \frac{\exp(-Tl(c) + P(c)) \sqrt{\sin(\pi H)}}{\sigma^c t^c \sqrt{2\pi T}} \left[ 1 + \sum_{k=1}^p \frac{d_{c,k}^H}{T^k} + \mathcal{O}\left(\frac{1}{T^{p+1}}\right) \right]$$

where

$$t^c = 2(c - \theta), \quad (\sigma^c)^2 = \frac{c^2}{2(2c - \theta)^3},$$

$$P(c) = -\frac{1}{2} \log \left( \frac{(c - \theta)(3c - \theta)}{4c^2} \right)$$



## Theorem (Bercu-Coutin-Savy)

- For  $c = 0$ , it exists a sequence  $(b_k^H)$  such that, for any  $p \geq 1$  and  $T$  large enough

$$\mathbb{P}(\hat{\theta}_T \geq 0) = \frac{\exp(\theta T) \sqrt{\sin(\pi H)}}{\sqrt{\pi T} \sqrt{-\theta}} \left[ 1 + \sum_{k=1}^p \frac{b_k^H}{T^k} + \mathcal{O}\left(\frac{1}{T^{p+1}}\right) \right].$$

- For  $c = \theta/3$ , it exists a sequence  $(d_k^H)$  such that, for any  $p \geq 1$  and  $T$  large enough, and  $\tau_\theta = (-\theta/3)^{1/4}/\Gamma(1/4)$ ,

$$\mathbb{P}(\hat{\theta}_T \geq c) = \frac{\exp(-Tl(c)) \sqrt{\sin(\pi H)}}{4\pi T^{1/4} \tau_\theta} \left[ 1 + \sum_{k=1}^{2p} \frac{d_k^H}{(\sqrt{T})^k} + \mathcal{O}\left(\frac{1}{T^p \sqrt{T}}\right) \right].$$

