



# Multilevel Monte Carlo Asymptotic-Preserving Particle Method for Kinetic Equations

Emil Løvbak, Stefan Vandewalle and Giovanni Samaey KU Leuven, Department of Computer Science, NUMA Section July 3, 2018



- ▶ Individual particles in position-velocity phase space  $(X_t, V_t, t)$
- Evolution of distribution follows kinetic equation

$$\partial_t f(x, v, t) + v \partial_x f(x, v, t) = Q(f(x, v, t))$$



- lndividual particles in position-velocity phase space  $(X_t, V_t, t)$
- Evolution of distribution follows kinetic equation

$$\varepsilon \partial_t f(x,v,t) + v \partial_x f(x,v,t) = \frac{1}{\varepsilon} Q(f(x,v,t))$$



- lndividual particles in position-velocity phase space  $(X_t, V_t, t)$
- Evolution of distribution follows kinetic equation

$$\partial_t f(x,v,t) + \frac{v}{\varepsilon} \partial_x f(x,v,t) = \frac{1}{\varepsilon^2} Q(f(x,v,t))$$

Velocity jump process



$$dX_t = \frac{V_t}{\varepsilon} dt, \quad V_t = \mathcal{V}^n, \quad t \in [t^n, t^{n+1}),$$
$$\mathcal{V}^n \sim \mathcal{M}(v), \quad t^{n+1} - t^n \sim \mathcal{E}(1/\varepsilon^2)$$



Velocity jump process

$$dX_t = \frac{V_t}{\varepsilon} dt, \quad V_t = \mathcal{V}^n, \quad t \in [t^n, t^{n+1})$$

▶  $\varepsilon \to 0$ : Time between collisions  $t^{n+1} - t^n \to 0$ 



Velocity jump process

$$dX_t = \frac{V_t}{\varepsilon}dt, \quad V_t = \mathcal{V}^n, \quad t \in [t^n, t^{n+1})$$

ε → 0: Time between collisions t<sup>n+1</sup> − t<sup>n</sup> → 0
 Brownian motion

$$X^{n+1} = X^n + \sqrt{2\Delta t}\sqrt{D}\xi^n, \quad \xi^n \sim \mathcal{N}(0,1)$$



Velocity jump process

$$dX_t = \frac{V_t}{\varepsilon} dt, \quad V_t = \mathcal{V}^n, \quad t \in [t^n, t^{n+1})$$

ε → 0: Time between collisions t<sup>n+1</sup> − t<sup>n</sup> → 0
 Brownian motion

$$X^{n+1} = X^n + \sqrt{2\Delta t}\sqrt{D}\xi^n, \quad \xi^n \sim \mathcal{N}(0,1)$$

▶ Interested in moments  $u(x,t) = \int m(v) f(x,v,t) dv$ 

Examples: Density, Flux, Variance, . . .

$$\rho(x,t) = \int f(x,v,t) dv$$



Velocity jump process

$$dX_t = \frac{V_t}{\varepsilon}dt, \quad V_t = \mathcal{V}^n, \quad t \in [t^n, t^{n+1})$$

ε → 0: Time between collisions t<sup>n+1</sup> − t<sup>n</sup> → 0
 Brownian motion

$$X^{n+1} = X^n + \sqrt{2\Delta t}\sqrt{D}\xi^n, \quad \xi^n \sim \mathcal{N}(0,1)$$

 $\blacktriangleright$  Interested in moments  $u(x,t) = \int m(v) f(x,v,t) dv$ 

Examples: Density, Flux, Variance, ...

$$\rho(x,t) = \int f(x,v,t) dv$$

• Limiting macroscopic equation for  $arepsilon o 0: \quad \partial_t 
ho = \partial_{xx} 
ho$ 



- Applications:
  - Nuclear fusion





KU Leuven Dept. Mech. Engineering;

- Applications:
  - Nuclear fusion
  - Chemotaxis



DEPARTMENT

KU Leuven Dept. Mech. Engineering; Wikipedia;

- Applications:
  - Nuclear fusion
  - Chemotaxis
  - Fluid dynamics

• . . .





KU Leuven Dept. Mech. Engineering; Wikipedia; Linkedin article Rahul Krishnan (Boeing)



- Applications:
  - Nuclear fusion
  - Chemotaxis
  - Fluid dynamics
  - . . .
- Often multiscale in nature
  - Short mean free path
  - Slow macroscopic dynamics



tumbling





KU Leuven Dept. Mech. Engineering; Wikipedia; Linkedin article Rahul Krishnan (Boeing)



- Applications:
  - Nuclear fusion
  - Chemotaxis
  - Fluid dynamics
  - . . .
- Often multiscale in nature
  - Short mean free path
  - Slow macroscopic dynamics
  - $\Rightarrow$  computationally expensive





KU Leuven Dept. Mech. Engineering; Wikipedia; Linkedin article Rahul Krishnan (Boeing)



Goldstein-Taylor model:

$$\begin{cases} \partial_t f_+ + \frac{1}{\varepsilon} \partial_x f_+ = \frac{1}{\varepsilon^2} \left( \frac{\rho}{2} - f_+ \right) \\ \partial_t f_- - \frac{1}{\varepsilon} \partial_x f_- = \frac{1}{\varepsilon^2} \left( \frac{\rho}{2} - f_- \right) \end{cases}$$



Goldstein-Taylor model:

$$\begin{cases} \partial_t f_+ + \frac{1}{\varepsilon} \partial_x f_+ = \frac{1}{\varepsilon^2} \left( \frac{\rho}{2} - f_+ \right) \\ \partial_t f_- - \frac{1}{\varepsilon} \partial_x f_- = \frac{1}{\varepsilon^2} \left( \frac{\rho}{2} - f_- \right) \end{cases}$$

In density flux representation:

$$\rho = f_{+} + f_{-}, \qquad j = \frac{f_{+} - f_{-}}{\varepsilon}$$

$$\begin{cases} \partial_t \rho + \partial_x j = 0\\ \partial_t j + \frac{1}{\varepsilon^2} \partial_x \rho = -\frac{1}{\varepsilon^2} j \end{cases}$$



Goldstein-Taylor model:

$$\begin{cases} \partial_t f_+ + \frac{1}{\varepsilon} \partial_x f_+ = \frac{1}{\varepsilon^2} \left( \frac{\rho}{2} - f_+ \right) \\ \partial_t f_- - \frac{1}{\varepsilon} \partial_x f_- = \frac{1}{\varepsilon^2} \left( \frac{\rho}{2} - f_- \right) \end{cases}$$

In density flux representation:

$$\rho = f_{+} + f_{-}, \qquad j = \frac{f_{+} - f_{-}}{\varepsilon}$$

$$\begin{cases} \partial_t \rho + \partial_x j = 0\\ \partial_t j + \frac{1}{\varepsilon^2} \partial_x \rho = -\frac{1}{\varepsilon^2} j \end{cases}$$

• Under limit  $\varepsilon \to 0$ :

$$\partial_t \rho = \partial_{xx} \rho$$



► A conventional Monte Carlo scheme with operator splitting:

• Transport step:

$$\begin{cases} \partial_t f_+ + \frac{1}{\varepsilon} \partial_x f_+ = 0\\ \partial_t f_- - \frac{1}{\varepsilon} \partial_x f_- = 0 \end{cases}$$



► A conventional Monte Carlo scheme with operator splitting:

• Transport step:

$$\begin{cases} \partial_t f_+ + \frac{1}{\varepsilon} \partial_x f_+ = 0\\ \partial_t f_- - \frac{1}{\varepsilon} \partial_x f_- = 0 \end{cases} \Rightarrow \quad X^{n+1} = X^n \pm \frac{1}{\varepsilon} \Delta t$$



► A conventional Monte Carlo scheme with operator splitting:

• Transport step:

$$\begin{cases} \partial_t f_+ + \frac{1}{\varepsilon} \partial_x f_+ = 0\\ \partial_t f_- - \frac{1}{\varepsilon} \partial_x f_- = 0 \end{cases} \Rightarrow \quad X^{n+1} = X^n \pm \frac{1}{\varepsilon} \Delta t$$

$$\begin{cases} \partial_t f_+ = \frac{1}{\varepsilon^2} \left( \frac{\rho}{2} - f_+ \right) \\ \partial_t f_- = \frac{1}{\varepsilon^2} \left( \frac{\rho}{2} - f_- \right) \end{cases}$$



A conventional Monte Carlo scheme with operator splitting:

• Transport step:

$$\begin{cases} \partial_t f_+ + \frac{1}{\varepsilon} \partial_x f_+ = 0\\ \partial_t f_- - \frac{1}{\varepsilon} \partial_x f_- = 0 \end{cases} \Rightarrow \quad X^{n+1} = X^n \pm \frac{1}{\varepsilon} \Delta t$$

$$\begin{cases} \partial_t f_+ = \frac{1}{\varepsilon^2} \left(\frac{\rho}{2} - f_+\right) \\ \partial_t f_- = \frac{1}{\varepsilon^2} \left(\frac{\rho}{2} - f_-\right) \end{cases} \begin{cases} f_+^{n+1} = \exp\left(-\frac{\Delta t}{\varepsilon^2}\right) \tilde{f}_+^n + \left(1 - \exp\left(-\frac{\Delta t}{\varepsilon^2}\right)\right) \frac{\tilde{\rho}^n}{2} \\ f_-^{n+1} = \exp\left(-\frac{\Delta t}{\varepsilon^2}\right) \tilde{f}_-^n + \left(1 - \exp\left(-\frac{\Delta t}{\varepsilon^2}\right)\right) \frac{\tilde{\rho}^n}{2} \end{cases}$$



► A conventional Monte Carlo scheme with operator splitting:

• Transport step:

$$\begin{cases} \partial_t f_+ + \frac{1}{\varepsilon} \partial_x f_+ = 0\\ \partial_t f_- - \frac{1}{\varepsilon} \partial_x f_- = 0 \end{cases} \Rightarrow \quad X^{n+1} = X^n \pm \frac{1}{\varepsilon} \Delta t$$

$$\begin{cases} \partial_t f_+ = \frac{1}{\varepsilon^2} \left(\frac{\rho}{2} - f_+\right) \\ \partial_t f_- = \frac{1}{\varepsilon^2} \left(\frac{\rho}{2} - f_-\right) \end{cases} \begin{cases} f_+^{n+1} = \overbrace{\exp\left(-\frac{\Delta t}{\varepsilon^2}\right)}^{\text{No collision}} \tilde{f}_+^n + \overbrace{\left(1 - \exp\left(-\frac{\Delta t}{\varepsilon^2}\right)\right)}^{\text{Collision}} \frac{\rho^n}{2} \\ f_-^{n+1} = \exp\left(-\frac{\Delta t}{\varepsilon^2}\right) \tilde{f}_-^n + \left(1 - \exp\left(-\frac{\Delta t}{\varepsilon^2}\right)\right) \frac{\rho^n}{2} \end{cases}$$



A conventional Monte Carlo scheme with operator splitting:

• Transport step:

$$\begin{cases} \partial_t f_+ + \frac{1}{\varepsilon} \partial_x f_+ = 0\\ \partial_t f_- - \frac{1}{\varepsilon} \partial_x f_- = 0 \end{cases} \Rightarrow \quad X^{n+1} = X^n \pm \frac{1}{\varepsilon} \Delta t$$

• Collision step:  

$$\begin{cases}
\partial_t f_+ = \frac{1}{\varepsilon^2} \left(\frac{\rho}{2} - f_+\right) \\
\partial_t f_- = \frac{1}{\varepsilon^2} \left(\frac{\rho}{2} - f_-\right)
\end{cases} \Rightarrow \begin{cases}
f_+^{n+1} = \exp\left(-\frac{\Delta t}{\varepsilon^2}\right) \tilde{f}_+^n + \left(1 - \exp\left(-\frac{\Delta t}{\varepsilon^2}\right)\right) \tilde{\rho}_-^n \\
f_-^{n+1} = \exp\left(-\frac{\Delta t}{\varepsilon^2}\right) \tilde{f}_-^n + \left(1 - \exp\left(-\frac{\Delta t}{\varepsilon^2}\right)\right) \tilde{\rho}_-^n
\end{cases}$$

• Time step restriction  $\Delta t = \mathcal{O}(\varepsilon)$ 



# Outline

- 1 Asymptotic-Preserving Particle Scheme
- 2 Multilevel Monte Carlo
- **3** Correlating Particle Pairs
- **4** Practical Results



# Outline

# 1 Asymptotic-Preserving Particle Scheme

- 2 Multilevel Monte Carlo
- **3** Correlating Particle Pairs
- Practical Results



Goldstein-Taylor model:

$$\begin{cases} \partial_t f_+ + \frac{1}{\varepsilon} \partial_x f_+ = \frac{1}{\varepsilon^2} \left( \frac{\rho}{2} - f_+ \right) \\ \partial_t f_- - \frac{1}{\varepsilon} \partial_x f_- = \frac{1}{\varepsilon^2} \left( \frac{\rho}{2} - f_- \right) \end{cases}$$

 Modified equation via IMEX method: [Dimarco, Pareschi, Samaey, 2018]

$$\begin{cases} \partial_t f_+ + \frac{\varepsilon}{\varepsilon^2 + \Delta t} \partial_x f_+ = \frac{\Delta t}{\varepsilon^2 + \Delta t} \partial_{xx} f_+ + \frac{1}{\varepsilon^2 + \Delta t} \left(\frac{\rho}{2} - f_+\right) \\ \partial_t f_- - \frac{\varepsilon}{\varepsilon^2 + \Delta t} \partial_x f_- = \frac{\Delta t}{\varepsilon^2 + \Delta t} \partial_{xx} f_- + \frac{1}{\varepsilon^2 + \Delta t} \left(\frac{\rho}{2} - f_-\right) \end{cases}$$

• Model bias  $\mathcal{O}(\Delta t)$ 

•  $\varepsilon \to 0 \Rightarrow$  Diffusion



Transport-diffusion step:

$$\begin{cases} \partial_t f_+ + \frac{\varepsilon}{\varepsilon^2 + \Delta t} \partial_x f_+ = \frac{\Delta t}{\varepsilon^2 + \Delta t} \partial_{xx} f_+ \\ \partial_t f_- - \frac{\varepsilon}{\varepsilon^2 + \Delta t} \partial_x f_- = \frac{\Delta t}{\varepsilon^2 + \Delta t} \partial_{xx} f_- \end{cases}$$



Transport-diffusion step:



Transport-diffusion step:

$$\begin{cases} \partial_t f_+ + \frac{\varepsilon}{\varepsilon^2 + \Delta t} \partial_x f_+ = \frac{\Delta t}{\varepsilon^2 + \Delta t} \partial_{xx} f_+ \\ \partial_t f_- - \frac{\varepsilon}{\varepsilon^2 + \Delta t} \partial_x f_- = \frac{\Delta t}{\varepsilon^2 + \Delta t} \partial_{xx} f_- \\ & \downarrow \end{cases}$$

$$X^{n+1} = X^n \pm \frac{\varepsilon}{\varepsilon^2 + \Delta t} \Delta t + \sqrt{2\Delta t} \sqrt{\frac{\Delta t}{\varepsilon^2 + \Delta t}} \xi^n, \quad \xi^n \sim \mathcal{N}(0, 1)$$

$$\begin{cases} \partial_t f_+ = \frac{1}{\varepsilon^2 + \Delta t} \left(\frac{\rho}{2} - f_+\right) \\ \partial_t f_- = \frac{1}{\varepsilon^2 + \Delta t} \left(\frac{\rho}{2} - f_-\right) \end{cases}$$



Transport-diffusion step:

$$X^{n+1} = X^n \pm \frac{\varepsilon}{\varepsilon^2 + \Delta t} \Delta t + \sqrt{2\Delta t} \sqrt{\frac{\Delta t}{\varepsilon^2 + \Delta t}} \xi^n, \quad \xi^n \sim \mathcal{N}(0, 1)$$

$$\begin{cases} \partial_t f_+ = \frac{1}{\varepsilon^2 + \Delta t} \left( \frac{\rho}{2} - f_+ \right) \\ \partial_t f_- = \frac{1}{\varepsilon^2 + \Delta t} \left( \frac{\rho}{2} - f_- \right) \end{cases} \Rightarrow & \text{No collision: } \exp\left( -\frac{\Delta t}{\varepsilon^2 + \Delta t} \right) \\ \text{Collision: } \left( 1 - \exp\left( -\frac{\Delta t}{\varepsilon^2 + \Delta t} \right) \right) \end{cases}$$



Transport-diffusion step:

$$\begin{cases} \partial_t f_+ + \frac{\varepsilon}{\varepsilon^2 + \Delta t} \partial_x f_+ = \frac{\Delta t}{\varepsilon^2 + \Delta t} \partial_{xx} f_+ \\ \partial_t f_- - \frac{\varepsilon}{\varepsilon^2 + \Delta t} \partial_x f_- = \frac{\Delta t}{\varepsilon^2 + \Delta t} \partial_{xx} f_- \\ & \downarrow \end{cases}$$

$$X^{n+1} = X^n \pm \frac{\varepsilon}{\varepsilon^2 + \Delta t} \Delta t + \sqrt{2\Delta t} \sqrt{\frac{\Delta t}{\varepsilon^2 + \Delta t}} \xi^n, \quad \xi^n \sim \mathcal{N}(0, 1)$$

$$\begin{cases} \partial_t f_+ = \frac{1}{\varepsilon^2 + \Delta t} \left( \frac{\rho}{2} - f_+ \right) & \Rightarrow \\ \partial_t f_- = \frac{1}{\varepsilon^2 + \Delta t} \left( \frac{\rho}{2} - f_- \right) & \Rightarrow \\ \end{cases} \quad \text{No collision: } \frac{\varepsilon^2}{\varepsilon^2 + \Delta t} \\ \text{Collision: } \frac{\Delta t}{\varepsilon^2 + \Delta t} \end{cases}$$



# Outline

# Asymptotic-Preserving Particle Scheme

- 2 Multilevel Monte Carlo
- **3** Correlating Particle Pairs
- Practical Results



• Monte Carlo for Quantity of Interest  $Y(t^*) = f(X(t^*))$ :

$$\hat{Y}(t^*) = \frac{1}{P} \sum_{p=1}^{P} f(X_{\Delta t,p}^n), \quad t^* = n\Delta t$$



• Monte Carlo for Quantity of Interest  $Y(t^*) = f(X(t^*))$ :

$$\hat{Y}(t^*) = \frac{1}{P} \sum_{p=1}^{P} f(X_{\Delta t,p}^n), \quad t^* = n\Delta t$$

▶ In this case moments:  $f(x) = x, x^2, x^3, ...$ 



• Monte Carlo for Quantity of Interest  $Y(t^*) = f(X(t^*))$ :

$$\hat{Y}(t^*) = \frac{1}{P} \sum_{p=1}^{P} f(X_{\Delta t,p}^n), \quad t^* = n\Delta t$$

▶ In this case moments: 
$$f(x) = x, x^2, x^3, ...$$

- Error:
  - Systematic:
    - Small  $\Delta t$ : Small bias, high cost
    - Large  $\Delta t$ : Large bias, low cost
  - Statistical:

$$\mathbb{V}[\hat{Y}(t^*)] = \frac{1}{P} \mathbb{V}\left[f(X_{\Delta t}^n)\right]$$



• Monte Carlo for Quantity of Interest  $Y(t^*) = f(X(t^*))$ :

$$\hat{Y}(t^*) = \frac{1}{P} \sum_{p=1}^{P} f(X_{\Delta t,p}^n), \quad t^* = n\Delta t$$

• In this case moments: 
$$f(x) = x, x^2, x^3, \dots$$

- Error:
  - Systematic:
    - Small  $\Delta t$ : Small bias, high cost
    - Large  $\Delta t$ : Large bias, low cost
  - Statistical:

$$\mathbb{V}[\hat{Y}(t^*)] = \frac{1}{P} \mathbb{V}\left[f(X_{\Delta t}^n)\right]$$

Fixed cost trade-off: Many samples or expensive samples?



- Multilevel Monte Carlo [Giles, 2015]:
  - Many cheap samples:

$$\hat{Y}_0(t^*) = \frac{1}{P_0} \sum_{p=1}^{P_0} f(X_{\Delta t_0,p}^n)$$

• Correction with increasingly fewer correlated pairs of expensive samples:

$$\hat{Y}_{l}(t^{*}) = \frac{1}{P_{l}} \sum_{p=1}^{P_{l}} \left( f(X_{\Delta t_{l},p}^{Mn}) - f(X_{\Delta t_{l-1},p}^{n}) \right), \ l = 1 \dots L, \ M = \frac{\Delta t_{l-1}}{\Delta t_{l}}$$



- Multilevel Monte Carlo [Giles, 2015]:
  - Many cheap samples:

$$\hat{Y}_0(t^*) = \frac{1}{P_0} \sum_{p=1}^{P_0} f(X_{\Delta t_0,p}^n)$$

• Correction with increasingly fewer correlated pairs of expensive samples:

$$\hat{Y}_{l}(t^{*}) = \frac{1}{P_{l}} \sum_{p=1}^{P_{l}} \left( f(X_{\Delta t_{l},p}^{Mn}) - f(X_{\Delta t_{l-1},p}^{n}) \right), \ l = 1 \dots L, \ M = \frac{\Delta t_{l-1}}{\Delta t_{l}}$$

• Telescopic sum:

$$\hat{Y}(t^*) = \sum_{l=0}^{L} \hat{Y}_l(t^*)$$



- Multilevel Monte Carlo [Giles, 2015]:
  - Many cheap samples:

$$\hat{Y}_0(t^*) = \frac{1}{P_0} \sum_{p=1}^{P_0} f(X_{\Delta t_0,p}^n)$$

• Correction with increasingly fewer correlated pairs of expensive samples:

$$\hat{Y}_{l}(t^{*}) = \frac{1}{P_{l}} \sum_{p=1}^{P_{l}} \left( f(X_{\Delta t_{l},p}^{Mn}) - f(X_{\Delta t_{l-1},p}^{n}) \right), \ l = 1 \dots L, \ M = \frac{\Delta t_{l-1}}{\Delta t_{l}}$$

• Telescopic sum:

$$\hat{Y}(t^*) = \sum_{l=0}^{L} \hat{Y}_l(t^*)$$

• If  $\mathbb{E}[Y_l]$  and  $\mathbb{V}[Y_l]$  decrease in absolute value with  $l \Rightarrow$  Convergence



# Outline

Asymptotic-Preserving Particle Scheme

- 2 Multilevel Monte Carlo
- **3** Correlating Particle Pairs
- Practical Results



$$X_{\Delta t_l}^{n,1} = X_{\Delta t_l}^{n,0} \pm \frac{\varepsilon}{\varepsilon^2 + \Delta t_l} + \sqrt{2\Delta t_l} \sqrt{\frac{\Delta t_l}{\varepsilon^2 + \Delta t_l}} \xi_l^{n,0}, \quad \xi_l^{n,0} \sim \mathcal{N}(0,1)$$





$$X_{\Delta t_l}^{\mathbf{n},1} = X_{\Delta t_l}^{n,0} \dots + \sqrt{2\Delta t_l} \sqrt{\frac{\Delta t_l}{\varepsilon^2 + \Delta t_l}} \xi_l^{\mathbf{n},0}, \quad \xi_l^{n,0} \sim \mathcal{N}(0,1)$$





$$X_{\Delta t_l}^{n+1,0} = X_{\Delta t_l}^{n,0} \cdots + \sqrt{2\Delta t_l} \sqrt{\frac{\Delta t_l}{\varepsilon^2 + \Delta t_l}} \sum_{m=1}^M \xi_l^{n,m}, \quad \xi_l^{n,m} \sim \mathcal{N}(0,1)$$





$$X_{\Delta t_l}^{n+1,0} = X_{\Delta t_l}^{n,0} \dots + \sqrt{2\Delta t_l} \sqrt{\frac{\Delta t_l}{\varepsilon^2 + \Delta t_l}} \sum_{m=1}^M \xi_l^{n,m}, \quad \xi_l^{n,m} \sim \mathcal{N}(0,1)$$

$$X_{\Delta t_{l-1}}^{n+1} = X_{\Delta t_{l-1}}^{n} \dots + \sqrt{2\Delta t_{l-1}} \sqrt{\frac{\Delta t_{l-1}}{\varepsilon^2 + \Delta t_{l-1}}} \xi_{l-1}^{n}, \quad \xi_{l-1}^{n} \sim \mathcal{N}(0,1)$$





$$X_{\Delta t_l}^{n+1,0} = X_{\Delta t_l}^{n,0} \dots + \sqrt{2\Delta t_l} \sqrt{\frac{\Delta t_l}{\varepsilon^2 + \Delta t_l}} \sum_{m=1}^M \xi_l^{n,m}, \quad \xi_l^{n,m} \sim \mathcal{N}(0,1)$$

$$X_{\Delta t_{l-1}}^{n+1} = X_{\Delta t_{l-1}}^{n} \dots + \sqrt{2\Delta t_{l-1}} \sqrt{\frac{\Delta t_{l-1}}{\varepsilon^2 + \Delta t_{l-1}}} \xi_{l-1}^{n}, \quad \xi_{l-1}^{n} \sim \mathcal{N}(0,1)$$



$$X_{\Delta t_l}^{n+1,0} = X_{\Delta t_l}^{n,0} \cdots + \sqrt{2\Delta t_l} \sqrt{\frac{\Delta t_l}{\varepsilon^2 + \Delta t_l}} \sum_{m=1}^M \xi_l^{n,m}, \quad \xi_l^{n,m} \sim \mathcal{N}(0,1)$$

$$X_{\Delta t_{l-1}}^{n+1} = X_{\Delta t_{l-1}}^{n} \dots + \sqrt{2\Delta t_{l-1}} \sqrt{\frac{\Delta t_{l-1}}{\varepsilon^2 + \Delta t_{l-1}}} \xi_{l-1}^{n}, \quad \xi_{l-1}^{n} \sim \mathcal{N}(0,1)$$



$$X_{\Delta t_l}^{n+1,0} = X_{\Delta t_l}^{n,0} \cdots + \sqrt{2\Delta t_l} \sqrt{\frac{\Delta t_l}{\varepsilon^2 + \Delta t_l}} \sum_{m=1}^M \xi_l^{n,m}, \quad \xi_l^{n,m} \sim \mathcal{N}(0,1)$$

$$X_{\Delta t_{l-1}}^{n+1} = X_{\Delta t_{l-1}}^n \dots + \sqrt{2M\Delta t_l} \sqrt{\frac{\Delta t_{l-1}}{\varepsilon^2 + \Delta t_{l-1}}} \xi_{l-1}^n, \quad \xi_{l-1}^n \sim \mathcal{N}(0,1)$$



$$X_{\Delta t_l}^{n+1,0} = X_{\Delta t_l}^{n,0} \dots + \sqrt{2\Delta t_l} \sqrt{\frac{\Delta t_l}{\varepsilon^2 + \Delta t_l}} \sum_{m=1}^M \xi_l^{n,m}, \quad \xi_l^{n,m} \sim \mathcal{N}(0,1)$$

$$X_{\Delta t_{l-1}}^{n+1} = X_{\Delta t_{l-1}}^n \dots + \sqrt{2\Delta t_l} \sqrt{\frac{\Delta t_{l-1}}{\varepsilon^2 + \Delta t_{l-1}}} \sqrt{M} \xi_{l-1}^n, \quad \xi_{l-1}^n \sim \mathcal{N}(0,1)$$



$$X_{\Delta t_l}^{n+1,0} = X_{\Delta t_l}^{n,0} \dots + \sqrt{2\Delta t_l} \sqrt{\frac{\Delta t_l}{\varepsilon^2 + \Delta t_l}} \sum_{m=1}^M \xi_l^{n,m}, \quad \xi_l^{n,m} \sim \mathcal{N}(0,1)$$

$$X_{\Delta t_{l-1}}^{n+1} = X_{\Delta t_{l-1}}^n \dots + \sqrt{2\Delta t_l} \sqrt{\frac{\Delta t_{l-1}}{\varepsilon^2 + \Delta t_{l-1}}} \sqrt{M} \xi_{l-1}^n, \quad \xi_{l-1}^n \sim \mathcal{N}(0,1)$$

► Different  $\Delta t \Rightarrow$  different diffusion coefficient ►  $\sqrt{M}\xi_{l-1}^n = \sum_{m=1}^M \xi_l^{n,m} \sim \mathcal{N}\left(0, \sqrt{M}\right)$ 





$$X_{\Delta t_l}^{n+1,0} = X_{\Delta t_l}^{n,0} \dots + \sqrt{2\Delta t_l} \sqrt{\frac{\Delta t_l}{\varepsilon^2 + \Delta t_l}} \sum_{m=1}^M \xi_l^{n,m}, \quad \xi_l^{n,m} \sim \mathcal{N}(0,1)$$

$$X_{\Delta t_{l-1}}^{n+1} = X_{\Delta t_{l-1}}^n \dots + \sqrt{2\Delta t_l} \sqrt{\frac{\Delta t_{l-1}}{\varepsilon^2 + \Delta t_{l-1}}} \sqrt{M} \xi_{l-1}^n, \quad \xi_{l-1}^n \sim \mathcal{N}(0,1)$$

- Different  $\Delta t \Rightarrow$  different diffusion coefficient
- ► Variance rescaling:  $\xi_{l-1}^n = \frac{1}{\sqrt{M}} \sum_{m=1}^M \xi_l^{n,m} \sim \mathcal{N}(0,1)$





- $\blacktriangleright$  Probability of collision is different for different  $\Delta t$
- ▶ Implementation: If  $\alpha_l^n > \frac{\varepsilon^2}{\varepsilon^2 + \Delta t_l}, \ \alpha_l^n \in \mathcal{U}[0,1]$  then collision



- $\blacktriangleright$  Probability of collision is different for different  $\Delta t$
- Implementation: If  $\alpha_l^n > \frac{\varepsilon^2}{\varepsilon^2 + \Delta t_l}, \ \alpha_l^n \in \mathcal{U}[0,1]$  then collision
- Generate uniformly distributed  $\alpha_{l-1}^n$  from  $\alpha_{\max} = \max_m \alpha_l^{n,m}$ :

$$\alpha_{l-1}^n = \alpha_{\max} \not\sim \mathcal{U}([0,1])$$



- $\blacktriangleright$  Probability of collision is different for different  $\Delta t$
- Implementation: If  $\alpha_l^n > \frac{\varepsilon^2}{\varepsilon^2 + \Delta t_l}, \ \alpha_l^n \in \mathcal{U}[0,1]$  then collision
- Generate uniformly distributed  $\alpha_{l-1}^n$  from  $\alpha_{\max} = \max_m \alpha_l^{n,m}$ :

$$\alpha_{l-1}^n = \alpha_{\max}^M \sim \mathcal{U}([0,1])$$



- Probability of collision is different for different  $\Delta t$
- Implementation: If  $\alpha_l^n > \frac{\varepsilon^2}{\varepsilon^2 + \Delta t_l}, \ \alpha_l^n \in \mathcal{U}[0,1]$  then collision

• Generate uniformly distributed  $\alpha_{l-1}^n$  from  $\alpha_{\max} = \max_m \alpha_l^{n,m}$ :

$$\alpha_{l-1}^n = \alpha_{\max}^M \sim \mathcal{U}([0,1])$$

• New speed is  $\beta_l^n \mathcal{V}_l$ ,  $\beta_l^n = \pm 1$  with equal probability

$$\beta_{l-1}^n = \beta_l^{n,i}, \quad i = \underset{1 \le m \le M}{\operatorname{arg\,max}} \left( m \middle| \alpha_l^{n,m} \ge \frac{\varepsilon^2}{\varepsilon^2 + \Delta t_{l-1}} \right)$$





- Probability of collision is different for different  $\Delta t$
- Implementation: If  $\alpha_l^n > \frac{\varepsilon^2}{\varepsilon^2 + \Delta t_l}, \ \alpha_l^n \in \mathcal{U}[0,1]$  then collision

• Generate uniformly distributed  $\alpha_{l-1}^n$  from  $\alpha_{\max} = \max_m \alpha_l^{n,m}$ :

$$\alpha_{l-1}^n = \alpha_{\max}^M \sim \mathcal{U}([0,1])$$

• New speed is  $\beta_l^n \mathcal{V}_l$ ,  $\beta_l^n = \pm 1$  with equal probability

$$\beta_{l-1}^n = \beta_l^{n,i}, \quad i = \underset{1 \le m \le M}{\operatorname{arg\,max}} \left( m \middle| \alpha_l^{n,m} \ge \frac{\varepsilon^2}{\varepsilon^2 + \Delta t_{l-1}} \right)$$





# Outline

Asymptotic-Preserving Particle Scheme

- 2 Multilevel Monte Carlo
- **3** Correlating Particle Pairs
- **4** Practical Results





# Applying MLMC to AP scheme: Results

Slide removed due to containing wrong results. We refer to future publications on this topic for a correction.



### Applying MLMC to AP scheme: Results





# Applying MLMC to AP scheme: Results

- $\blacktriangleright$  Variance increases for  $\Delta t \gg \varepsilon^2$  and decreases for  $\Delta t \ll \varepsilon^2$
- For small  $\Delta t$ , general theory behind MLMC applies
- For large  $\Delta t$ , it seems that extra levels increase overall cost
- Proposed strategy:
  - Level 0 at roughest possible time step
  - Level 1 correlates roughest time step with  $arepsilon^2$
  - Levels 2 . . . L are a geometric series of time steps
  - Optimal geometric factor  $\in 2,3,4$  and depends on  $\varepsilon$  and the simulation length
- Experimental verification of strategy in progress



#### References

#### G. Dimarco, L. Pareschi and G. Samaey (2018)

Asymptotic-Preserving Monte Carlo methods for transport equations in the diffusive limit

SIAM J. Sci. Comput. 40, pp. A504-A528

#### M. B. Giles (2015)

Multilevel Monte Carlo methods

Acta Numerica 24, pp. 259-328

