

Parameter estimation of Ornstein-Uhlenbeck process generating a stochastic graph

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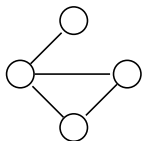
Overview

- 1 Stochastic graphs
- 2 Mixing properties for multidimensional Ornstein-Uhlenbeck processes
- 3 Convergence of statistics of binary observations

Stochastic graphs

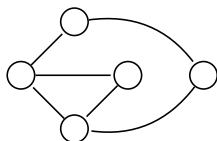
Typical graph evolution (preferential attachment)

Step n



Step $n + 1$

Node/Edge
addition/deletion



Evolution in **continuous time**?

Ornstein-Uhlenbeck processes

Definition: Ornstein-Uhlenbeck process X

Take $A \in \mathcal{M}_{d,d}(\mathbb{R})$ and $\Sigma \in \mathcal{M}_{d,q}(\mathbb{R})$ where $d, q \in \mathbb{N}^+$, $(W_t)_{t \in \mathbb{R}^+}$ a q -dimensional Brownian motion with respect to \mathcal{F} . $X = (X_t : t \geq 0)$ is an Ornstein-Uhlenbeck process when it solves

$$dX_t = -AX_t dt + \Sigma dW_t, \quad X_0 \text{ given.} \quad (1)$$

Standing assumptions

- $\Sigma \Sigma^*$ is invertible
- $a_0 := \min_{\lambda \in \text{Sp}(A)} \text{Re}(\lambda) > 0$
- $X_0 \stackrel{d}{=} \mathcal{N}(0, V_\infty)$, $V_t = \int_0^t e^{-Au} \Sigma \Sigma^* e^{-A^*u} du$

X is **ergodic** and **stationary**.

Graph generation

Definition: Graph observation Y

Take S a measurable subset of \mathbb{R}^d . Define:

$$Y_t^S = \mathbb{1}_{X_t \in S} \quad (2)$$

Take for example $S^{ij} := \{x : x^i \geq 1, x^j \geq 1\}$ and $Y_t^{ij} := Y_t^{S^{ij}}$. Then Y_t is a graph.

A, Σ

Represents underlying relations

Stable

Y_t

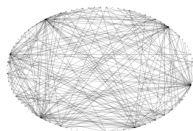
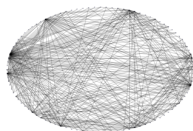
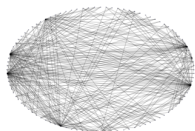
Represents observed relations

Evolves in time

Interbank lending model

The preceding is inspired by a model of interbank lending [CFS15, FI13]:

$$dX_t^i = -\frac{a}{D} \sum_{j=0}^D (X_t^i - X_t^j) dt + \sigma^i dW_t^i$$



How to estimate $(A, \Sigma\Sigma^*)$ from the observation of Y ?

- Use long time limit ($n\Delta_n \rightarrow +\infty$) to apply ergodic properties (estimate V_∞)
- Use high frequency ($\Delta_n \rightarrow 0$) to estimate parameters related to local fluctuations (estimate $\Sigma\Sigma^*$)

Related: estimation from sign changes [Flo87], estimation from thresholded process [IUY09]

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Gebelein inequality

Theorem ([Jan97, Theorem 10.11])

Take H, K two closed subspaces of some Gaussian Hilbert space. Define P_{HK} the restriction to H of the orthogonal projection onto K . Define the maximal correlation coefficient between variables A, B respectively measurable w.r.t. the sigma field generated by H and K :

$$\rho(H, K) = \sup_{A \in L^2(H), B \in L^2(K)} |\text{Cor}(A, B)|.$$

Then we have:

$$\rho(H, K) = \|P_{HK}\|$$

where $\|\cdot\|$ is the operator norm.

In practice, it means that

$$\text{Cov}(f(X), g(Y)) \leq \rho(X, Y) \sqrt{\text{Var}(f(X)) \text{Var}(g(Y))}$$

Gebelein inequality for Ornstein-Uhlenbeck processes

Proposition

Take (X, Y) a Gaussian vector. Assume that $\text{Cov}(X)$, $\text{Cov}(Y)$ are non-degenerate. Then we have

$$\rho(X, Y) = \|\text{Cov}(X)^{-1/2} \text{Cov}(X, Y) \text{Cov}(Y)^{-1/2}\|.$$

For stationary OU processes, we have:

$$\text{Cov}(X_s) = \text{Cov}(X_t) = V_\infty, \quad \text{Cov}(X_t, X_s) = e^{-A(t-s)} V_\infty.$$

Therefore, with $v_M = \max_{\lambda \in \text{Sp}(V_\infty)} \lambda$, $v_m = \min_{\lambda \in \text{Sp}(V_\infty)} \lambda$:

$$\rho(X_s, X_t) = \|V_\infty^{-1/2} e^{-A(t-s)} V_\infty^{1/2}\| \leq \sqrt{\frac{v_M}{v_m}} e^{-a_0|t-s|}.$$

Correlation inequality for Ornstein-Uhlenbeck processes

Theorem (Mixing properties)

There exists a finite constant $C_{(3)}$, depending only on V_∞ , such that for any $t \geq s \geq 0$ and functions φ, ϕ , square-integrable w.r.t. the law of X :

$$\begin{aligned} & |\text{Cov}(\varphi((X_u)_{u \leq s}), \phi((X_v)_{v \geq t}))| \\ & \leq C_{(3)} e^{-a_0|t-s|} \sqrt{\text{Var}(\varphi((X_u)_{u \leq s})) \text{Var}(\phi((X_v)_{v \geq t}))}. \quad (3) \end{aligned}$$

Proof.

$$\begin{aligned} \mathbb{E}[\varphi_s \phi_t] &= \mathbb{E}[\varphi_s \mathbb{E}[\phi_t | X_s]] \\ &= \mathbb{E}[\mathbb{E}[\varphi_s | X_s] \mathbb{E}[\phi_t | X_s]] \\ &= \mathbb{E}[\mathbb{E}[\varphi_s | X_s] \phi_t] \\ &= \mathbb{E}[\mathbb{E}[\varphi_s | X_s] \mathbb{E}[\phi_t | X_t]] \\ &\leq \rho(X_s, X_t) \sqrt{\text{Var}(\mathbb{E}[\varphi_s | X_s]) \text{Var}(\mathbb{E}[\phi_t | X_t])} \\ &\leq \rho(X_s, X_t) \sqrt{\text{Var}(\varphi_s) \text{Var}(\phi_t)}. \end{aligned}$$

Bound on variance of sums of functionals of X

Corollary

Consider a measurable function $g : \mathbb{N} \times \mathbb{N} \times \mathcal{C}^0([0, 1], \mathbb{R}^d) \rightarrow \mathbb{R}$ such that $\mathbb{E} [g(k, n, (X_s)_{k\Delta_n \leq s \leq (k+1)\Delta_n})^2] < +\infty$ for any $k, n \in \mathbb{N}$. For $n \in \mathbb{N}$ define

$$v_n^2 = \sup_{k < n} \text{Var} (g(k, n, (X_s)_{k\Delta_n \leq s \leq (k+1)\Delta_n})),$$
$$\xi_k^{(n)} = \sqrt{\frac{\Delta_n}{n}} g(k, n, (X_s)_{k\Delta_n \leq s \leq (k+1)\Delta_n}).$$

Then, there is a finite constant $C_{(4)}$, dependent only on the parameters A, Σ of the model, such that:

$$\text{Var} \left(\sum_{k=0}^{n-1} \xi_k^{(n)} \right) \leq C_{(4)} v_n^2. \quad (4)$$

Bound on variance of sums of functionals of X

Proof.

Denote $g_k = g(k, n, (X_s)_{s \in I(k)})$ where $I_n(k) = [k\Delta_n, (k+1)\Delta_n]$.

$$\begin{aligned}\text{Var} \left(\sum_{k=0}^{n-1} \xi_k^{(n)} \right) &= \frac{\Delta_n}{n} \sum_{k=0}^{n-1} \text{Var}(g_k) + \frac{2\Delta_n}{n} \sum_{k=0}^{n-1} \sum_{l=k+1}^{n-1} \text{Cov}(g_k, g_l) \\ &\leq \frac{\Delta_n}{n} n v_n^2 + \frac{2\Delta_n}{n} n \sum_{m \geq 0} C_{(3)} v_n^2 e^{-a_0 m \Delta_n} \\ &\leq v_n^2 \left(\Delta_n + 2C_{(3)} \frac{\Delta_n}{1 - e^{-a_0 \Delta_n}} \right) \\ &\leq C_{(4)} v_n^2\end{aligned}$$

Where we use that for $l > k$, $u \in I_n(k)$, $v \in I_n(l)$, we have $u \leq (k+1)\Delta_n \leq l\Delta_n \leq v$, and apply Theorem 2:

$$\text{Cov}(g_k, g_l) \leq C_{(3)} e^{-a_0 |k+1-l|\Delta_n} \sqrt{\text{Var}(g_k) \text{Var}(g_l)}. \quad (5)$$

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Occupation time convergence

Definition

The occupation time statistic is defined as:

$$\text{OT}_n^S = \frac{1}{n} \sum_{k=0}^{n-1} Y_{k\Delta_n}^S = \frac{1}{n} \sum_{k=0}^{n-1} \mathbb{1}_{X_{k\Delta_n} \in S}. \quad (6)$$

$$\text{OT}_n^S = \sum_{k=0}^{n-1} \sqrt{\frac{\Delta_n}{n}} \frac{\mathbb{1}_{X_{k\Delta_n} \in S}}{\sqrt{n\Delta_n}}$$
$$\text{Var} \left(\frac{\mathbb{1}_{X_{k\Delta_n} \in S}}{\sqrt{n\Delta_n}} \right) \propto \frac{1}{n\Delta_n}$$

Using Corollary 1, we have $\text{Var} \left(\text{OT}_n^S \right) = O \left(n^{-1} \Delta_n^{-1} \right)$ and convergence in L^2 under the assumption $n\Delta_n \rightarrow +\infty$.

Crossing number convergence

Definition

We define the crossings statistic by:

$$C_n^S = \frac{1}{n\sqrt{\Delta_n}} \sum_{k=0}^{n-1} \mathbb{1}_{Y_{k\Delta_n}^S \neq Y_{(k+1)\Delta_n}^S}. \quad (7)$$

We choose here $S = \{x^1 \geq 1\}$ and consider only crossings from 0 to 1. Write $Z_k^{(n)} = \mathbb{1}_{X_{k\Delta_n}^1 < 1} \mathbb{1}_{X_{(k+1)\Delta_n}^1 \geq 1}$.

$$\frac{1}{n\sqrt{\Delta_n}} \sum_{k=0}^{n-1} Z_k^{(n)} = \sum_{k=0}^{n-1} \sqrt{\frac{\Delta_n}{n}} \frac{Z_k^{(n)}}{\sqrt{n\Delta_n}}, \quad \text{and } \mathbb{E} [Z_k^{(n)}] \sim \text{Var} (Z_k^{(n)}) \sim \sqrt{\Delta_n}$$

$$\text{Var} \left(\frac{Z_k^{(n)}}{\sqrt{n\Delta_n}} \right) = O \left(\frac{1}{n\Delta_n^{3/2}} \right)$$

Expectations and CLT

We have $\mathbb{E} [\text{OT}_n^S] = \nu_\infty(S)$. Assuming $n\Delta_n \rightarrow +\infty$,

$$\text{OT}_n^S \xrightarrow{L^2} \nu_\infty(S)$$

We also have:

Theorem

$$\sqrt{n\Delta_n} \left(\text{OT}_n^{[1, +\infty[} - \nu_\infty([1, +\infty[) \right) \xrightarrow{d} \mathcal{N} \left(0, \nu_\infty(\sigma^2 F'^2) \right) \quad (8)$$

as $n \rightarrow +\infty$, where F solves $LF + (\mathbb{1}_{x \geq 1} - \nu_\infty([1, +\infty[)) = 0$ with L the infinitesimal generator of the OU.

We have $\mathbb{E} [Z_k^{(n)}] \sim \sqrt{\Delta_n} \sqrt{\frac{(\Sigma \Sigma^*)^{11}}{2\pi}} \mu_{V_\infty^{11}}(1)$. Assuming $n\Delta_n^{3/2} \rightarrow +\infty$,

$$C_n \xrightarrow{L^2} 2 \sqrt{\frac{(\Sigma \Sigma^*)^{11}}{2\pi}} \mu_{V_\infty^{11}}(1)$$

How to estimate $(A, \Sigma\Sigma^*)$ from the observation of Y ?

Assume we observe Y^{ij} for $S^{ij} = \{x^i \geq 1, x^j \geq 1\}$.

Assume $A = \text{diag}(a_1, \dots, a_d)$. Then

$$V_{\infty}^{ij} = \frac{(\Sigma\Sigma^*)^{ij}}{a_i + a_j}.$$

- Using $\mathcal{C}_n^{S^{ii}}$, we can estimate $(\Sigma\Sigma^*)^{ii}$
- Using $\text{OT}_n^{S^{ii}}$, we can estimate V_{∞}^{ii} , and we get a_i
- Using $\text{OT}_n^{S^{ij}}$, we can estimate V_{∞}^{ij} , and we get $(\Sigma\Sigma^*)^{ij}$

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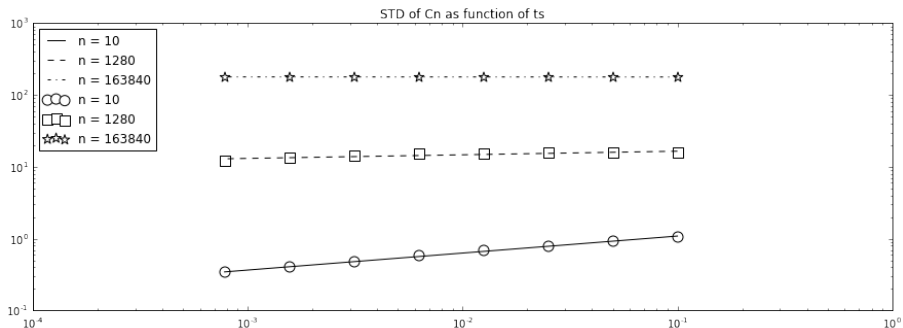
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Optimality of C_n convergence speed?



$$\sqrt{\text{Var} \left(\sum_k Z_k^{(n)} \right)} \propto \Delta_n^0$$

Proof of CLT for OT_n

$$OT_t^c = \frac{1}{t} \int_0^t \mathbb{1}_{X_s \geq 1} ds$$

$$\int_0^t \hat{f}(X_s) ds = t (OT_t^c - \nu_\infty([1, +\infty[)) \quad \hat{f}(x) = f(x) - \nu_\infty([1, +\infty[)$$

$$L = -ax \frac{\partial}{\partial x} + \frac{\sigma^2}{2} \frac{\partial^2}{\partial x^2} \quad LF = -\hat{f}$$

$$M_t = F(X_t) - F(X_0) + \int_0^t \hat{f}(X_s) ds = \int_0^t \sigma F'(X_s) dW_s$$

$$\frac{M_t}{\sqrt{t}} = \frac{F(X_t) - F(X_0) + (OT_t^c - \nu_\infty([1, +\infty[)) t}{\sqrt{t}} \xrightarrow{d} \mathcal{N}(0, \nu_\infty(\sigma^2 F'^2))$$

Proof of CLT for OT_n

$$\frac{\text{OT}_t^c}{\sqrt{t}} \xrightarrow{d} \mathcal{N}(0, \nu_\infty(\sigma^2 F'^2))$$

$$\begin{aligned} D_n &:= \sqrt{n\Delta_n} \left(\text{OT}_n^{[1, +\infty[} - \text{OT}_{n\Delta_n}^c \right) \\ &= \sqrt{\frac{\Delta_n}{n}} \sum_{k=0}^{n-1} \int_0^{\Delta_n} \frac{f(X_{k\Delta_n}) - f(X_{k\Delta_n+u})}{\Delta_n} du \end{aligned}$$

$$\sqrt{n\Delta_n} \left(\text{OT}_n^{[1, +\infty[} - \nu_\infty([1, +\infty[) \right) \xrightarrow{d} \mathcal{N}(0, \nu_\infty(\sigma^2 F'^2))$$