

# MLMC for reflected diffusions

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# Outline

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- 1D particles with mass
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  - ▶ expanded domain
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- 1D massless particles
  - ▶ new treatment
  - ▶ results
- multi-dimensional generalisations

# Multilevel Monte Carlo

MLMC is based on the telescoping sum

$$\mathbb{E}[\widehat{P}_L] = \mathbb{E}[\widehat{P}_0] + \sum_{\ell=1}^L \mathbb{E}[\widehat{P}_\ell - \widehat{P}_{\ell-1}]$$

where  $\widehat{P}_\ell$  represents an approximation using on level  $\ell$ .

In SDE applications with uniform timestep  $h_\ell = 2^{-\ell} h_0$ , if the weak convergence is

$$\mathbb{E}[\widehat{P}_\ell - P] = O(2^{-\alpha\ell}),$$

$\widehat{Y}_\ell$  is an unbiased estimator for  $\mathbb{E}[\widehat{P}_\ell - \widehat{P}_{\ell-1}]$ , based on  $N_\ell$  samples, with variance

$$\mathbb{V}[\widehat{Y}_\ell] = O(N_\ell^{-1} 2^{-\beta\ell}),$$

and expected cost

$$\mathbb{E}[C_\ell] = O(N_\ell 2^{\gamma\ell}), \quad \dots$$

# Multilevel Monte Carlo

... then the finest level  $L$  and the number of samples  $N_\ell$  on each level can be chosen to achieve an RMS error of  $\varepsilon$  at an expected cost

$$C = \begin{cases} O(\varepsilon^{-2}), & \beta > \gamma, \\ O(\varepsilon^{-2}(\log \varepsilon)^2), & \beta = \gamma, \\ O(\varepsilon^{-2-(\gamma-\beta)/\alpha}), & 0 < \beta < \gamma. \end{cases}$$

# Multilevel Monte Carlo

The standard estimator for SDE applications is

$$\hat{Y}_\ell = N_\ell^{-1} \sum_{n=0}^{N_\ell} \left( \hat{P}_\ell(W^{(n)}) - \hat{P}_{\ell-1}(W^{(n)}) \right)$$

using the same Brownian motion  $W^{(n)}$  for the  $n^{\text{th}}$  sample on the fine and coarse levels.

However, there is some freedom in how we construct the coupling provided  $\hat{Y}_\ell$  is an unbiased estimator for  $\mathbb{E}[\hat{P}_\ell - \hat{P}_{\ell-1}]$ .

Also, uniform timestepping is not required – it is fairly straightforward to implement MLMC using non-nested adaptive timestepping.

(G, Lester, Whittle: MCQMC14 proceedings)

# 1D particles with mass

Position  $x_t$ , and velocity  $u_t$  subject to steady and stochastic forcing:

$$du_t = a(x_t, u_t, t) dt + b(x_t, t) dw_t$$

$$dx_t = u_t dt$$

Domain  $x \geq 0$ , with reflection so that when it hits  $x=0$  at time  $\tau$  then the velocity is reflected, so

$$u_{\tau+} = -u_{\tau-}.$$

# 1D particles with mass

Euler-Maruyama treatment with uniform timestep  $h$ :

$$\begin{aligned}\hat{u}_{n+1} &= s_n (\hat{u}_n + a(\hat{x}_n, \hat{u}_n, t) h + b(\hat{x}_n, t_n) \Delta w_n) \\ \hat{x}_{n+1} &= s_n (\hat{x}_n + \hat{u}_n h)\end{aligned}$$

with  $s_n = \pm 1$  chosen so that  $\hat{x}_{n+1} \geq 0$ .

Problem: only  $O(h^{1/2})$  strong convergence

Reason: doesn't account for reflection occurring part-way through a timestep.

# 1D particles with mass

Key idea: if  $A(X, U, t)$ ,  $B(X, t)$  are sufficiently smooth, get  $O(h)$  convergence using an extended domain:

$$\begin{aligned}dU_t &= A(X_t, U_t, t) dt + B(X_t, t) dW_t \\dX_t &= U_t dt,\end{aligned}$$

with

$$\begin{aligned}A(X, U, t) &= \begin{cases} a(X, U, t), & X \geq 0 \\ -a(-X, -U, t), & X < 0 \end{cases} \\B(X, t) &= \begin{cases} b(X, t), & X \geq 0 \\ b(-X, t), & X < 0 \end{cases}\end{aligned}$$

and then take  $x = |X|$  as output.



# 1D particles with mass

Why does that give  $O(h)$  strong convergence, but the original doesn't?

If we define

$$\begin{pmatrix} u_t \\ x_t \end{pmatrix} = S(X_t) \begin{pmatrix} U_t \\ X_t \end{pmatrix},$$

where  $S(X) \equiv \text{sign}(X)$ , then  $u_t, x_t$  satisfy

$$\begin{aligned} du_t &= a(x_t, u_t, t) dt + b(x_t, t) S(X_t) dW_t \\ dx_t &= u_t dt, \end{aligned}$$

By setting  $dw_t = S(X_t) dW_t$ , we see that this is equivalent in distribution to the original model problem.

Note: strong convergence is now at fixed  $W_t$  – not the same as fixed  $w_t$ .

# 1D particles with mass

New MLMC treatment:

$$\begin{aligned}\hat{u}_{n+1}^p &= \hat{u}_n + a(\hat{x}_n, \hat{u}_n, t_n) h + b(\hat{x}_n, t_n) \hat{s}_n \Delta W_n \\ \hat{x}_{n+1}^p &= \hat{x}_n + \hat{u}_n h\end{aligned}$$

followed by a correction/reflection step:

$$\begin{aligned}\hat{u}_{n+1} &= \text{sign}(\hat{x}_{n+1}^p) \hat{u}_{n+1}^p \\ \hat{x}_{n+1} &= \text{sign}(\hat{x}_{n+1}^p) \hat{x}_{n+1}^p \\ \hat{s}_{n+1} &= \text{sign}(\hat{x}_{n+1}^p) \hat{s}_n\end{aligned}$$

with same Brownian path for coarse and fine levels.

Can show that when  $a$  and  $b$  are both constant, the coarse and fine paths are identical at coarse timesteps.

# 1D particles with mass

Test case 1:

$$x_0 = 0.2, \quad u_0 = -0.2, \quad a(x, t) = 0, \quad b(x, t) = 0.5.$$

in domain  $0 \leq x \leq 1$ , with reflection at both boundaries.

Output of interest:  $\int_0^1 x_t \, dt$  approximated by  $\sum_{n=1}^{2^\ell} h_\ell \hat{x}_n$ .

Test case 2: changes drift, volatility to

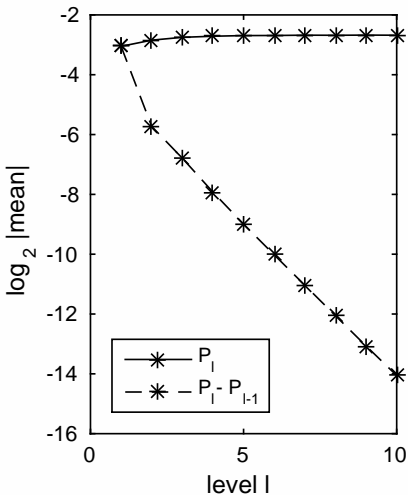
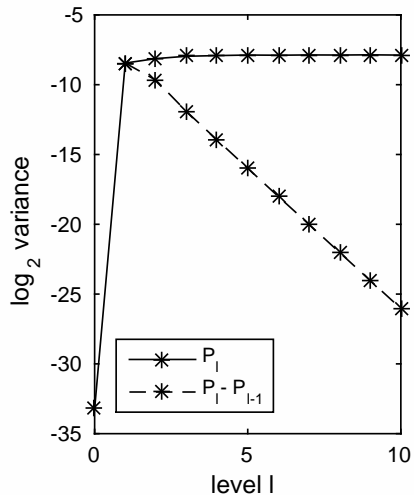
$$a(x, t) = -0.2, \quad b(x, t) = 0.5 + 0.5x.$$

– standard  $O(h)$  numerical analysis no longer applies

# 1D particles with mass

Test case 1:  $\mathbb{V}[\widehat{P}_\ell - \widehat{P}_{\ell-1}] \sim h_\ell^2$

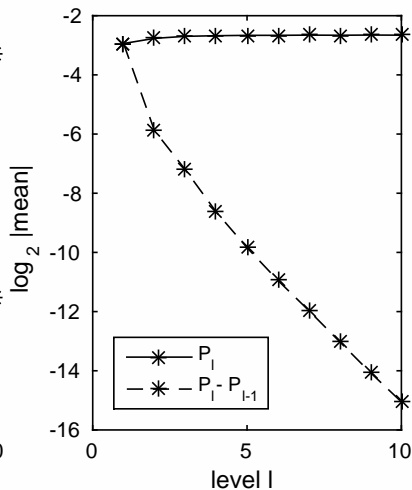
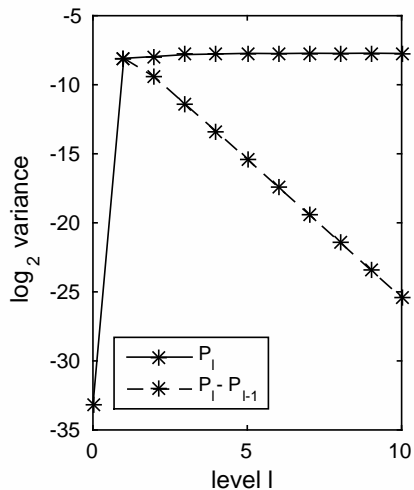
$\mathbb{E}[\widehat{P}_\ell - \widehat{P}_{\ell-1}] \sim h_\ell$



# 1D particles with mass

Test case 2:  $\mathbb{V}[\hat{P}_\ell - \hat{P}_{\ell-1}] \sim h_\ell^2$

$\mathbb{E}[\hat{P}_\ell - \hat{P}_{\ell-1}] \sim h_\ell$



# 1D massless particles

Without mass, the SDE is

$$dx_t = a(x_t, t) dt + b(x_t, t) dw_t$$

and if the domain is  $x \geq 0$ , particles are prevented from crossing  $x=0$ .

Euler-Maruyama treatment with uniform timestep  $h$ :

$$\hat{x}_{n+1} = \left| \hat{x}_n + a(\hat{x}_n, t) h + b(\hat{x}_n, t_n) \Delta w_n \right|$$

Again only  $O(h^{1/2})$  strong convergence, even when  $b$  is uniform

# 1D massless particles

Thinking about the extended domain leads to

$$dx_t = a(x_t, t) dt + b(x_t, t) S(X_t) dW_t$$

where  $S(X) \equiv \text{sign}(X)$ , and hence the numerical approximation is

$$\hat{x}_{n+1}^p = \hat{x}_n + a(\hat{x}_n, t_n) h + b(\hat{x}_n, t_n) \hat{s}_n \Delta W_n$$

followed by a correction/reflection step:

$$\begin{aligned}\hat{x}_{n+1} &= \text{sign}(\hat{x}_{n+1}^p) \hat{x}_{n+1}^p \\ \hat{s}_{n+1} &= \text{sign}(\hat{x}_{n+1}^p) \hat{s}_n\end{aligned}$$

with same Brownian path for coarse and fine levels.

Note: if  $b$  is not uniform then we need to use first order Milstein approximation to get  $O(h)$  strong convergence.

# 1D massless particles

Test case 1:

$$x_0 = 0.2, \quad a(x, t) = 0, \quad b(x, t) = 0.5.$$

in domain  $0 \leq x \leq 1$ , with reflection at both boundaries.

Output of interest:  $\int_0^1 x_t \, dt$  approximated by  $\sum_{n=1}^{2^\ell} h_\ell \hat{x}_n$ .

Test case 2: changes drift, volatility to

$$a(x, t) = -0.2, \quad b(x, t) = 0.5 + 0.5x.$$

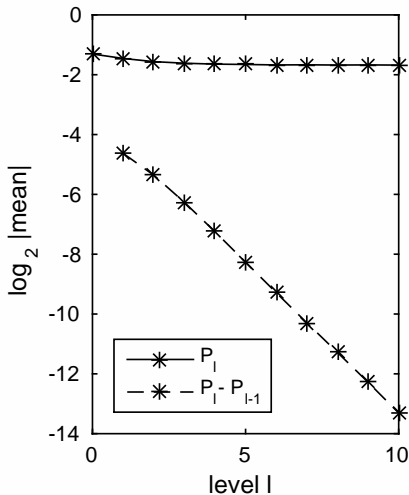
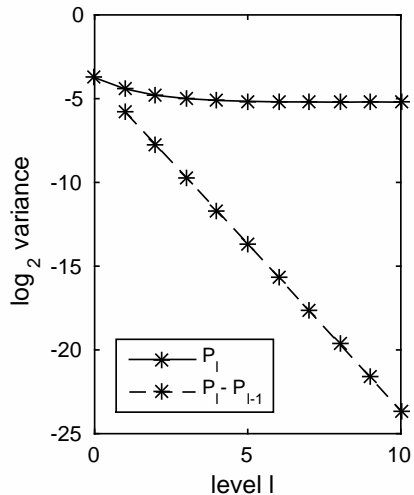
– standard  $O(h)$  numerical analysis no longer applies



# 1D massless particles

Test case 1:  $\mathbb{V}[\widehat{P}_\ell - \widehat{P}_{\ell-1}] \sim h_\ell^2$

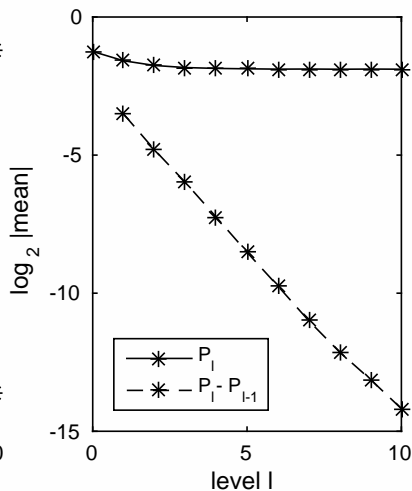
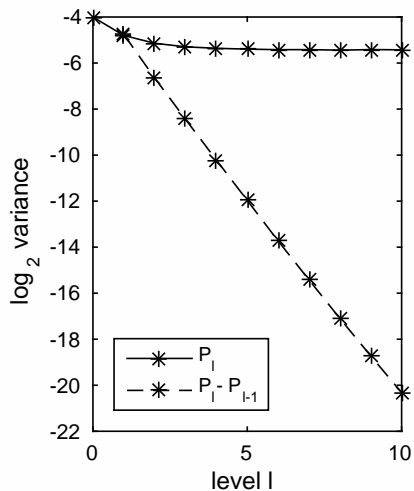
$\mathbb{E}[\widehat{P}_\ell - \widehat{P}_{\ell-1}] \sim h_\ell$



# 1D massless particles

Test case 2:  $\mathbb{V}[\widehat{P}_\ell - \widehat{P}_{\ell-1}] \sim h_\ell^{3/2}$

$\mathbb{E}[\widehat{P}_\ell - \widehat{P}_{\ell-1}] \sim h_\ell$



# 1D massless particles

Why is the variance  $O(h^{3/2})$ ?

Ad-hoc explanation:

- $O(1)$  path density near  $x=0$
- $O(h^{1/2})$  movement in each timestep
- $\implies O(h^{1/2})$  probability of crossing boundary in each timestep
- $\implies O(h^{-1/2})$  total crossings per path
- each crossing gives error which is  $O(h)$  but has near-zero mean
- if crossings are approximately independent, then

$$\mathbb{V}[\widehat{P}_\ell - \widehat{P}_{\ell-1}] = O(h^{-1/2} \times h^2) = O(h^{3/2})$$

Note: in the case with mass, the velocity is  $O(1)$ , the movement in each timestep is  $O(h)$ , so the number of crossings is  $O(1) \implies V_\ell = O(h^2)$ .

## Multi-dimensional extensions

Start with particles with mass, and 2D domain with boundary at  $x=0$ .

If

$$a = \begin{pmatrix} a_x(x, y) \\ a_y(x, y) \end{pmatrix}, \quad b = I,$$

then for  $x < 0$  extended domain SDE naturally has

$$A = \begin{pmatrix} -a_x(-x, y) \\ a_y(-x, y) \end{pmatrix}, \quad B = I,$$

This leads to an SDE in the regular half-plane in which the  $x$ -component of  $dW$  is “flipped” each time the boundary is hit.

## Multi-dimensional extensions

However, if

$$a = \begin{pmatrix} a_x(x, y) \\ a_y(x, y) \end{pmatrix}, \quad b = \begin{pmatrix} 1 & 0 \\ \beta & 1 \end{pmatrix},$$

then when  $x < 0$

$$A = \begin{pmatrix} -a_x(-x, y) \\ a_y(-x, y) \end{pmatrix}, \quad B = \begin{pmatrix} 1 & 0 \\ -\beta & 1 \end{pmatrix},$$

because if  $X = -x$  then

$$\mathbb{E}[dX dy] = -\mathbb{E}[dx dy].$$

This gives a discontinuity in  $B$ , and there seems no way to get  $O(h)$  strong convergence.

## Multi-dimensional extensions

Hence, multi-dimensional extension for particles with mass will only work in simple cases.

For massless particles, there is extra complication of oblique reflections.

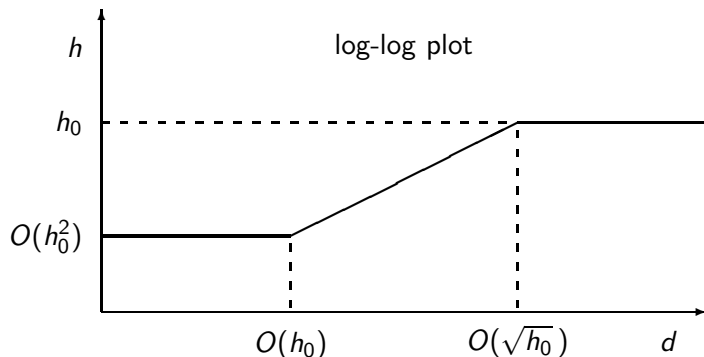
If diffusion is isotropic (i.e.  $b$  is a multiple of the identity matrix) and reflections are normal, then can probably get  $O(h)$  strong convergence.

Otherwise, probably not.

## Multi-dimensional extensions

What else can we do for massless case?

Go back to starting point with standard reflection treatment, and use adaptive timesteps based on distance  $d$  to boundary.



$O(h_0^2)$  timestep near boundary  $\implies O(h_0)$  strong error

## Multi-dimensional extensions

In MLMC, on level  $\ell$  would use

$$h = \min \left( 2^{-\ell} h_0, \max \left( 2^{-2\ell} h_0, \left( \frac{1}{3} d / \|b\|_2 \right)^2 \right) \right)$$

where  $d$  is the distance to the boundary

- $2^{-\ell} h_0$  in interior
- $2^{-2\ell} h_0$  next to boundary
- $\left( \frac{1}{3} d / \|b\|_2 \right)^2$  in layer in-between

The factor  $\frac{1}{3}$  implies  $3\sqrt{h} \|b\|_2 < d$  so that boundary crossings from the intermediate zone (or interior zone) are unlikely.

Most will come from boundary zone, with resultant  $O(2^{-\ell})$  strong error.



## Multi-dimensional extensions

Key observation: the computational cost is proportional to  $\int_D h^{-1} dx$  and this is  $O(2^\ell)$ .

Hence, in the usual MLMC theorem, we should get

$$\alpha = 1, \quad \beta = 2, \quad \gamma = 1,$$

and hence obtain  $O(\varepsilon^{-2})$  complexity.

# Conclusions

- simple reflection “trick” improves the MLMC variance for 1D reflected diffusions, for particles with or without mass
- the extension to multiple dimensions should work in simple cases, but not in more general cases
- more difficult cases can use adaptive timestepping

Webpages: <http://people.maths.ox.ac.uk/gilesm/>