

Numerical Simulation of Stochastic Differential Equations: Lecture 2, Part 2

Des Higham
Department of Mathematics
University of Strathclyde



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Lecture 2, Part 2: Mean Exit Times

- Statement of Problem
- Differential Equation Formulation
- SDE/Monte Carlo Algorithm
- Convergence Property

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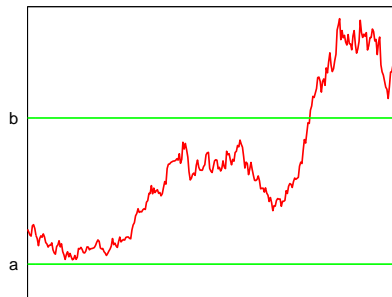
$$d\mathbf{X}(t) = f(\mathbf{X}(t))dt + g(\mathbf{X}(t))d\mathbf{W}(t), \quad \mathbf{X}(0) = \mathbf{X}_0$$

Suppose \mathbf{X}_0 is a constant in (a, b)

Define the random variable \mathbf{T}_{exit} to be

$$\mathbf{T}_{\text{exit}} := \inf\{t : \mathbf{X}(t) = a \text{ or } \mathbf{X}(t) = b\}$$

In words: \mathbf{T}_{exit} is first time solution leaves (a, b)



Problem: find the **mean exit time** $T_{\text{exit}}^{\text{mean}} := \mathbb{E}[\mathbf{T}_{\text{exit}}]$

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Monte Carlo for Mean Exit Time

Choose a stepsize, Δt

Choose a number of paths, M

for $s = 1$ to M

Set $t_n = 0$ and $X_n = X_0$

While $X_n > a$ and $X_n < b$

Compute a $N(0, 1)$ sample ξ_n

Replace X_n by $X_n + \Delta t f(X_n) + \sqrt{\Delta t} \xi_n g(X_n)$

Replace t_n by $t_n + \Delta t$

end

set $T_{\text{exit}}^s = t_n - \frac{1}{2}\Delta t$

end

set $a_M = \frac{1}{M} \sum_{s=1}^M T_{\text{exit}}^s$

set $b_M^2 = \frac{1}{M-1} \sum_{s=1}^M (T_{\text{exit}}^s - a_M)^2$

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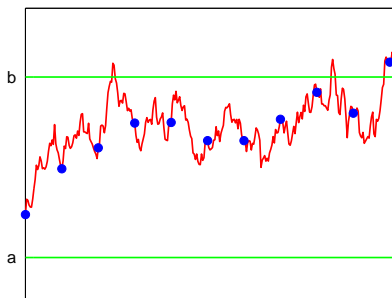
Errors

Two sources of error

- **Sampling error:** sample mean \approx expected value
- **Numerical SDE error:** EM \approx SDE paths

Third source of error

- **Discrete time:** $\{t_i\}$ is monitored, not continuous time



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Analysis

Let $X_0 = x$. Then $T_{\text{exit}}^{\text{mean}} = u(x)$, where

$$\frac{1}{2}g(x)^2 \frac{d^2u}{dx^2} + f(x) \frac{du}{dx} = -1, \quad \text{for } a < x < b$$

with b.c.'s $u(a) = u(b) = 0$

We can solve (analytically or numerically) to get “exact” solution. Then investigate accuracy of SDE/Monte Carlo.

SDE/Monte Carlo approach is attractive for

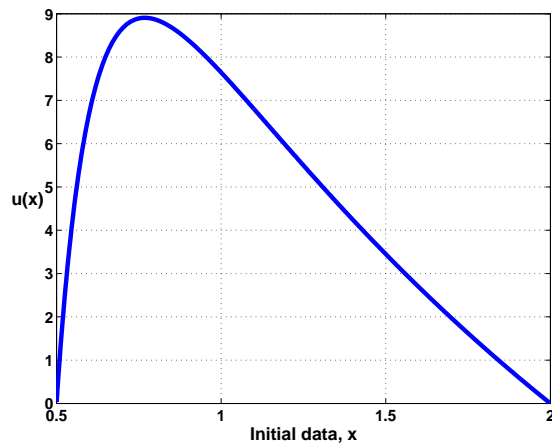
- **high-dimensional** problems, e.g. $\mathbf{X} \in \mathbb{R}^{32}$
- **complicated geometries**,
- computing $u(x)$ at a **single point**

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$$f(x) = \mu x \text{ and } g(x) = \sigma x$$

$$u(x) = \frac{1}{\frac{1}{2}\sigma^2 - \mu} \left(\log(x/a) - \frac{1 - (x/a)^{1-2\mu/\sigma^2}}{1 - (b/a)^{1-2\mu/\sigma^2}} \log(b/a) \right)$$

E.g. $\mu = 0.1$, $\sigma = 0.2$, $a = 0.5$ and $b = 2$:



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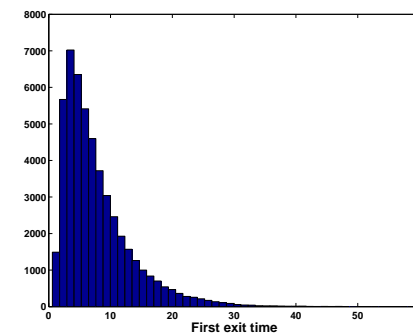
$$f(x) = \mu x \text{ and } g(x) = \sigma x$$

$$\text{Replace } X_n \text{ by } X_n + \Delta t \mu X_n + \sqrt{\Delta t} \xi_n \sigma X_n$$

can be improved:

$$\text{Replace } X_n \text{ by } X_n \exp \left((\mu - \frac{1}{2}\sigma^2) \Delta t + \sqrt{\Delta t} \xi_n \sigma \right)$$

E.g. $\mu = 0.1$, $\sigma = 0.2$, $a = 0.5$, $b = 2$ and $X_0 = 1$
with $M = 5 \times 10^4$ and $\Delta t = 10^{-2}$:



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Accuracy? $T_{\text{exit}}^{\text{mean}} = 7.6450$

With $M = 5 \times 10^4$ and $\Delta t = 10^{-2}$ we get

$a_M = 7.8056$ with a 95% conf. int. of [7.7561, 7.8552]

- exact answer **well outside** conf. int.
- Monte Carlo method **overestimates** mean exit time

Explanation: error from checking paths only at discrete time points $\{t_i\}$ is dominating the statistical sampling error

\Rightarrow decrease Δt rather than increase M

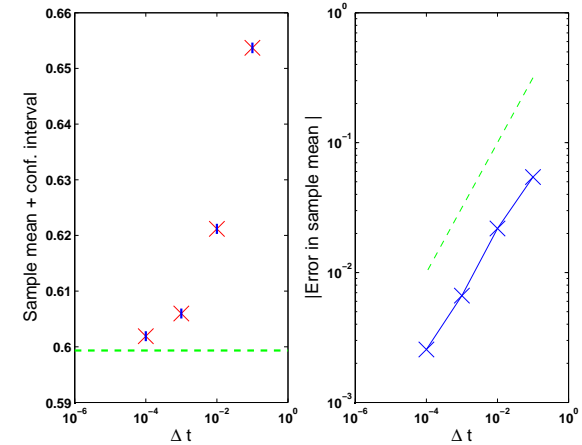
$\Delta t = 10^{-3}$: $a_M = 7.7137$ conf. int. [7.6641, 7.7634]

$\Delta t = 10^{-4}$: $a_M = 7.6688$ conf. int. [7.6200, 7.7177]

Convergence rate ...

$M = 5 \times 10^5$ and try $\Delta t = 10^{-1}, 10^{-2}, 10^{-3}, 10^{-4}$

$\mu = 0.5, \sigma = 0.2, a = 0.5, b = 2, X_0 = 1.5$:



Least-squares fit: **power = 0.45**, (resid = 0.12)

Convergence Rate

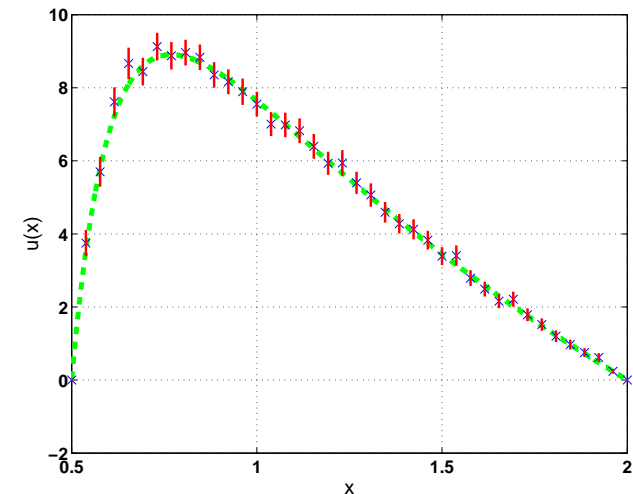
The rate $O(\Delta t^{\frac{1}{2}})$ has been widely reported

Overall error is then $O(\Delta t^{\frac{1}{2}} + 1/\sqrt{M})$

\Rightarrow take $M \propto \Delta t^{-1}$

$M = 10^4, \Delta t = 10^{-4}, 40 X_0$ values

$\mu = 0.1, \sigma = 0.2, a = 0.5, b = 2$:

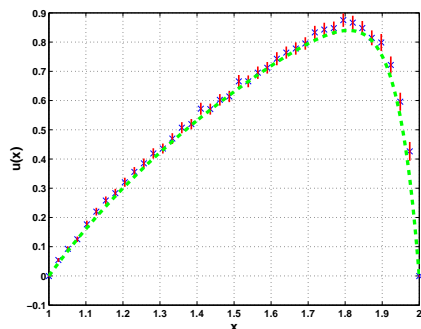


$$f(x) = \lambda(\mu - x) \text{ and } g(x) = \sigma\sqrt{x}$$

Safe EM step is

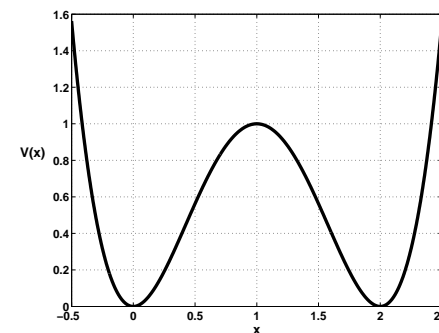
$$\text{Replace } X_n \text{ by } X_n + \Delta t\lambda(\mu - X_n) + \sqrt{\Delta t}\xi_n\sigma\sqrt{|X_n|}$$

Take $\lambda = 1$, $\mu = 0.5$, $\sigma = 0.3$, $a = 1$ and $b = 2$,
 $M = 10^3$ and $\Delta t = 10^{-3}$:



“Exact” solution from `bvp4c.m`

$$\text{Double-Well Potential: } V(x) = x^2(x - 2)^2$$

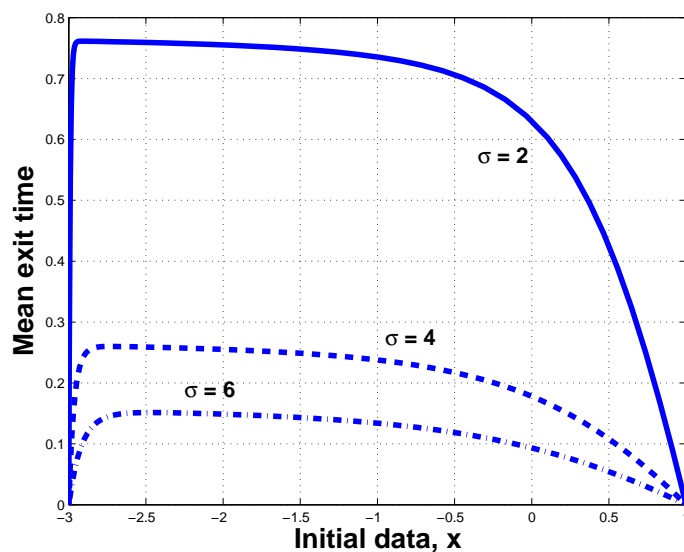


$$d\mathbf{X}(t) = -V'(\mathbf{X}(t))dt + \sigma d\mathbf{W}(t)$$

Take $a = -3$ and $b = 1$

Measuring expected time to **climb over the central hump**

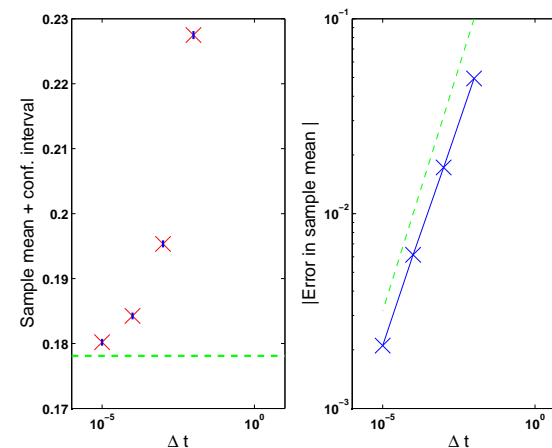
$$\frac{1}{2}\sigma^2 \frac{d^2u}{dx^2} - V'(x) \frac{du}{dx} = -1$$



Convergence

Fix $X_0 = 0$ and $\sigma = 4$

$M = 5 \times 10^5$ and $\Delta t = 10^{-2}, 10^{-3}, 10^{-4}, 10^{-5}$:



Least-squares fit: **power = 0.46**, (resid = 0.017)

Monte Carlo/SDE for Mean Exit Time

Research problems:

- Develop a provably $O(\Delta t)$ algorithm. Ideas:
 - **Adaptively reduce** Δt near boundary.
 - After each step, **calculate probability that exit was missed**. Then draw from a uniform $(0, 1)$ random number generator in order to decide whether to record an exit.
 - Use **random** Δt_n from a suitable exponential distribution.
- Develop an efficient method for high-dimension/complicated region