

## Variance reduction with importance weights

The idea is to reduce the variance of non-equilibrium simulation using its correlation to an equilibrium simulation with known analytical moments. Let us rewrite  $R(\mathbf{v}) \in \{1, \mathbf{v}, \dots\}$  moments of particle distribution  $f$  as

$$\int R(\mathbf{v}) f(\mathbf{v}|\mathbf{x}, t) d^3\mathbf{v} = \int R(\mathbf{v}) (1 - w(\mathbf{v}|\mathbf{x}, t)) f(\mathbf{v}|\mathbf{x}, t) d^3\mathbf{v} + \int R(\mathbf{v}) f^{\text{eq}}(\mathbf{v}|\mathbf{x}, t) d^3\mathbf{v}$$

where  $w(\mathbf{v}|\mathbf{x}, t) = \frac{f^{\text{eq}}(\mathbf{v}|\mathbf{x}, t)}{f(\mathbf{v}|\mathbf{x}, t)}$ .

Instead of explicitly performing the parallel equilibrium simulation, the weight  $w$  allows computing its moments using particles of non-equilibrium simulation [1]. Hence, the variance-reduced estimate is computed via

$$\langle R(\mathbf{v}) f(\mathbf{v}|\mathbf{x}, t) \rangle_{\text{VR}} = N_{\text{eff}} \sum_{i=1}^{N_p} R(\mathbf{V}^{(i)}) (1 - W^{(i)}) + \underbrace{\int R(\mathbf{v}) f^{\text{eq}}(\mathbf{v}|\mathbf{x}, t) d^3\mathbf{v}}_{\text{analytical computation}}.$$

Orders of magnitude speed-up with the minimal change in the base code.

## Variance reduction for stochastic collision operator

Unfortunately, weight evolution for most collision operators, e.g. the Boltzmann eq.

$$\frac{\partial f^{\text{eq}}}{\partial t} \Big|_{\text{col}} = \frac{1}{2} \int \int \int (\delta'_1 + \delta'_2 - \delta_1 - \delta_2) w_1 w_2 f_1 f_2 v_r \sigma d\Omega d\mathbf{v}_1 d\mathbf{v}_2,$$

becomes **unstable** due to its multiplicative process with diverging fixed points.

## Maximum cross-entropy formulation

The stability and conservation laws can be enforced by combining a stabilized estimate of post-collision weight distribution  $\mathcal{F}^{\text{prior}}$  with the exact post-collision moments of equilibrium simulation via the functional [2]

$$\begin{aligned} \mathcal{C}[\mathcal{F}(\mathbf{v}|\mathbf{x}, t)] &:= \int \mathcal{F}(\mathbf{v}|\mathbf{x}, t) \log(\mathcal{F}(\mathbf{v}|\mathbf{x}, t) / \mathcal{F}^{\text{prior}}(\mathbf{v}|\mathbf{x}, t)) d^3\mathbf{v} \\ &+ \sum_{i=1}^M \lambda_i \left( \int R_i(\mathbf{v}) \mathcal{F}(\mathbf{v}|\mathbf{x}, t) d^3\mathbf{v} - \mu_i(\mathbf{x}, t) \right). \end{aligned}$$

The extremum of this objective functional gives the maximum cross-entropy formulation

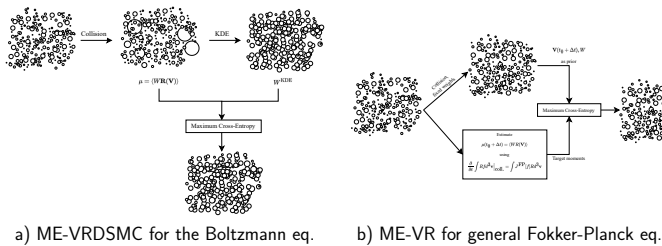
$$\mathcal{F}(\mathbf{v}|\mathbf{x}, t) = \mathcal{F}^{\text{prior}}(\mathbf{v}|\mathbf{x}, t) \exp \left( \sum_{i=1}^M \lambda_i(\mathbf{x}, t) R_i(\mathbf{v}) \right).$$

The Lagrange multipliers can be found using the unconstrained dual formulation  $D(\lambda)$  with the gradient  $\mathbf{g} = \nabla D(\lambda)$  and Hessian  $\mathbf{H}(\lambda) = \nabla^2 D(\lambda)$  leading to an iterative scheme

$$\lambda^{(k+1)} = \lambda^{(k)} - \mathbf{H}^{-1}(\lambda^{(k)}) \mathbf{g}(\lambda^{(k)}).$$

Having computed the Lagrange multipliers, the weight of particles can be evaluated as

$$W^{(k)} = W^{\text{prior}, (k)} \exp \left( \sum_{i=1}^M \lambda_i R_i(\mathbf{V}^{(k)}) \right) \quad \text{for } k = 1, \dots, N_p.$$



Guaranteed stability and conservation with the least bias.

## ME-VRDSMC for Shock Tube problem

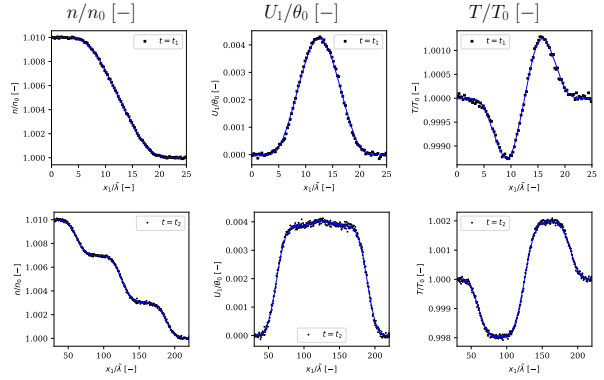


Figure 1: Solution at  $t/\Delta t \in \{200, 1000\}$  with initial density  $\rho_0 \in \{10^{-6}, 10^{-5}\} \text{ kg m}^{-3}$  at the right side of initial discontinuity with thermal velocity  $\theta_0 = \sqrt{k_B T_0/m}$  and temperature  $T_0 = 273 \text{ K}$ . The DSMC solution is obtained using  $10^5$  ensembles (black dots) and the ME-VRDSMC using 50 ensembles matching up to heat flux are shown (blue lines). Here,  $\lambda$  denotes the mean free path of hard-sphere molecules.

## ME-VRDSMC solution to cubic Fokker-Planck eq.

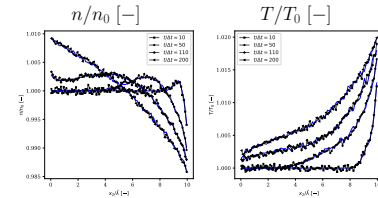


Figure 2: Solution at  $t/\Delta t \in \{10, 50, 110, 200\}$  following a gradient in boundary temperature  $\Delta T^W = 7 \text{ K}$ . The benchmark FP solution is obtained with  $10^5$  ensembles (black dots), and MEVR-FP solution using the maximum cross-entropy formulation with 10 ensembles (blue lines).

## ME-VRDSMC for Lid-Driven Cavity problem

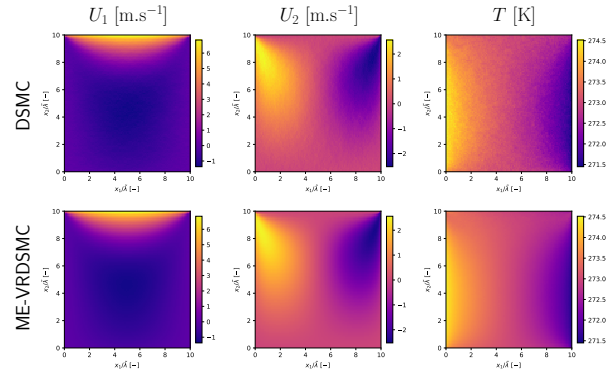


Figure 3: The steady-state solution of the Boltzmann eq. to the lid-driven Cavity problem at  $\text{Kn} = 0.1$  with thermal walls  $(T^{\text{NW}}, T^{\text{SW}}) = ([10, 0, 0]^T, 273)$ ,  $(U^{\text{SW}}, T^{\text{SW}}) = (0, 273)$ ,  $(U^{\text{RW}}, T^{\text{RW}}) = (0, 273)$ ,  $(U^{\text{LW}}, T^{\text{LW}}) = (0, 275)$ . DSMC result is obtained using  $10^5$  and ME-VRDSMC using 1000 ensembles.

## Performance

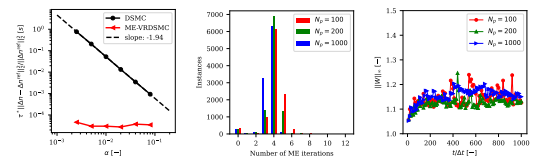


Figure 4: Speed-up of variance-reduction method compared to DSMC as a function of signal magnitude (left), number of iterations required for convergence of the maximum entropy iteration (middle) and evolution of weights in  $\|\cdot\|_\infty$  norm for the ME-VRDSMC solution to shock tube problem.

## References

- [1] Husain A. Al-Mohsen & Nicolas G Hadjiconstantinou, Esaim Math. Model. Numer. Anal., Vol. 44, (2010).
- [2] Mohsen Sadr & Nicolas G. Hadjiconstantinou, J. Comput. Phys. Vol. 472, (2023).

