

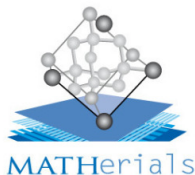
Extending the regime of linear response with synthetic forcings

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- **General setting**
 - ▶ (Non)equilibrium dynamics
 - ▶ Analytical framework
 - ▶ Linear response and transport coefficients
- **Optimizing the perturbation**
 - ▶ Notion of synthetic forcings
 - ▶ Examples
- **Numerical illustrations**

General setting

- The measure μ has associated density ψ
- \mathcal{A}^\dagger denotes the L^2 -adjoint of the operator \mathcal{A} , i.e.

$$\int (\mathcal{A}\varphi)\phi = \int \varphi(\mathcal{A}^\dagger\phi), \quad \forall \varphi, \phi \in C_0^\infty$$

- \mathcal{A}^* denotes the $L^2(\psi)$ -adjoint of the operator \mathcal{A} , i.e.

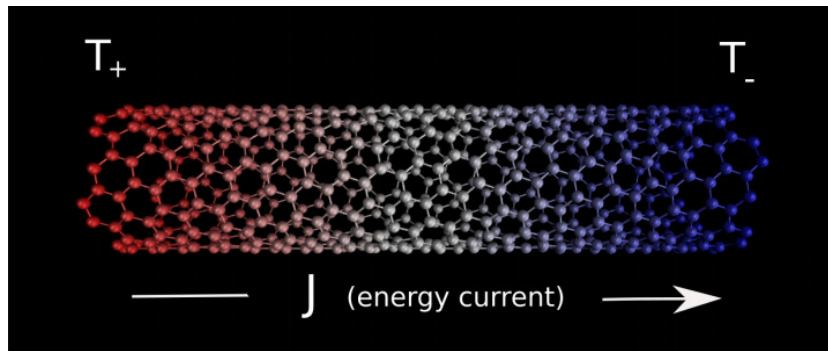
$$\int (\mathcal{A}\varphi)\phi \psi = \int \varphi(\mathcal{A}^*\phi) \psi, \quad \forall \varphi, \phi \in C_0^\infty$$

Physical context and motivation

Transport coefficients are **quantitative** estimates.

Example (thermal conductivity): Fourier's law

$$J = -\kappa \nabla T$$



Long computational times to estimate κ ; can take up to weeks/months.

Nonequilibrium framework

Setting: $\mathcal{X} = \mathbb{T}^d$, **nongradient** force F , periodic C^∞ potential V

Overdamped Langevin dynamics

$$dq_t = (-\nabla V(q_t) + \eta F(q_t)) dt + \sqrt{\frac{2}{\beta}} dW_t$$

Generator $\mathcal{L}_\eta = \mathcal{L}_0 + \eta \tilde{\mathcal{L}}_{\text{phys}}$, with

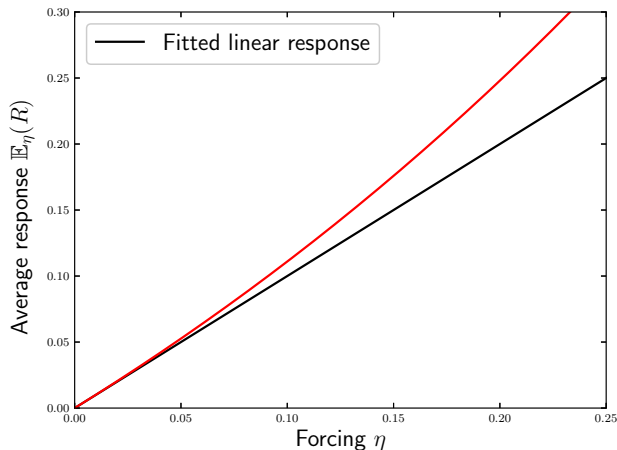
$$\mathcal{L}_0 = -\nabla V^T \nabla + \beta^{-1} \Delta, \quad \tilde{\mathcal{L}}_{\text{phys}} = F^T \nabla$$

Invariant probability measure ψ_η solves the Fokker–Planck

$$\mathcal{L}_\eta^\dagger \psi_\eta = 0, \quad \psi_0(q) = \frac{1}{Z} e^{-\beta V(q)}$$

The perturbation $\eta F(q)$ induces a response $\mathbb{E}_\eta(R)$ for some observable $R(q)$. For small η , the response is linear in η (linear response regime).

Illustration - linear response



Linear response formally defined as

$$\rho_1 = \lim_{\eta \rightarrow 0} \frac{\mathbb{E}_\eta(R) - \mathbb{E}_0(R)}{\eta} = \lim_{\eta \rightarrow 0} \frac{\mathbb{E}_\eta(R)}{\eta} = \lim_{\eta \rightarrow 0} \frac{1}{\eta} \int_{\mathcal{X}} R \psi_\eta$$

Assumptions

- 1 Uniqueness of the invariant probability measure, trajectorial ergodicity.

$$\frac{1}{t} \int_0^t R(q_s^\eta) ds \xrightarrow[t \rightarrow +\infty]{\text{a.s.}} \mathbb{E}_\eta(R) := \int_{\mathcal{X}} R \psi_\eta$$

- 2 Lyapunov estimates
- 3 Stability of *regular* functions by inverse operators
- 4 Stability of *regular* functions by the perturbation operator

Regular: smooth functions that (and whose derivatives) grow at most polynomially

Expansion of the invariant measure

Although unique, ψ_η has closed form unknown

Perturbative regime:¹ Write ψ_η as a perturbation of ψ_0

$$\psi_\eta = f_\eta \psi_0,$$

with f_η a perturbation of the constant function **1**:

$$f_\eta = \mathbf{1} + \eta \mathbf{f}_1 + \eta^2 \mathbf{f}_2 + \cdots$$

Formal asymptotics on the Fokker–Planck $(\mathcal{L}_0 + \eta \tilde{\mathcal{L}}_{\text{phys}})^\dagger \psi_\eta = 0$ leads to

$$-\mathcal{L}_0^* \mathbf{f}_1 = \tilde{\mathcal{L}}_{\text{phys}}^* \mathbf{1}, \quad \mathbf{f}_{n+1} = (-\mathcal{L}_0^*)^{-1} \tilde{\mathcal{L}}_{\text{phys}}^* \mathbf{f}_n$$

¹T. Lelièvre and G. Stoltz, *Acta Numerica* **25**, (2016)

(Non)linear response

Since $\psi_\eta = f_\eta \psi_0$, write ρ_1 as

$$\rho_1 = \lim_{\eta \rightarrow 0} \frac{1}{\eta} \int_{\mathcal{X}} R \psi_\eta = \lim_{\eta \rightarrow 0} \frac{1}{\eta} \int_{\mathcal{X}} R f_\eta \psi_0 = \int_{\mathcal{X}} R \mathfrak{f}_1 \psi_0$$

More generally, the n -th order response is given by

$$\rho_n = \int_{\mathcal{X}} R \mathfrak{f}_n \psi_0$$

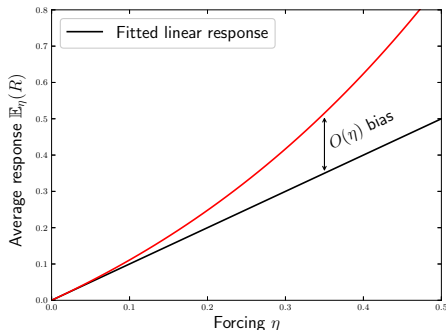
Full response can be written as a polynomial in η

$$r(\eta) = \mathbb{E}_\eta(R) = \eta \rho_1 + \eta^2 \rho_2 + \eta^3 \rho_3 + \cdots$$

Estimating linear response - variance vs bias

Estimator of linear response

$$\hat{\rho}_{\eta,t} = \frac{1}{\eta t} \int_0^t R(q_s) ds \xrightarrow[t \rightarrow +\infty]{\text{a.s.}} \frac{1}{\eta} \int_{\mathcal{X}} R f_{\eta} \psi_0 = \rho_1 + O(\eta)$$



Main issue: Statistical error with asymptotic variance $O(\eta^{-2})$

Idea: Reduce variance by increasing η , but at which values of η does the nonlinear response develop?

Goal: Want to stay in the linear regime for η as large as possible.

Optimizing the perturbation Synthetic forcings

Optimizing the perturbation

Idea: Introduce perturbation with generator $\tilde{\mathcal{L}}_{\text{extra}}$, where

$$\tilde{\mathcal{L}}_{\text{extra}}^* \mathbf{1} = 0$$

Resulting dynamics has generator

$$\mathcal{L}_\eta = \mathcal{L}_0 + \eta(\tilde{\mathcal{L}}_{\text{phys}} + \alpha\tilde{\mathcal{L}}_{\text{extra}})$$

The resulting perturbation is called a **synthetic forcing**².

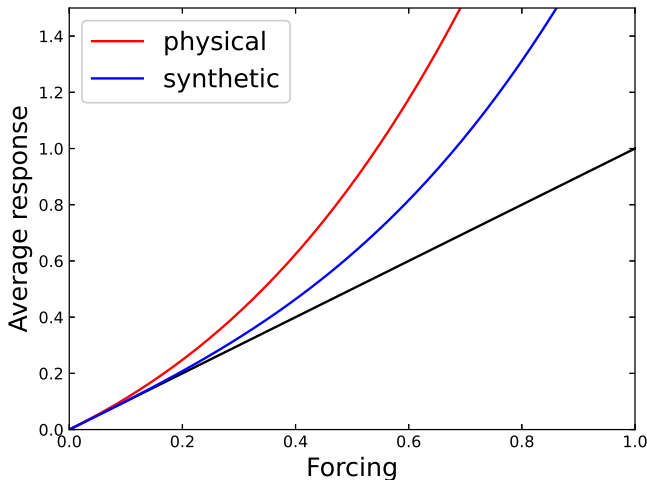
With the addition of the extra forcing, f_1 remains unchanged

$$\begin{aligned} f_1 &= -\mathcal{L}_0^{-1}(\tilde{\mathcal{L}}_{\text{phys}} + \alpha\tilde{\mathcal{L}}_{\text{extra}})^* \mathbf{1} \\ &= -\mathcal{L}_0^{-1} \tilde{\mathcal{L}}_{\text{phys}}^* \mathbf{1} \end{aligned}$$

²Evans, Morriss, (2008)

Illustration - effect of synthetic forcing

In theory, we can find some $\tilde{\mathcal{L}}_{\text{extra}}$ that extends the linear regime



Classes of synthetic forcings

- 1 *First-order differential operators $\tilde{\mathcal{L}}_{\text{extra}} = G^T \nabla_x$, with $\text{div}(G\psi_0) = 0$.*
- 2 *Second-order differential operators of the form $\tilde{\mathcal{L}}_{\text{extra}} = -\partial_{x_i}^* \partial_{x_i}$. In this case, the operator is self-adjoint, i.e. $\tilde{\mathcal{L}}_{\text{extra}} = \tilde{\mathcal{L}}_{\text{extra}}^*$.*
- 3 *First-order differential operators with nontrivial zero order parts, such as $\tilde{\mathcal{L}}_{\text{extra}} = \partial_{x_i}^* = \partial_{x_i} U - \partial_{x_i}$ for $\psi_0(x) = e^{-U(x)}$.*

Examples of synthetic forcings (overdamped Langevin)

Example 1: Divergence-free vector field

$$\begin{cases} \tilde{\mathcal{L}}_{\text{extra}} = G(q)^T \nabla, \quad \text{such that} \quad \text{div}(G e^{-\beta V}) = 0 \\ dq_t = -\nabla V(q_t) dt + \eta F(q_t) dt + \alpha \eta G(q_t) dt + \sigma dW \end{cases}$$

Example 2: Modified fluctuation-dissipation

$$\begin{cases} \tilde{\mathcal{L}}_{\text{extra}} = -\beta^{-1} \nabla^* \nabla = -\nabla V^T \nabla + \beta^{-1} \Delta \\ dq_t = -(1 + \alpha \eta) \nabla V(q_t) dt + \eta F(q_t) dt + \sqrt{\frac{2(1 + \alpha \eta)}{\beta}} dW \end{cases}$$

Example 3: Feynman–Kac forcing

$$\begin{cases} \tilde{\mathcal{L}}_{\text{extra}} = \xi^T \nabla^* = -\xi^T \nabla + \xi^T \nabla V \\ dq_t = -\nabla V(q_t) dt + \eta F(q_t) dt - \eta \alpha \xi dt + \sigma dW \\ \omega_t \propto \exp \left(\alpha \eta \int_0^t \xi^T V(q_s) ds \right) \end{cases}$$

Examples of synthetic forcings (Langevin dynamics)

Example 1: Divergence-free vector field $\tilde{\mathcal{L}}_{\text{extra}} = G_1^T \nabla_q + G_2^T \nabla_p$

$$\begin{cases} dq_t = M^{-1} p_t dt + \alpha \eta G_1(q_t, p_t) dt, \\ dp_t = -\nabla V(q_t) dt + \eta(F(q_t) + \alpha G_2(q_t, p_t)) dt - \gamma M^{-1} p_t dt + \sqrt{\frac{2\gamma}{\beta}} dW_t. \end{cases}$$

Example 2: Modified fluctuation-dissipation $\tilde{\mathcal{L}}_{\text{extra}} = -\beta^{-1} \nabla_q^* \nabla_q - \beta^{-1} \nabla_p^* \nabla_p$

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

Example 3: Feynman-Kac forcing $\tilde{\mathcal{L}}_{\text{extra}} = \xi_1(p)^T \nabla_q^* + \xi_2(q)^T \nabla_p^*$

$$\begin{cases} dq_t = M^{-1} p_t dt - \alpha \eta \xi_1(p_t) dt, \\ dp_t = -\nabla V(q_t) dt + \eta(F(q_t) - \alpha \xi_2(q_t)) dt - \gamma M^{-1} p_t dt + \sqrt{\frac{2\gamma}{\beta}} dW_t, \end{cases}$$

Choosing magnitude of perturbation

Recall: Response as a polynomial in η

$$r_\alpha(\eta) = \mathbb{E}_{\eta,\alpha}(R) = \eta\rho_1 + \eta^2\rho_2(\alpha) + \eta^3\rho_3(\alpha) + \dots$$

- **First approach:** Choose α s.t. the second-order response is killed:

$$\rho_2(\alpha^\star) = 0$$

- **Second approach:** Choose α s.t. $\delta_\alpha(\eta) < \varepsilon$ for as long as possible, namely $\alpha_\star(\varepsilon)$, where

$$\delta_\alpha(\eta) = \left| \frac{r_\alpha(\eta) - \rho_1\eta}{\rho_1\eta} \right|.$$

Numerical illustration

Choosing the observable

Setting: Overdamped Langevin dynamics in 1D, potential $V(q) = \cos(2\pi q)$. We consider the observable

$$R(q) = (a \cos(2\pi q) + b \sin(2\pi q)) e^{\beta V(q)}$$

where $a, b \in \mathbb{R}$.

- b is chosen such that $\rho_1 = 1$, i.e.,

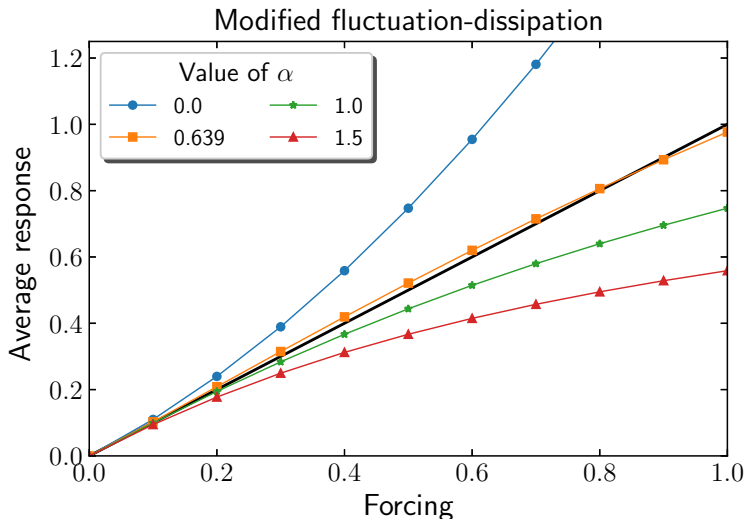
$$b = \left(Z^{-1} \int_{\mathcal{X}} \sin(2\pi q) f_1(q) dq \right)^{-1}, \quad Z = \int_{\mathcal{X}} e^{-\beta V(q)} dq$$

- Similarly, a can be chosen such that ρ_2 is arbitrarily large.

For nonsymmetric potentials, the above still gives $\rho_1, \rho_2 \sim O(1)$.

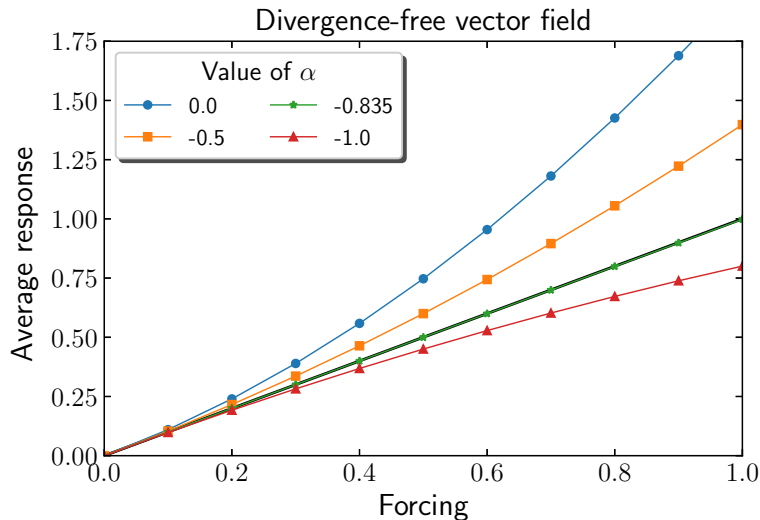
Numerical illustration: modified FD

$$\alpha^* = 1.0, \quad \alpha_*(\varepsilon = 0.05) = 0.639$$



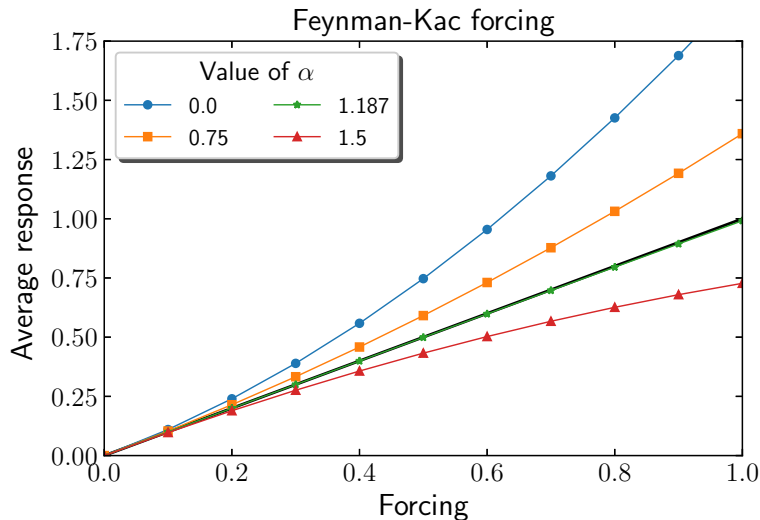
Numerical illustration: div-free vector field

$$\alpha^* = -0.835$$

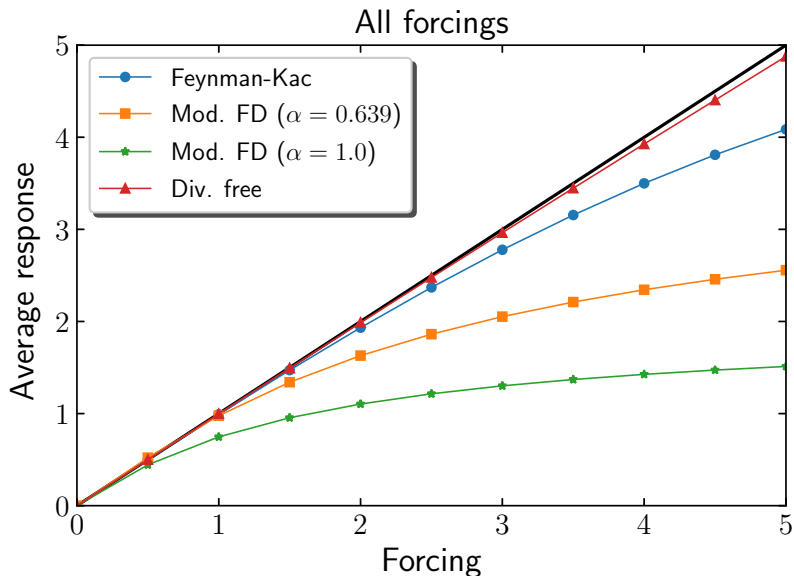


Numerical illustration: Feynman–Kac forcing

$$\alpha^* = 1.187$$



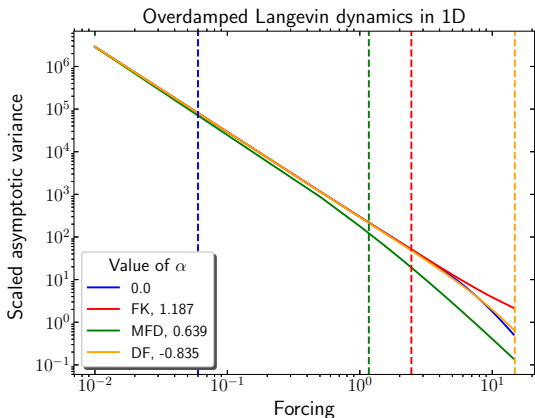
Numerical illustration: all forcings



Numerical illustration: variance reduction (1)

Asymptotic variance $\sigma_{R,\eta}^2$ same order as $\sigma_{R,0}^2$, up to small bias $O(\eta)$:

$$\frac{\sigma_{R,\eta}^2}{\eta^2} = \frac{\sigma_{R,0}^2}{\eta^2} + O\left(\frac{1}{\eta}\right)$$



Numerical illustration: variance reduction (2)

Define the gain as

$$\text{gain} = \left(\frac{\sigma_{R, \eta_0(\varepsilon)}^2}{\eta_0(\varepsilon)^2} \right) \left(\frac{\sigma_{R, \eta_\alpha(\varepsilon)}^2}{\eta_\alpha(\varepsilon)^2} \right)^{-1}.$$

"ratio of the variances of physical system to the synthetic system"

Dynamics	Extra forcing				
	none	MFD	FK	DF (e^V)	DF ($A\nabla V$)
Ovd. 1D	1	6.56×10^2	1.58×10^3	1.28×10^5	-
Ovd. 2D	1	7.65×10^2	3.23×10^4	3.33×10^3	4.03×10^0
Lang. 1D	1	2.18×10^3	1.29×10^3	1.42×10^3	-

- **Promising method:** Can reduce variance by several orders of magnitude
- **Potential applications:** Lennard–Jones fluids (shear viscosity), systems of atom chains (thermal transport)
- **Extension to actual MD systems:** Transport coefficients are *intensive quantities*, i.e. not dependent on system size
⇒ Notion of *prescreening*: two small simulations with $\alpha_1 \neq \alpha_2$, from which optimal α can be extrapolated