

# PARAMETER ESTIMATION FOR THE LANGEVIN EQUATION WITH STATIONARY-INCREMENT GAUSSIAN NOISE

Tommi Sottinen

University of Vaasa, Finland

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# ABSTRACT

We study the Langevin equation with stationary-increment Gaussian noise. We show the strong consistency and the asymptotic normality with Berry–Esseen bound of the so-called alternative estimator (AE) of the mean reversion parameter. The conditions and results are stated in terms of the variance function of the noise. We consider both the case of continuous and discrete observations.

As examples we consider fractional and bifractional Ornstein–Uhlenbeck processes.

We discuss the maximum likelihood and the least squares estimators.

This is joint work with Lauri Viitasaari (Aalto University, Finland).

# OUTLINE

1 LANGEVIN EQUATION

2 ALTERNATIVE ESTIMATOR

3 EXAMPLES

4 DISCUSSION ON OTHER ESTIMATORS

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2 ALTERNATIVE ESTIMATOR

3 EXAMPLES

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# LANGEVIN EQUATION

## GENERAL SETTING

We consider statistical parameter estimation for the unknown parameter  $\theta > 0$  in the (generalized) **LANGEVIN EQUATION**

$$\begin{aligned}dU_t^{\theta,\xi} &= -\theta U_t^{\theta,\xi} dt + dG_t, & t \geq 0, \\U_0^{\theta,\xi} &= \xi.\end{aligned}$$

The solution of the Langevin equation above is

$$U_t^{\theta,\xi} = e^{-\theta t} \xi + \int_0^t e^{-\theta(t-s)} dG_s,$$

which can be seen by using the integration by parts.

**NOTHING WAS ASSUMED HERE, EXCEPT THE FINITENESS OF  $G$ !**

# LANGEVIN EQUATION

## GENERAL SETTING

Our estimation will be based on the solution that starts from zero. We denote  $X^\theta = U^{\theta,0}$ .

For the existence of the **STATIONARY SOLUTION**,  $G$  must have **STATIONARY INCREMENTS**. By extending  $G$  to the negative half-line with an independent copy, the stationary solution is

$$U_t^\theta = \int_{-\infty}^t e^{-\theta(t-s)} dG_s, \quad t \geq 0.$$

In other words, the stationary solution is  $U^\theta = U^{\theta, \xi_{\text{stat}}}$ , with

$$\xi_{\text{stat}} = \int_{-\infty}^0 e^{-\theta t} dG_t.$$

In particular, the stationary solution exists if and only if the integral above converges (almost surely), and in this case

$$X_t^\theta = U_t^\theta - e^{-\theta t} U_0^\theta.$$

# LANGEVIN EQUATION

## GAUSSIAN STATIONARY-INCREMENT SETTING

Assume that the noise  $G$  is **CENTERED GAUSSIAN PROCESS WITH STATIONARY INCREMENTS**. Denote

$$v(t) = \mathbf{E}[G_t^2] \quad \text{and} \quad r_\theta(t) = \mathbf{E}[U_0^\theta U_t^\theta].$$

Then

$$\begin{aligned} r_\theta(t) = & \theta \int_{-\infty}^0 e^{\theta s} g(t, s) \, ds \\ & - \theta^2 e^{-\theta t} \int_{-\infty}^t \int_{-\infty}^0 e^{\theta(s+u)} g(s, u) \, ds du, \end{aligned}$$

where

$$g(t, s) = \frac{1}{2} [v(t) + v(s) - v(t - s)]$$

is the covariance of  $G$ .



# LANGEVIN EQUATION

## ASSUMPTIONS ON THE NOISE

The following assumption ensures the **EXISTENCE** of the AE

### ASSUMPTION (E)

The variance function  $v$  is strictly increasing.

The following assumption ensures the strong **CONSISTENCY** of the AE

### ASSUMPTION (C)

$$\lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T |r_\theta(t)| dt = 0.$$

# LANGEVIN EQUATION

## ASSUMPTIONS ON THE NOISE

Denote

$$w_{\theta}(T) = \frac{2}{T^2} \int_0^T \int_0^T r_{\theta}(t-s)^2 ds dt,$$
$$R_{\theta}(T) = \frac{\int_0^T |r_{\theta}(t)| dt}{T \sqrt{w_{\theta}(T)}}.$$

- $w_{\theta}$  is the asymptotic variance.
- $R_{\theta}$  is the Berry–Esseen bound.

For the asymptotic **NORMALITY** of the AE, we assume

**ASSUMPTION (N)**

$$\lim_{T \rightarrow \infty} R_{\theta}(T) = 0.$$

# OUTLINE

1 LANGEVIN EQUATION

2 ALTERNATIVE ESTIMATOR

3 EXAMPLES

4 DISCUSSION ON OTHER ESTIMATORS

# ALTERNATIVE ESTIMATOR

## CONSTRUCTION OF THE ESTIMATOR

If (E) holds, then  $\theta \mapsto r_\theta(0)$  is invertible, and we can define:

### DEFINITION (ALTERNATIVE ESTIMATOR)

The alternative estimator (AE) is

$$\tilde{\theta}_T = \psi^{-1} \left( \frac{1}{T} \int_0^T (X_t^\theta)^2 dt \right),$$

where

$$\psi(\theta) = r_\theta(0) = \frac{\theta}{2} \int_0^\infty e^{-\theta t} v(t) dt$$

is the variance of the stationary solution.

# ALTERNATIVE ESTIMATOR

## STRONG CONSISTENCY

If, in addition to (E), (C) holds, then  $U^\theta$  is ergodic, and we obtain:

### THEOREM (STRONG CONSISTENCY)

*Suppose (E) and (C) hold. Then  $\tilde{\theta}_T \rightarrow \theta$  almost surely.*

### REMARK

Theorem (Strong Consistency) hold also without Gaussianity, if Assumption (C) is replaced by a suitable assumption ensuring the ergodicity of the stationary solution  $U^\theta$ .

# ALTERNATIVE ESTIMATOR

## ASYMPTOTIC NORMALITY

If (E), (C) and (N) hold, then we can invoke the **FOURTH MOMENT THEOREM**, and we obtain

### THEOREM (ASYMPTOTIC NORMALITY)

*Suppose (E) and (C) hold. Then for all  $K > 0$ ,*

$$\sup_{|x| \leq K} \left| \mathbf{P} \left[ \frac{|\psi'(\theta)|}{\sqrt{w_\theta(T)}} (\tilde{\theta}_T - \theta) \leq x \right] - \Phi(x) \right| \leq C_{\theta, K} R_\theta(T).$$

*In particular, if (N) holds, then*

$$\frac{|\psi'(\theta)|}{\sqrt{w_\theta(T)}} (\tilde{\theta}_T - \theta) \xrightarrow{d} \mathcal{N}(0, 1).$$

# ALTERNATIVE ESTIMATOR

## ASYMPTOTIC NORMALITY

### COROLLARY (CLASSICAL RATE)

*Suppose (E) holds. Assume  $\int_0^\infty r_\theta(t)^2 dt < \infty$ . Then  $\tilde{\theta}_T$  is asymptotically normal with rate  $\sqrt{T}$ .*

### COROLLARY (MIXED MODELS)

*Let  $G^i$ 's be independent, each satisfying (E) and (C), with  $r_{\theta,i} \geq 0$ . Then, for the mixed model*

$$\begin{aligned} & \sup_{x \in [-K, K]} \left| \mathbf{P} \left[ \frac{|\psi'(\theta)|}{\sqrt{w_\theta(T)}} \left( \tilde{\theta}_T - \theta \right) \leq x \right] - \Phi(x) \right| \\ & \leq C_{\theta, K} \max_{i=1, \dots, n} \frac{\int_0^T r_{\theta,i}(t) dt}{\sqrt{\int_0^T \int_0^T r_{\theta,i}(t-s)^2 ds dt}}. \end{aligned}$$

# ALTERNATIVE ESTIMATOR

## DISCRETE OBSERVATIONS

In practice continuous observations are rarely available. Therefore, it is important to consider the case of discrete observations. To control the error introduced by the unobserved time-points, we assume that the driving noise  $G$  is **HÖLDER CONTINUOUS** with some index  $H \in (0, 1)$ . The general idea is, that the smaller the  $H$  the more care must be taken in choosing the time-mesh of the observations. The following assumption is necessary and sufficient for the Hölder continuity.

### ASSUMPTION (H)

Let  $H \in (0, 1)$ . For all  $\varepsilon > 0$  there exists a constant  $C_\varepsilon$  such that

$$v(t) \leq C_\varepsilon t^{2H-\varepsilon}.$$



# ALTERNATIVE ESTIMATOR

## DISCRETE OBSERVATIONS

Let  $t_k = k\Delta_N$ ,  $k = 0, \dots, N$ . Denote  $T_N = N\Delta_N$  and assume that  $\Delta_N \rightarrow 0$  with  $T_N \rightarrow \infty$ . The AE based on the discrete observations is

$$\tilde{\theta}_N = \psi^{-1} \left( \frac{1}{T_N} \sum_{k=1}^N (X_{k\Delta_N}^\theta)^2 \Delta_N \right).$$

### ASSUMPTION (M)

Assume that

$$N\Delta_N^\beta \rightarrow 0,$$

where

$$\beta = \beta(H) = \frac{2H + \frac{1}{2}}{H + \frac{1}{2}} - \delta$$

for some  $\delta > 0$ .

# ALTERNATIVE ESTIMATOR

## DISCRETE OBSERVATIONS

### THEOREM (DISCRETE OBSERVATIONS)

*Suppose (E), (C), (H) and (M) hold. Then,*

$$\tilde{\theta}_N \rightarrow \theta \quad \text{a.s.}$$

*Moreover, if (N) holds, then*

$$\frac{|\psi'(\theta)|}{\sqrt{w_\theta(T_N)}} \left( \tilde{\theta}_N - \theta \right) \xrightarrow{d} \mathcal{N}(0, 1).$$

### REMARK (BOUNDS FOR DISCRETE ASYMPTOTIC NORMALITY)

Berry–Esseen type upper bounds for the asymptotic normality are possible, but complicated.

# OUTLINE

1 LANGEVIN EQUATION

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# EXAMPLES

## FRACTIONAL ORNSTEIN–UHLENBECK PROCESS OF THE FIRST KIND

The **FRACTIONAL BROWNIAN MOTION**  $B^H$  with Hurst index  $H \in (0, 1)$  is the stationary-increment Gaussian process with variance function

$$v_H(t) = t^{2H}.$$

The Hurst index  $H$  is both the index of **SELF-SIMILARITY** and the **HÖLDER CONTINUITY**.

The **FRACTIONAL ORNSTEIN–UHLENBECK PROCESS (OF THE FIRST KIND)** is the stationary solution to the Langevin equation

$$dU_t^{H,\theta} = -\theta U_t^{H,\theta} dt + dB_t^H, \quad t \geq 0.$$

# EXAMPLES

## FRACTIONAL ORNSTEIN–UHLENBECK PROCESS OF THE FIRST KIND

We have

$$\begin{aligned}r_{H,\theta}(t) &\sim \frac{H(2H-1)}{\theta^2} t^{2H-2}, \\ \psi_H(\theta) &= \frac{H\Gamma(2H)}{\theta^{2H}}.\end{aligned}$$

Consequently, (E), (C) and (H) are satisfied for all  $H$ , and (N) is satisfied for  $H \leq 3/4$ .

For  $H < 3/4$ ,

$$\int_0^\infty r_{H,\theta}(t)^2 dt = \theta^{-2H} \sigma_H^2,$$

where we have denoted

$$\sigma_H^2 = \int_0^\infty r_{H,1}(t)^2 dt.$$

# EXAMPLES

## FRACTIONAL ORNSTEIN–UHLENBECK PROCESS OF THE FIRST KIND

### PROPOSITION (FRACTIONAL ORNSTEIN–UHLENBECK PROCESS OF THE FIRST KIND)

**1** Let  $H \in (0, 1/2]$ . Then

$$\sup_{x \in [-K, K]} \left| \mathbf{P} \left[ \sqrt{\frac{T}{\theta \sigma_H^2}} \left( \tilde{\theta}_T^H - \theta \right) \leq x \right] - \Phi(x) \right| \leq \frac{C_{H, \theta, K}}{\sqrt{T}}.$$

**2** Let  $H \in (1/2, 3/4)$ . Then

$$\sup_{x \in [-K, K]} \left| \mathbf{P} \left[ \sqrt{\frac{T}{\theta \sigma_H^2}} \left( \tilde{\theta}_T^H - \theta \right) \leq x \right] - \Phi(x) \right| \leq \frac{C_{H, \theta, K}}{\sqrt{T^{3-4H}}}.$$

**3** Let  $H = 3/4$ . Then

$$\sup_{x \in [-K, K]} \left| \mathbf{P} \left[ \sqrt{\frac{T}{\theta \sigma^2 \log T}} \left( \tilde{\theta}_T^{3/4} - \theta \right) \leq x \right] - \Phi(x) \right| \leq \frac{C_{3/4, \theta, K}}{\sqrt{\log T}}.$$

# EXAMPLES

## FRACTIONAL ORNSTEIN–UHLENBECK PROCESS OF THE SECOND KIND

The **FRACTIONAL ORNSTEIN–UHLENBECK PROCESS OF THE SECOND KIND** is the stationary solution of the Langevin equation with the noise

$$G_t^H = \int_0^t e^{-s} dB_{He^{s/H}}^H.$$

The idea of the construction above is to use the **SELF-SIMILARITY** of the fractional Brownian motion and the associated **LAMPERTI TRANSFORM** (a.k.a. Doob transform).

For Brownian motion the Ornstein–Uhlenbeck processes of the first and second kind are the same. In general they are different.

# EXAMPLES

## FRACTIONAL ORNSTEIN–UHLENBECK PROCESS OF THE SECOND KIND

The autocovariance  $r_{H,\theta}$  of the fractional Ornstein–Uhlenbeck process of the second kind has **EXPONENTIAL DECAY**. Therefore, we have the following:

**PROPOSITION (FRACTIONAL ORNSTEIN–UHLENBECK PROCESS OF THE SECOND KIND)**

$$\sup_{x \in [-K, K]} \left| \mathbf{P} \left[ \frac{\sqrt{T}}{\sigma_{H,\theta}(\theta)} \left( \tilde{\theta}_T^H - \theta \right) \leq x \right] - \Phi(x) \right| \leq \frac{C_{H,\theta,K}}{\sqrt{T}},$$

where

$$\sigma_{H,\theta}^2(\theta) = 4 \int_0^\infty r_{H,\theta}(t)^2 dt.$$



# EXAMPLES

## BIFRACTIONAL ORNSTEIN–UHLENBECK PROCESS OF THE SECOND KIND

The **BIFRACTIONAL BROWNIAN MOTION**  $B^{H,K}$  with parameters  $H \in (0, 1)$  and  $K \in (0, 1]$  is the Gaussian process with covariance

$$\mathbf{E} \left[ B_t^{H,K} B_t^{H,K} \right] = \frac{1}{2^K} \left[ (t^{2H} + s^{2H})^K - |t - s|^{2HK} \right].$$

It does not have stationary increments, except for  $K = 1$ . Consequently, there is no way to define the bifractional Ornstein–Uhlenbeck process of the first kind that would have a stationary version.

The bifractional Brownian motion is  $HK$ -self-similar. Consequently, we can define the **BIFRACTIONAL ORNSTEIN–UHLENBECK PROCESS** by replacing  $B^{HK}$  with  $B^{H,K}$  in the case for fractional Ornstein–Uhlenbeck process of the second kind.

# EXAMPLES

## BIFRACTIONAL ORNSTEIN–UHLENBECK PROCESS OF THE SECOND KIND

The autocovariance  $r_{H,K,\theta}$  of the bifractional Ornstein–Uhlenbeck process of the second kind has exponential decay. Therefore:

PROPOSITION (THE BIFRACTIONAL ORNSTEIN–UHLENBECK PROCESSES OF THE SECOND KIND)

$$\sup_{x \in [-L, L]} \left| \mathbf{P} \left[ \frac{\sqrt{T}}{\sigma_{H,K,\theta}(\theta)} \left( \tilde{\theta}_T^{H,K,\theta} - \theta \right) \leq x \right] - \Phi(x) \right| \leq \frac{C_{H,K,\theta,L}}{\sqrt{T}},$$

where

$$\sigma_{H,K,\theta}^2(\theta) = 4 \int_0^\infty r_{H,K,\theta}(t)^2 dt.$$

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# DISCUSSION ON OTHER ESTIMATORS

## LEAST SQUARES ESTIMATOR (LSE)

On the one hand, the LSE

$$\hat{\theta}_T = - \frac{\int_0^T X_t^\theta \delta X_t^\theta}{\int_0^T (X_t^\theta)^2 dt}$$

arises heuristically by minimizing

$$\int_0^T |\dot{X}_t^\theta + \theta X_t^\theta|^2 dt.$$

On the other hand, one would hope that

$$\int_0^T X_t^\theta \delta X_t^\theta = -\theta \int_0^T (X_t^\theta)^2 dt + \int_0^T X_t^\theta \delta G_t.$$

This would lead to the LSE

$$\hat{\theta}_T = \theta - \frac{\int_0^T X_t^\theta \delta G_t}{\int_0^T (X_t^\theta)^2 dt}.$$

# DISCUSSION ON OTHER ESTIMATORS

## LEAST SQUARES ESTIMATOR (LSE)

Unfortunately, the Skorohod integral is not (bi)linear. In particular, the equation for it in the previous slide does not hold.

Consequently,  $\hat{\theta}_T$  and  $\hat{\theta}_T$  not the same.

$\hat{\theta}_T$  has been shown to be consistent for some fractional Ornstein–Uhlenbeck processes. However, the  $\hat{\theta}_T$  depends on  $\theta$ , the parameter we want to estimate!  $\hat{\theta}_T$  is even worse: it will fail under rather general assumptions:

### PROPOSITION ( $\hat{\theta}_T$ FAILURE)

*Assume that  $U^\theta$  is ergodic. If  $(X_T^\theta)^2/T \rightarrow 0$  in  $L^1(\Omega)$  and almost surely, then*

$$\hat{\theta}_T \rightarrow 0 \quad \text{a.s.}$$

# DISCUSSION ON OTHER ESTIMATORS

## MAXIMUM LIKELIHOOD ESTIMATOR (MLE)

Assume the following (Inverse) Volterra representation: There exists a Gaussian martingale  $M$  with bracket  $\langle M \rangle$  and a kernel  $k \in L^2_{\text{loc}}(\mathbb{R}^2_+, d\langle M \rangle \times d\langle M \rangle)$  such that

$$\begin{aligned}G_t &= \int_0^t k(t, s) dM_s, \\M_t &= \int_0^t k^*(t, s) dG_s.\end{aligned}$$

The authors have very little idea, when such representations exist!

Moreover, assume the existence of

$$\begin{aligned}M_t^\theta &= \int_0^t k^*(t, s) dX_s^\theta, \\ \Xi_t^\theta &= \frac{d}{d\langle M \rangle_t} \int_0^t k^*(t, s) X_s^\theta ds.\end{aligned}$$

# DISCUSSION ON OTHER ESTIMATORS

## MAXIMUM LIKELIHOOD ESTIMATOR (MLE)

### PROPOSITION (MLE)

*Assume that  $\Xi^\theta \in L^2(\Omega \times [0, T], d\mathbf{P} \times d\langle M \rangle)$ . Then the MLE based on the observations  $X_t^\theta$ ,  $t \in [0, T]$ , is*

$$\bar{\theta}_T = -\frac{\int_0^T \Xi_t^\theta dM_t^\theta}{\int_0^T (\Xi_t^\theta)^2 d\langle M \rangle_t}.$$

*Moreover, if  $\int_0^T (\Xi_t^\theta)^2 d\langle M \rangle_t \rightarrow \infty$  almost surely, then the MLE is strongly consistent.*

Thank you for listening!  
Any questions?