

Numerical Exploration of Dynamic Behavior of the Ornstein-Uhlenbeck Process via Ehrenfest Process Approximation

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1 Ornstein-Uhlenbeck Process

The Ornstein-Uhlenbeck (O-U) process is of practical importance in many application areas such as statistics, meteorology and financial engineering. The O-U process $\{X_{OU}(t) : t \geq 0\}$ is a Markov diffusion process on the real continuum $-\infty < x < \infty$. Its probability density function $f(x, t) = \frac{d}{dx} P[X_{OU}(t) \leq x]$ is governed by the forward diffusion equation

$$\frac{\partial}{\partial t} f(x, t) = \frac{\partial^2}{\partial x^2} f(x, t) + \frac{\partial}{\partial x} [x f(x, t)]. \quad (1.1)$$

The O-U process is characterized by its Markov property, normal distribution, and exponential covariance function. A basic function describing this process is the conditional transition density $g(x_0, x, \tau) = \frac{d}{dx} P[X(t + \tau) \leq x | X(t) = x_0]$ given by

$$g(x_0, x, \tau) = \frac{1}{\sqrt{2\pi\sqrt{1-e^{-2\tau}}}} \exp\left\{-\frac{(x-x_0 e^{-\tau})^2}{2(1-e^{-2\tau})}\right\}, \quad (1.2)$$

with $-\infty < x < \infty$.

While transition probabilities of the O-U process are readily accessible, quantifying its dynamic behavior is numerically cumbersome.

2 Convergence of the Ehrenfest Process to the O-U Process

We consider $2V$ independent and identical Markov chains $\{J_j(t) : t \geq 0\}$, $j = 1, \dots, 2V$, in continuous time on $\{0, 1\}$ governed by transition rates $\nu_{01} = \nu_{10} = \frac{1}{2}$. Let $\{N_{2V}(t) : t \geq 0\}$ be defined by

$$N_{2V}(t) \stackrel{\text{def}}{=} \sum_{j=1}^{2V} J_j(t). \quad (2.1)$$

Then $\{N_{2V}(t) : t \geq 0\}$ is a birth-death process on $\mathcal{N} = \{0, 1, \dots, 2V\}$ governed by the upward transition rates $\lambda_n = \frac{1}{2}(2V - n)$ and the downward transition rates $\mu_n = \frac{n}{2}$, $n \in \mathcal{N}$. We note that $\nu_n \stackrel{\text{def}}{=} \lambda_n + \mu_n = V$, $n \in \mathcal{N}$, which is independent of state n . This birth-death

process is called the Ehrenfest process.

Let $\{X_V(t) : t \geq 0\}$ be a stochastic process defined by

$$X_V(t) \stackrel{\text{def}}{=} \sqrt{\frac{2}{V}} N_{2V}(t) - \sqrt{2V}. \quad (2.2)$$

We note that $\{X_V(t) : t \geq 0\}$ has a discrete support on $\{r(0), \dots, r(2V)\}$ where

$$r(n) = \sqrt{\frac{2}{V}} n - \sqrt{2V}, \quad n = 0, 1, \dots \quad (2.3)$$

Clearly $r(n+1) - r(n) = \sqrt{\frac{2}{V}} \rightarrow 0$ as $V \rightarrow \infty$. When $N_{2V}(0)$ is chosen appropriately, $\{X_V(t) : t \geq 0\}$ converges in law to $\{X_{OU}(t) : t \geq 0\}$ as $V \rightarrow \infty$.

It can be shown that the first passage time and the historical maximum of $\{X_V(t) : t \geq 0\}$ also converges in law to those of $\{X_{OU}(t) : t \geq 0\}$ as $V \rightarrow \infty$. Hence the dynamic behavior of $\{X_{OU}(t) : t \geq 0\}$ can be approximated by that of $\{X_V(t) : t \geq 0\}$.

3 First Passage Time Structure of the Ehrenfest Process

Let T_{mn} ($m < n$) be the first passage time of a general birth-death process with probability density function $s_{mn}(\tau)$ and its Laplace transform $\sigma_{mn}(s)$. For notational convenience, we denote $T_{m, m+1}$ by T_m^+ , and $s_m^+(\tau)$ and $\sigma_m^+(s)$ are defined similarly. From the consistency relations, one has

$$\sigma_n^+(s) = \frac{\nu_n}{s + \nu_n} \left[\frac{\lambda_n}{\nu_n} + \frac{\mu_n}{\nu_n} \sigma_{n-1}^+(s) \sigma_n^+(s) \right], \quad n \geq 1, \quad (3.1)$$

where $\nu_n = \lambda_n + \mu_n$.

Let $g_n(s)$ be a polynomial of order n defined by $\sigma_{0n}(s) = \frac{1}{g_n(s)}$, $n \geq 1$, $g_0(s) = 1$. From $\sigma_{0n}(s) = \sigma_{0n-1}(s) \sigma_{n-1}^+(s)$, $n \geq 0$, one then sees

$$g_{n+1}(s) = \frac{1}{\lambda_n} [(s + \nu_n) g_n(s) - \mu_n g_{n-1}(s)], \quad n \geq 0, \quad (3.2)$$

where $g_{-1}(s) = 0$ and $g_0(s) = 1$. It should be noted that

$$\sigma_n^+(s) = \frac{g_n(s)}{g_{n+1}(s)}, \quad n \geq 0. \quad (3.3)$$

As shown in Keilson [1], $\{g_n(s)\}$ are orthogonal polynomials. Consequently, from (3.3), $\sigma_n^+(s)$ can be written as

$$\sigma_n^+(s) = \sum_{j=0}^n r_{n+1,j} \frac{\alpha_{n+1,j}}{s + \alpha_{n+1,j}}, \quad (3.4)$$

where $-\alpha_{n+1,j}$ are the zeros of $g_{n+1}(s)$, $r_{n+1,j} = \lim_{s \rightarrow -\alpha_{n+1,j}} \frac{s + \alpha_{n+1,j}}{\alpha_{n+1,j}} \frac{g_n(s)}{g_{n+1}(s)} \geq 0$ and $\sum_{j=0}^n r_{n+1,j} = \sigma_n^+(0+) = 1$.

In case of the Ehrenfest process, this becomes

$$g_{n+1}(s) = \frac{2}{2V - n} \left[(s + V)g_n(s) - \frac{n}{2}g_{n-1}(s) \right], \quad (3.5)$$

with $g_{-1}(s) = 0$ and $g_0(s) = 1$.

4 Dynamic Behavior and its Numerical Algorithm

In order to evaluate the first passage times $s_{mn}(\tau)$ ($m < n$) with corresponding Laplace transforms $\sigma_{mn}(s) = \sigma_m^+(s) \cdots \sigma_{n-1}^+(s) = g_m(s)/g_n(s)$, the zeros of $g_n(s)$ are needed. These zeros in turn enables one to quantify the historical maximum. In principle, the zero search of $g_n(s)$ can be accomplished via a straightforward bisection approach since the zeros of $g_n(s)$ and $g_{n+1}(s)$ interleave because of the underlying orthogonality. Let $h_n(s) = g_n(s - V)$, $n \geq 0$, then the recursive formula can be rewritten as

$$h_{n+1}(s) = \frac{2}{2V - n} \left[s h_n(s) - \frac{n}{2} h_{n-1}(s) \right], \quad n \geq 0, \quad (4.1)$$

Clearly the zeros of $h_n(s)$ are symmetric about 0 while the zeros of $g_n(x)$ are symmetric about $-V$. Consequently the computational time of the zero search can be reduced approximately by a factor of 4. More specifically, one can write

$$\begin{cases} h_{2m}(s) = \sum_{j=0}^m w_{2m,2j} s^{2j}, & m \geq 0, \\ h_{2m+1}(s) = \sum_{j=0}^m w_{2m+1,2j+1} s^{2j+1}, & m \geq 0. \end{cases}$$

Since $h_{2m}(s)$ is an even function and $h_{2m+1}(s)$ is an odd function, it then follows from the recursive formula

for $m \geq 0$, that

$$\begin{cases} w_{2m,0} = -\frac{2}{2(V-m)+1} \left(m - \frac{1}{2}\right) w_{2m-2,0}, \\ w_{2m,2j} = \frac{2}{2(V-m)+1} \left\{ w_{2m-1,2j-1} - \left(m - \frac{1}{2}\right) w_{2m-2,2j} \right\}, & j = 1, \dots, m-1, \\ w_{2m,2m} = \frac{2}{2(V-m)+1} w_{2m-1,2m-1}, \end{cases}$$

and

$$\begin{cases} w_{2m+1,2j+1} = \frac{w_{2m,2j} - m w_{2m-1,2j+1}}{V-m}, & j = 0, \dots, m-1, \\ w_{2m+1,2m+1} = \frac{w_{2m,2m}}{V-m}, \end{cases}$$

where $h_0(s) = w_{0,0} = 1$.

For both $h_{2m}(s)$ and $h_{2m+1}(s)$, it suffices to search m zeros in $(0, \infty)$. For $h_n(s)$ with $1 \leq n \leq 4$, the zeros can be obtained explicitly by solving the underlying equations. For higher values of n , a straightforward bisection method can be employed by exploiting the fact that zeros of $h_{n+1}(s)$ interleave those of $h_n(s)$.

Let ξ_{nj} ($0 \leq j \leq n-1$) be zeros of $h_n(s)$ and $-\alpha_{nj}$ ($0 \leq j \leq n-1$) be zeros of $g_n(s)$, one then has $\alpha_{nj} = V - \xi_{nj}$, $0 \leq j \leq n-1$.

From $\sigma_{mn}(s) = \sigma_m^+(s) \cdots \sigma_{n-1}^+(s)$, one has that

$$\sigma_{mn}(s) = \frac{g_m(s)}{g_n(s)} = c_{mn} \frac{\prod_{j=0}^{m-1} (s + \alpha_{mj})}{\prod_{j=0}^{n-1} (s + \alpha_{nj})}; \quad c_{mn} = \frac{\prod_{j=0}^{n-1} \alpha_{mj}}{\prod_{j=0}^{m-1} \alpha_{nj}}. \quad (4.2)$$

Since $\sigma_{mn}(s)$ is regular apart from singular points $-\alpha_{nj}$, $0 \leq j \leq n-1$, this can be rewritten as

$$\sigma_{mn}(s) = \sum_{j=0}^{n-1} A_{mn;j} \frac{\alpha_{nj}}{s + \alpha_{nj}}; \quad A_{mn;k} = \frac{\prod_{j=0}^{m-1} \left(1 - \frac{\alpha_{nk}}{\alpha_{mj}}\right)}{\prod_{j=0, j \neq k}^{n-1} \left(1 - \frac{\alpha_{nk}}{\alpha_{nj}}\right)}. \quad (4.3)$$

In real domain, this leads to the probability function $s_{mn}(\tau)$ and its corresponding survival function $\bar{S}_{mn}(\tau) = \int_{\tau}^{\infty} s_{mn}(y) dy$ given as

$$s_{mn}(\tau) = \sum_{j=0}^{n-1} A_{mn;j} \cdot \alpha_{nj} e^{-\alpha_{nj}\tau}; \quad (4.4)$$

$$\bar{S}_{mn}(\tau) = \sum_{j=0}^{n-1} A_{mn;j} e^{-\alpha_{nj}\tau}. \quad (4.5)$$

References

- [1] Keilson, J. (1979), *Markov chain models: rarity and exponentiality*, (Applied Mathematical Science Series, 28), Springer, New York.