

Numerical methods for the linear response of nonequilibrium stochastic dynamics

Gabriel STOLTZ

(CERMICS, Ecole des Ponts & MATHERIALS team, Inria Paris)

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Outline

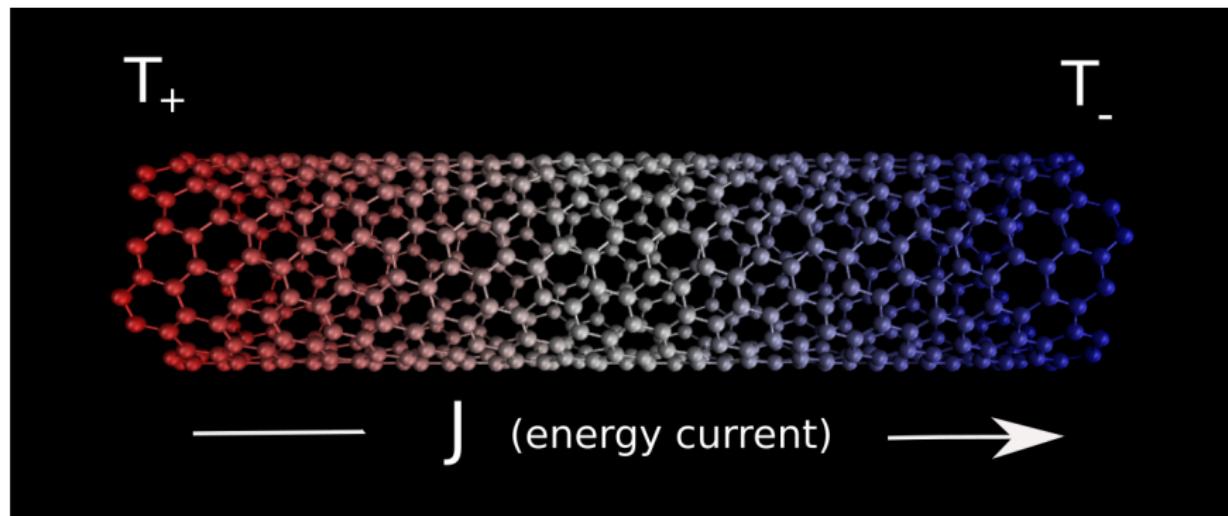
- **Linear response for steady-state nonequilibrium dynamics**
 - Equilibrium dynamics and their perturbations
 - Definition of transport coefficients
- **Error estimates (variance, bias)**
 - Nonequilibrium molecular dynamics (NEMD)
 - Green–Kubo formulas
- **Perspectives**
 - Variance reduction strategies
 - Alternative numerical approaches

Linear response for steady-state nonequilibrium dynamics

Physical context and motivations

Transport coefficients (e.g. thermal conductivity): **quantitative** estimates

$$J = -\kappa \nabla T \quad (\text{Fourier's law})$$



Slow convergence due to **large noise to signal ratio**

Long computational times to estimate κ (up to several weeks/months)

Reference equilibrium dynamics

Positions $q \in \mathcal{D}$ and momenta $p \in \mathbb{R}^d$, phase-space $\mathcal{E} = \mathcal{D} \times \mathbb{R}^d$

Hamiltonian $H(q, p) = V(q) + \frac{1}{2}p^T M^{-1}p$

Langevin dynamics (for given $\gamma > 0$)

$$\begin{cases} dq_t = M^{-1}p_t dt \\ dp_t = -\nabla V(q_t) dt - \gamma M^{-1}p_t dt + \sqrt{\frac{2\gamma}{\beta}} dW_t \end{cases}$$

Generator $\mathcal{L} = \mathcal{L}_{\text{ham}} + \gamma \mathcal{L}_{\text{FD}}$ with

$$\mathcal{L}_{\text{ham}} = p^T M^{-1} \nabla_q - \nabla V^T \nabla_p, \quad \mathcal{L}_{\text{FD}} = -p^T M^{-1} \nabla_p + \frac{1}{\beta} \Delta_p$$

Unique invariant measure $\mu(dq dp) = Z^{-1} e^{-\beta H(q,p)} dq dp = \nu(dq) \kappa(dp)$

Ergodicity results for Langevin dynamics (1)

Almost-sure convergence¹ of ergodic averages $\hat{\varphi}_t = \frac{1}{t} \int_0^t \varphi(q_s, p_s) ds$

Asymptotic variance of ergodic averages (with $\Pi_0 \varphi = \varphi - \mathbb{E}_\mu(\varphi)$)

$$\sigma_\varphi^2 = \lim_{t \rightarrow +\infty} t \text{Var} [\hat{\varphi}_t^2] = 2 \int_{\mathcal{E}} (-\mathcal{L}^{-1} \Pi_0 \varphi) \Pi_0 \varphi d\mu$$

Central limit theorem² when Poisson equation can be solved in $L^2(\mu)$

$$-\mathcal{L}\Phi = \Pi_0 \varphi$$

Well-posedness for \mathcal{L} invertible on subsets of $L_0^2(\mu) = \Pi_0 L^2(\mu)$

$$-\mathcal{L}^{-1} = \int_0^{+\infty} e^{t\mathcal{L}} dt$$

¹Kliemann, *Ann. Probab.* **15**(2), 690-707 (1987)

²Bhattacharya, *Z. Wahrscheinlichkeitstheorie Verw. Gebiete* **60**, 185–201 (1982)

Ergodicity results for Langevin dynamics (2)

Prove **exponential convergence** of the semigroup $e^{t\mathcal{L}}$ on $E \subset L_0^2(\mu)$

- Lyapunov techniques³ $L_W^\infty(\mathcal{E}) = \left\{ \varphi \text{ measurable, } \sup \left| \frac{\varphi}{W} \right| < +\infty \right\}$
- standard **hypocoercive**⁴ setup $H^1(\mu)$
- $E = L^2(\mu)$ after hypoelliptic regularization⁵ from $H^1(\mu)$
- Direct transfer from $H^1(\mu)$ to $E = L^2(\mu)$ by spectral argument⁶
- Directly⁷ $E = L^2(\mu)$ (recently⁸ Poincaré using $\partial_t - \mathcal{L}_{\text{ham}}$)
- **coupling** arguments⁹
- Direct estimates on the resolvent using Schur complements¹⁰

Rate of convergence $\min(\gamma, \gamma^{-1})$ in all cases

³Wu ('01); Mattingly/Stuart/Higham ('02); Rey-Bellet ('06); Hairer/Mattingly ('11)

⁴Villani (2009) and before Talay (2002), Eckmann/Hairer (2003), Hérau/Nier (2004),...

⁵F. Hérau, *J. Funct. Anal.* (2007)

⁶G. Deligiannidis, D. Paulin and A. Doucet, *Ann. Appl. Probab.* (2020)

⁷Hérau (2006), Dolbeault/Mouhot/Schmeiser (2009, 2015)

⁸Armstrong/Mourrat (2019), Cao/Lu/Wang (2019)

⁹A. Eberle, A. Guillin and R. Zimmer, *Ann. Probab.* (2019)

¹⁰E. Bernard, M. Fathi, A. Levitt, G. Stoltz, *Annales Henri Lebesgue* (2022)

Definition of transport coefficients (1)

Linear response of **nonequilibrium dynamics**

Example: $\mathcal{D} = (L\mathbb{T})^d$, **non-gradient** force $F \in \mathbb{R}^{3N}$

$$\begin{cases} dq_t = M^{-1} p_t dt \\ dp_t = \left(-\nabla V(q_t) + \eta F \right) dt - \gamma M^{-1} p_t dt + \sqrt{\frac{2\gamma}{\beta}} dW_t \end{cases}$$

Existence and uniqueness of invariant measure (Lyapunov techniques)

Generator $\mathcal{L} + \eta \tilde{\mathcal{L}}$, **invariant measure** $f_\eta \mu$ with $(\mathcal{L}^* + \eta \tilde{\mathcal{L}}^*) f_\eta = 0$

$$f_\eta = 1 + \eta \mathfrak{f}_1 + \eta^2 \mathfrak{f}_2 + \dots, \quad -\mathcal{L}^* \mathfrak{f}_1 = \tilde{\mathcal{L}}^* \mathbf{1} = \Pi_0 \tilde{\mathcal{L}}^* \mathbf{1}.$$

where adjoints are taken on $L^2(\mu)$ and $\Pi_0 \varphi = \varphi - \int_{\mathcal{E}} \varphi d\mu$

Definition of transport coefficients (2)

Response property $R \in L_0^2(\mu) = \Pi_0 L_0^2(\mu)$, conjugated response $S = \tilde{\mathcal{L}}^* \mathbf{1}$:

$$\begin{aligned}\alpha &= \lim_{\eta \rightarrow 0} \frac{\mathbb{E}_\eta(R)}{\eta} = \int_{\mathcal{E}} R f_1 d\mu = \int_{\mathcal{E}} R \left[(-\mathcal{L}^*)^{-1} S \right] d\mu = \int_{\mathcal{E}} (-\mathcal{L}^{-1} R) S d\mu \\ &= \int_0^{+\infty} \mathbb{E}_0 \left(R(q_t, p_t) S(q_0, p_0) \right) dt\end{aligned}$$

In practice:

- Identify the response function
- Construct a physically meaningful perturbation (bulk or boundary driven)
- Obtain the transport coefficient α (thermal cond., shear viscosity,...)

For the previous example, definition of mobility with $R(q, p) = F^T M^{-1} p$

$$\lim_{\eta \rightarrow 0} \frac{\mathbb{E}_\eta(F^T M^{-1} p)}{\eta} = \beta F^T D F, \quad D = \int_0^{+\infty} \mathbb{E}_0 \left((M^{-1} p_t) \otimes (M^{-1} p_0) \right) dt$$

Error estimates for NEMD

Principle of nonequilibrium molecular dynamics

Example: $\mathcal{D} = (L\mathbb{T})^d$, non-gradient force $F \in \mathbb{R}^{3N}$

$$\begin{cases} dq_t^\eta = M^{-1} p_t^\eta dt \\ dp_t^\eta = \left(-\nabla V(q_t^\eta) + \eta F \right) dt - \gamma M^{-1} p_t^\eta dt + \sqrt{\frac{2\gamma}{\beta}} dW_t \end{cases}$$

Estimator of linear response (observable R with equilibrium average 0)

$$\hat{A}_{\eta,t} = \frac{1}{\eta t} \int_0^t R(q_s^\eta, p_s^\eta) ds \xrightarrow[t \rightarrow +\infty]{\text{a.s.}} \alpha_\eta := \frac{1}{\eta} \int_{\mathcal{E}} R f_\eta d\mu = \alpha + O(\eta)$$

Issues with linear response methods:

- Statistical error with **asymptotic variance** $O(\eta^{-2})$
- Bias $O(\eta)$ due to $\eta \neq 0$
- Bias from finite integration time
- **Timestep discretization bias**

Analysis of variance / finite integration time bias

- **Statistical error** dictated by Central Limit Theorem:

$$\sqrt{t} \left(\widehat{A}_{\eta,t} - \alpha_\eta \right) \xrightarrow[t \rightarrow +\infty]{\text{law}} \mathcal{N} \left(0, \frac{\sigma_{R,\eta}^2}{\eta^2} \right), \quad \sigma_{R,\eta}^2 = \sigma_{R,0}^2 + O(\eta)$$

so $\widehat{A}_{\eta,t} = \alpha + O \left(\frac{1}{\eta \sqrt{t}} \right)$ → requires **long simulation times** $t \sim \eta^{-2}$

- **Finite time integration bias:** $\left| \mathbb{E} \left(\widehat{A}_{\eta,t} \right) - \alpha_\eta \right| \leq \frac{K}{\eta t}$

Bias due to $t < +\infty$ is $O \left(\frac{1}{\eta t} \right)$ → typically **smaller than statistical error**

- Key equality for the proofs: introduce $- \left(\mathcal{L} + \eta \widetilde{\mathcal{L}} \right) \mathcal{R}_\eta = R - \int_{\mathcal{E}} R f_\eta d\mu$

$$\widehat{A}_{\eta,t} - \frac{1}{\eta} \int_{\mathcal{E}} R f_\eta d\mu = \frac{\mathcal{R}_\eta(q_0^\eta, p_0^\eta) - \mathcal{R}_\eta(q_t^\eta, p_t^\eta)}{\eta t} + \frac{\sqrt{2\gamma}}{\eta t \sqrt{\beta}} \int_0^t \nabla \mathcal{R}_\eta(q_s^\eta, p_s^\eta)^T dW_s$$

Analysis of the timestep discretization bias (1)

- **Numerical scheme:** **Markov chain** characterized by evolution operator

$$P_{\Delta t} \varphi(q, p) = \mathbb{E} \left(\varphi(q^{n+1}, p^{n+1}) \mid (q^n, p^n) = (q, p) \right)$$

- Discretization of the Langevin dynamics: **splitting** strategy

$$A = M^{-1} p \cdot \nabla_q, \quad B_\eta = (-\nabla V(q) + \eta F) \cdot \nabla_p, \quad C = -M^{-1} p \cdot \nabla_p + \beta^{-1} \Delta_p$$

First and second order splittings, determined by order of operators

- **Example:** $P_{\Delta t}^{B_\eta, A, \gamma C}$ corresponds to (with $\alpha_{\Delta t} = \exp(-\gamma M^{-1} \Delta t)$)

$$\begin{cases} \tilde{p}^{n+1} = p^n + \Delta t (-\nabla V(q^n) + \eta F), \\ q^{n+1} = q^n + \Delta t M^{-1} \tilde{p}^{n+1}, \\ p^{n+1} = \alpha_{\Delta t} \tilde{p}^{n+1} + \sqrt{\beta^{-1}(1 - \alpha_{\Delta t}^2) M} G^n, \end{cases} \quad (1)$$

where G^n are i.i.d. standard Gaussian random variables

Analysis of the timestep discretization bias (2)

Invariant measure $\mu_{\gamma,\eta,\Delta t}$ of the numerical scheme; $a \geqslant$ weak order

$$\int_{\mathcal{E}} R d\mu_{\gamma,\eta,\Delta t} = \int_{\mathcal{E}} R \left(1 + \eta f_{0,1,\gamma} + \Delta t^a f_{a,0,\gamma} + \eta \Delta t^a f_{a,1,\gamma} \right) d\mu + r_{\varphi,\gamma,\eta,\Delta t},$$

where the remainder is compatible with linear response

$$|r_{\varphi,\gamma,\eta,\Delta t}| \leqslant K(\eta^2 + \Delta t^{a+1}), \quad |r_{\varphi,\gamma,\eta,\Delta t} - r_{\varphi,\gamma,0,\Delta t}| \leqslant K\eta(\eta + \Delta t^{a+1})$$

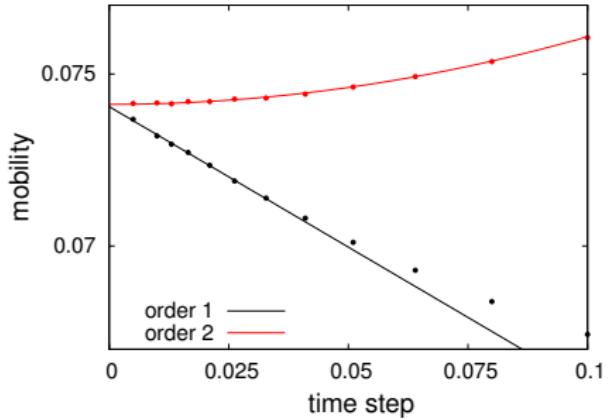
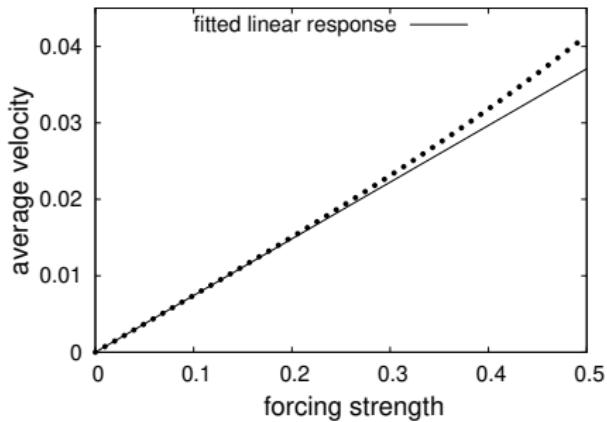
Corollary: error estimates on the numerically computed mobility

$$\begin{aligned} \alpha_{\Delta t} &= \lim_{\eta \rightarrow 0} \frac{1}{\eta} \left(\int_{\mathcal{E}} F^T M^{-1} p \mu_{\gamma,\eta,\Delta t}(dq dp) - \int_{\mathcal{E}} F^T M^{-1} p \mu_{\gamma,0,\Delta t}(dq dp) \right) \\ &= \alpha + \Delta t^a \int_{\mathcal{E}} F^T M^{-1} p f_{a,1,\gamma} d\mu + \Delta t^{a+1} r_{\gamma,\Delta t} \end{aligned}$$

Results in the overdamped limit $\gamma \rightarrow +\infty$

B. Leimkuhler, Ch. Matthews and G. Stoltz, The computation of averages from equilibrium and nonequilibrium Langevin molecular dynamics, *IMA J. Numer. Anal.* **36**(1), 13-79 (2016)

Numerical results



Left: Linear response of the average velocity as a function of η for the scheme associated with $P_{\Delta t}^{\gamma C, B_\eta, A, B_\eta, \gamma C}$ and $\Delta t = 0.01, \gamma = 1$.

Right: Scaling of the mobility $\nu_{F, \gamma, \Delta t}$ for the first order scheme $P_{\Delta t}^{A, B_\eta, \gamma C}$ and the second order scheme $P_{\Delta t}^{\gamma C, B_\eta, A, B_\eta, \gamma C}$.

Error estimates for Green–Kubo formulas

Error estimates on the Green-Kubo formula (1)

- Aim: approximate $\alpha = \int_0^{+\infty} \mathbb{E}_0 \left(R(q_t, p_t) S(q_0, p_0) \right) dt$
- Issues with Green-Kubo formula:
 - Truncature of time (exponential convergence of $e^{t\mathcal{L}}$)
 - The **statistical error** for correlations increases a lot with time lag¹¹
 - Timestep bias and quadrature formula

Possible benefits from...

- Fourier approaches and time series analysis¹²
- importance sampling on trajectory space¹³

¹¹de Sousa Oliveira/Greaney, *Phys. Rev. E* **95** (2017)

¹²Ercole/Marcolongo/Baroni, *Sci. Rep.* **7** (2017)

¹³Donati/Hartmann/Keller, *J. Chem. Phys.* **146** (2017)

Truncation of time and statistical error

“Natural” estimator $\widehat{A}_{K,T} = \frac{1}{K} \sum_{k=1}^K \int_0^T R(q_t^k, p_t^k) S(q_0^k, p_0^k) dt$

- **Truncation bias:** small due to generic exponential decay of correlations

$$\left| \mathbb{E} \left(\widehat{A}_{K,T} \right) - \alpha \right| \leq C e^{-\kappa T}$$

- **Statistical error:** large, increases with the integration time

$$\forall T \geq 1, \quad \text{Var} \left(\widehat{A}_{K,T} \right) \leq C \frac{T}{K}$$

Proof based on the following equality, with $-\mathcal{LR} = R$:

$$\int_0^T R(q_t, p_t) dt = \mathcal{R}(q_0, p_0) - \mathcal{R}(q_t, p_t) + \sqrt{\frac{2\gamma}{\beta}} \int_0^T \nabla \mathcal{R}(q_t, p_t) \cdot dW_t$$

Timestep bias for Green–Kubo formulas

Generic stochastic dynamics satisfying certain technical conditions:

- uniform-in- Δt convergence (relies on $P_{\Delta t}^{[T/\Delta t]}(X_0, dX) \geq a m(dX)$)
- error on the invariant measure of order Δt^a
- $P_{\Delta t} = \text{Id} + \Delta t \mathcal{L} + \Delta t^2 S_1 + \dots + \Delta t^a S_{a-1} + \dots$

Riemann–like formula

For R, S with average 0 w.r.t. μ ,

$$\int_0^{+\infty} \mathbb{E}(R(X_t)S(X_0)) dt = \Delta t \sum_{n=0}^{+\infty} \mathbb{E}_{\Delta t} \left(\tilde{R}_{\Delta t}(X^n) S(X^0) \right) + O(\Delta t^a)$$

with $\tilde{R}_{\Delta t} = (\text{Id} + \Delta t S_1 \mathcal{L}^{-1} + \dots + \Delta t^{a-1} S_{a-1} \mathcal{L}^{-1}) R - \mu_{\Delta t}(\dots)$

Reduces to trapezoidal rule for second order schemes

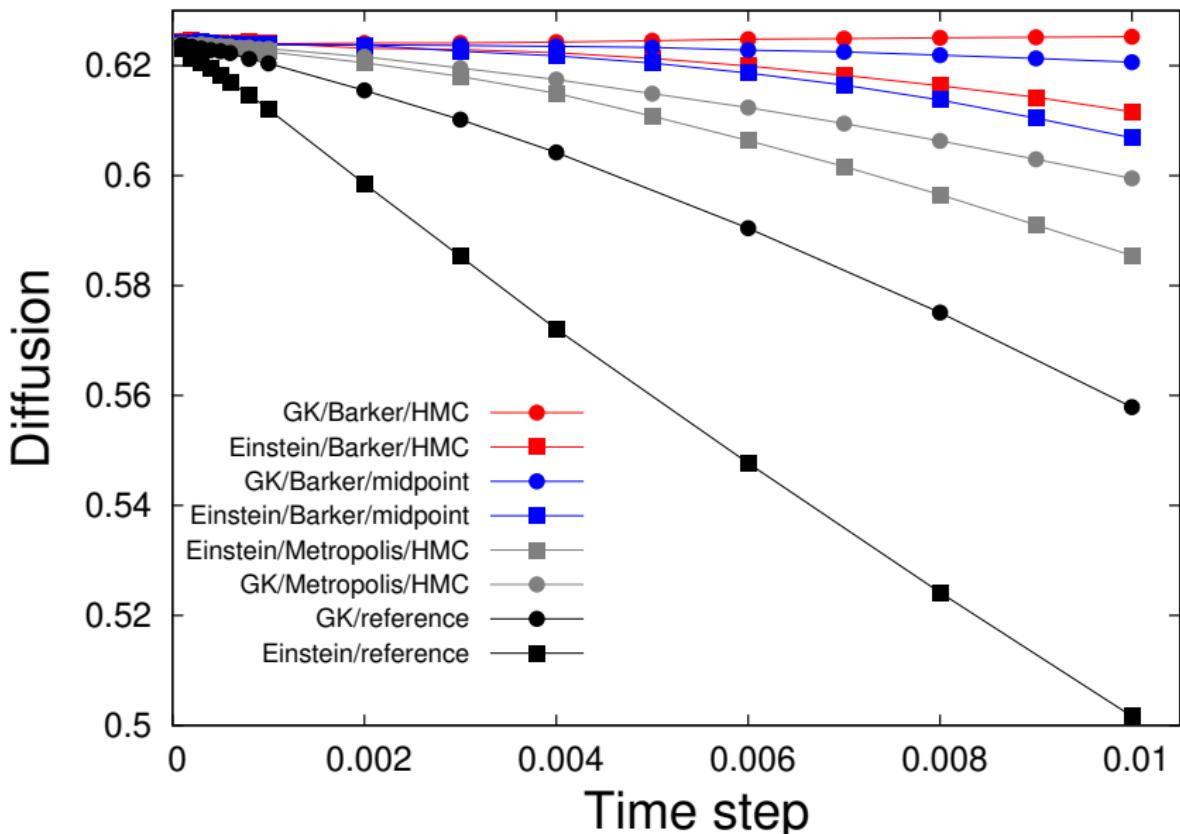
Side result: statistical error for numerical schemes \approx continuous process

B. Leimkuhler, Ch. Matthews and G. Stoltz, *IMA J. Numer. Anal.* **36**(1), 13–79 (2016)

T. Lelièvre and G. Stoltz, *Acta Numerica* **25** (2016)

A. Durmus, A. Enfroy, E. Moulaines, G. Stoltz, *arXiv preprint 2107.14542*

1D overdamped Langevin, $R = S = V'$, cosine potential



Variance reduction techniques and alternative dynamics

Variance reduction for NEMD and Einstein methods

- **Control variate approach:** reduce variance by subtracting a quantity with known average, correlated (in a good way) with the target quantity
- Some instances of control variate techniques for transport coefficients¹⁴
- In the NEMD context, consider

$$\frac{\mathbb{E}_\eta(R)}{\eta} = \frac{\mathbb{E}_\eta(R - \mathcal{L}_\eta \Phi)}{\eta} \quad \text{with} \quad \text{Var}_\eta(R - \mathcal{L}_\eta \Phi) \ll \text{Var}_\eta(R)$$

Zero variance control variate $\Phi_\eta = \mathcal{L}_\eta^{-1}(R - \mu_\eta(R))$

More practical choice¹⁵ $-\mathcal{L}_0 \Phi = R$ for some approximate operator \mathcal{L}_0

Variance of order η^2 when $\mathcal{L}_0 = \mathcal{L} \rightarrow$ relative error $O(1)$

- Extension to time-dependent quantities (Einstein formula)¹⁶

¹⁴Ciccotti/Jacucci (1975); Mangaud/Rotenberg (2020); ...

¹⁵Roussel/Stoltz, SIAM MMS (2019)

¹⁶G. Pavliotis, G. Stoltz, U. Vaes (2022)

Sensitivity estimator: motivation

General non-degenerate stochastic dynamics on $\mathcal{D} = \mathbb{T}^d$

- Reference dynamics $dX_t^0 = b(X_t^0) dt + \sigma(X_t^0) dW_t$
- Perturbed dynamics $dX_t^\eta = (b(X_t^\eta) + \eta F(X_t^\eta)) dt + \sigma(X_t^\eta) dW_t$
- Assume $\sigma\sigma^T$ positive definite \rightarrow unique invariant measure ν_η

Estimator of the linear response

$$\alpha = \lim_{\eta \rightarrow 0} \frac{\nu_\eta(R) - \nu_0(R)}{\eta} = \lim_{t \rightarrow \infty} \mathbb{E}_0 \left\{ \left(\frac{1}{t} \int_0^t (R(X_s^0) - \nu_0(R)) ds \right) Z_t \right\}$$

with $Z_t = \int_0^t U(X_s^0) \cdot dW_s$ and $\sigma U = F$

Motivation: Girsanov theorem, linearization, and longtime limit (formal)

$$\mathbb{E}_\eta \left[\frac{1}{t} \int_0^t R(X_s^\eta) ds \right] = \mathbb{E}_0 \left[\left(\frac{1}{t} \int_0^t R(X_s^0) ds \right) \exp \left(\eta \int_0^t U(X_s^0)^T dW_s - \frac{\eta^2}{2} \int_0^t |U(X_s^0)|^2 ds \right) \right]$$

Sensitivity estimator: proof

Proof of consistency: Generator $\mathcal{L} + \eta\tilde{\mathcal{L}}$, Poisson equation $-\mathcal{L}\hat{R} = \Pi_0 R$ (well posed)

Rewrite the time integral as a martingale, up to remainder terms

$$\int_0^t \Pi_0 R(X_s^0) ds = M_t + \hat{R}(X_0^0) - \hat{R}(X_t^0), \quad M_t = \int_0^t \nabla \hat{R}(X_s)^T \sigma(X_s^0) dW_s$$

and use Itô isometry to write $\frac{1}{t}\mathbb{E}(M_t Z_t)$ as

$$\frac{1}{t} \int_0^t \mathbb{E} \left(U(X_s^0)^T \sigma(X_s^0)^T \nabla \hat{R}(X_s^0) \right) ds \xrightarrow[t \rightarrow +\infty]{} \int_{\mathcal{D}} F^T \nabla \hat{R} d\nu_0 = \alpha$$

Variance uniformly bounded in time: by similar manipulations,

$$\forall t > 0, \quad \text{Var} \left\{ \left(\frac{1}{t} \int_0^t (R(X_s^0) - \nu_0(R)) ds \right) Z_t \right\} \leq C$$

Sensitivity estimator: discretization

Discrete sensitivity estimator (slightly idealized)

$$\mathcal{M}_{\Delta t, N_{\text{iter}}}^{[1]}(R) = \frac{1}{N_{\text{iter}}} \sum_{n=0}^{N_{\text{iter}}-1} (R(X^n) - \mathbb{E}_{\Delta t}(R)) Z^{N_{\text{iter}}}$$

with $Z^{N_{\text{iter}}} = \sum_{n=0}^{N_{\text{iter}}-1} (\sigma(X^n)^{-1} F(X^n))^T G^n$

$$\left| \mathbb{E}_{\Delta t} \left\{ \mathcal{M}_{\Delta t, N_{\text{iter}}}^{[1]}(R) \right\} - \alpha \right| \leq C \left(\Delta t + \frac{1}{\sqrt{N_{\text{iter}} \Delta t}} \right)$$

$$\text{Var}_{\Delta t} \left\{ \mathcal{M}_{\Delta t, N_{\text{iter}}}^{[1]}(R) \right\} \leq C_1 + C_2 \left(\Delta t + \frac{1}{N_{\text{iter}} \Delta t} \right)$$

Finite-time bias $O(\text{time}^{-1/2})$ (time^{-1} for standard time averages)

Extension to Langevin dynamics; **not yet used in actual MD simulations**

P. Plechac, G. Stoltz and T. Wang, *M2AN* **55** (2021)

P. Plechac, G. Stoltz, T. Wang, *arXiv preprint 2112.00126*

Extensions and future work

Study of alternative approaches: several year workplan!

- **Alternative approaches**, possibly with some **blending**
 - Rely on tangent dynamics¹⁷
 - Resort to efficient **coupling methods** such as sticky coupling¹⁸
 - Optimize **synthetic forcings**¹⁹
 - Large deviation techniques to estimate second order cumulants²⁰
 - Consider using transient dynamics
 - ... other options too prospective to be mentioned...
- For all methods...
 - **quantify variance and bias** (related to Δt , η , ...)
 - Application to model systems (atom chains, LJ fluid)

¹⁷ Assaraf/Jourdain/Lelièvre/Roux, *Stoch. Partial Differ. Equ. Anal. Comput.* (2018)

¹⁸ Eberle/Zimmer (2019); Durmus/Eberle/Enfroy/Guillin/Monmarché (2021)

¹⁹ Evans/Morriß (2008); work in progress with Renato Spacek

²⁰ Limmer/Gao/Poggiali, *Eur. Phys. J. B* (2021)