

European Research Council
Established by the European Commission

Optimizing the diffusion for overdamped Langevin dynamics

Régis SANTET

(CERMICS, École des Ponts & MATHERIALS Team, Inria Paris)

Joint work with: T. Lelièvre, G. Pavliotis, G. Robin, G. Stoltz

S26: Modeling, analysis and simulation of molecular systems

System: average total energy of the system is fixed (NVT)

Canonical ensemble: system samples the Boltzmann–Gibbs measure μ

$$d\mu = Z_\mu^{-1} e^{-\beta H(q,p)} dq dp, \quad H(q,p) = V(q) + \frac{1}{2} p^\top M^{-1} p.$$

Langevin dynamics: configurational space $\mathcal{E} = \mathbb{T}^d \times \mathbb{R}^d$

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

Compute averages of observables $f \in L^1(\mu)$, rely on ergodic averages:

$$\int_{\mathcal{E}} f d\mu = \lim_{t \rightarrow +\infty} \frac{1}{t} \int_0^t f(q_s, p_s) ds$$

Sampling the **marginal** in position is the problem !

$$d\mu = \underbrace{Z_{\pi}^{-1} e^{-\beta V(q)} dq}_{=: d\pi} Z_{\kappa}^{-1} e^{-\frac{\beta}{2} p^{\top} M^{-1} p} dp$$

Sampling the **marginal** in position is the problem !

$$d\mu = \underbrace{Z_{\pi}^{-1} e^{-\beta V(q)} dq}_{=: d\pi} Z_{\kappa}^{-1} e^{-\frac{\beta}{2} p^{\top} M^{-1} p} dp$$

Idea: only consider the position variable using the **overdamped limit**

$$dq_t = -\nabla V(q_t) dt + \sqrt{2\beta^{-1}} dW_t$$

Sampling the **marginal** in position is the problem !

$$d\mu = \underbrace{Z_{\pi}^{-1} e^{-\beta V(q)} dq}_{=: d\pi} Z_{\kappa}^{-1} e^{-\frac{\beta}{2} p^{\top} M^{-1} p} dp$$

Idea: only consider the position variable using the **overdamped limit**

$$dq_t = -\nabla V(q_t) dt + \sqrt{2\beta^{-1}} dW_t$$

Generalization: **Position dependent pos. def. sym. matrix \mathcal{D}^1**

$$dq_t = \left(-\mathcal{D}(q_t) \nabla V(q_t) + \beta^{-1} \operatorname{div} \mathcal{D}(q_t) \right) dt + \sqrt{2\beta^{-1}} \mathcal{D}(q_t)^{1/2} dW_t$$

$\mathcal{D} \equiv$ inverse of position-dependent mass tensor

¹Jardat/Bernard/Turq/Kneller (1999)

From physics to statistics \rightarrow we can choose \mathcal{D} !

- **Estimate** $\mathbb{E}_\pi[f] = \int_{\mathbb{T}^d} f(q)\pi(q)dq$

with

$$\hat{I}_N := \frac{1}{N} \sum_{i=1}^N f(q^i), \quad q^i \sim \pi$$

From physics to statistics \rightarrow we can choose \mathcal{D} !

- **Estimate** $\mathbb{E}_\pi[f] = \int_{\mathbb{T}^d} f(q)\pi(q)dq$

with

$$\hat{I}_N := \frac{1}{N} \sum_{i=1}^N f(q^i), \quad q^i \sim \pi$$

- **Difficulty**: explore **anisotropic** potentials with **multiple minima**

From physics to statistics \rightarrow we can choose \mathcal{D} !

- **Estimate** $\mathbb{E}_\pi[f] = \int_{\mathbb{T}^d} f(q)\pi(q)dq$

with

$$\hat{I}_N := \frac{1}{N} \sum_{i=1}^N f(q^i), \quad q^i \sim \pi$$

- **Difficulty**: explore **anisotropic** potentials with **multiple minima**
- Find **optimal diffusion coefficient** \mathcal{D} to accelerate convergence

Quantify convergence rate

- Related to the **spectral gap** of the dynamics' generator $\mathcal{L}_{\mathcal{D}}$:

$$\mathcal{L}_{\mathcal{D}}\varphi = (-\mathcal{D}\nabla V + \beta^{-1} \operatorname{div} \mathcal{D}) \cdot \nabla\varphi + \beta^{-1} \mathcal{D} : \nabla^2\varphi$$

Then the law π_t of the process q_t satisfies²

$$\left\| \frac{\pi_t}{\pi} - 1 \right\|_{L^2(\pi)} \leq e^{-\Lambda(\mathcal{D})\beta^{-1}t} \left\| \frac{\pi_0}{\pi} - 1 \right\|_{L^2(\pi)}$$

$\Lambda(\mathcal{D})$: **spectral gap** of $-\beta\mathcal{L}_{\mathcal{D}} \geq 0$

²Lelièvre/Nier/Pavliotis (2013)

Quantify convergence rate

- Related to the **spectral gap** of the dynamics' generator $\mathcal{L}_{\mathcal{D}}$:

$$\mathcal{L}_{\mathcal{D}}\varphi = (-\mathcal{D}\nabla V + \beta^{-1} \operatorname{div} \mathcal{D}) \cdot \nabla \varphi + \beta^{-1} \mathcal{D} : \nabla^2 \varphi$$

Then the law π_t of the process q_t satisfies²

$$\left\| \frac{\pi_t}{\pi} - 1 \right\|_{L^2(\pi)} \leq e^{-\Lambda(\mathcal{D})\beta^{-1}t} \left\| \frac{\pi_0}{\pi} - 1 \right\|_{L^2(\pi)}$$

$\Lambda(\mathcal{D})$: **spectral gap** of $-\beta\mathcal{L}_{\mathcal{D}} \geq 0$

- **Goal**: Compute, explicitly or numerically, \mathcal{D}^* leading to **largest spectral gap**

²Lelièvre/Nier/Pavliotis (2013)

Quantify convergence rate

- Related to the **spectral gap** of the dynamics' generator $\mathcal{L}_{\mathcal{D}}$:

$$\mathcal{L}_{\mathcal{D}}\varphi = (-\mathcal{D}\nabla V + \beta^{-1} \operatorname{div} \mathcal{D}) \cdot \nabla \varphi + \beta^{-1} \mathcal{D} : \nabla^2 \varphi$$

Then the law π_t of the process q_t satisfies²

$$\left\| \frac{\pi_t}{\pi} - 1 \right\|_{L^2(\pi)} \leq e^{-\Lambda(\mathcal{D})\beta^{-1}t} \left\| \frac{\pi_0}{\pi} - 1 \right\|_{L^2(\pi)}$$

$\Lambda(\mathcal{D})$: **spectral gap** of $-\beta\mathcal{L}_{\mathcal{D}} \geq 0$

- **Goal**: Compute, explicitly or numerically, \mathcal{D}^* leading to **largest spectral gap**
- Need to set **normalizing constraints** on \mathcal{D} : $\Lambda(a\mathcal{D}) = a\Lambda(\mathcal{D}) \xrightarrow{a \rightarrow +\infty} +\infty$

²Lelièvre/Nier/Pavliotis (2013)

Quantify convergence rate

- Related to the **spectral gap** of the dynamics' generator $\mathcal{L}_{\mathcal{D}}$:

$$\mathcal{L}_{\mathcal{D}}\varphi = (-\mathcal{D}\nabla V + \beta^{-1} \operatorname{div} \mathcal{D}) \cdot \nabla \varphi + \beta^{-1} \mathcal{D} : \nabla^2 \varphi$$

Then the law π_t of the process q_t satisfies²

$$\left\| \frac{\pi_t}{\pi} - 1 \right\|_{L^2(\pi)} \leq e^{-\Lambda(\mathcal{D})\beta^{-1}t} \left\| \frac{\pi_0}{\pi} - 1 \right\|_{L^2(\pi)}$$

$\Lambda(\mathcal{D})$: **spectral gap** of $-\beta\mathcal{L}_{\mathcal{D}} \geq 0$

- **Goal**: Compute, explicitly or numerically, \mathcal{D}^* leading to **largest spectral gap**
 - Need to set **normalizing constraints** on \mathcal{D} : $\Lambda(a\mathcal{D}) = a\Lambda(\mathcal{D}) \xrightarrow{a \rightarrow +\infty} +\infty$
 - **Examples**: Approach mainly used in Bayesian Inference³: $\mathcal{D} \equiv (\nabla^2 V)^{-1}$
- Other works⁴ suggest $\mathcal{D} \propto e^{\beta V} \mathbf{I}_d$

²Lelièvre/Nier/Pavliotis (2013)

³Girolami/Calderhead (2011)

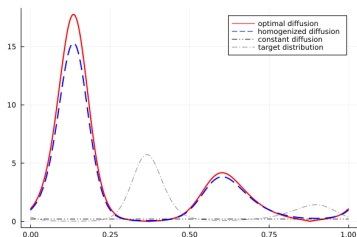
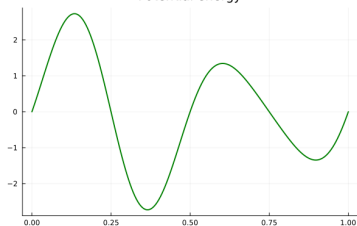
⁴Roberts/Stramer (2002), Lelièvre/Pavliotis/Robin/Santet/Stoltz (In prep.)

Which diffusion coefficient? Metastability case

- Example with $V(q) = \sin(4\pi q)(2 + \sin(2\pi q))$

$\mathcal{D}_{\text{opt}}, \mathcal{D}_{\text{exp}} = e^{\beta V}, \mathcal{D}_{\text{cst}} = a \in \mathbb{R}$ (all three normalized in $L^2(\pi)$)

Potential energy

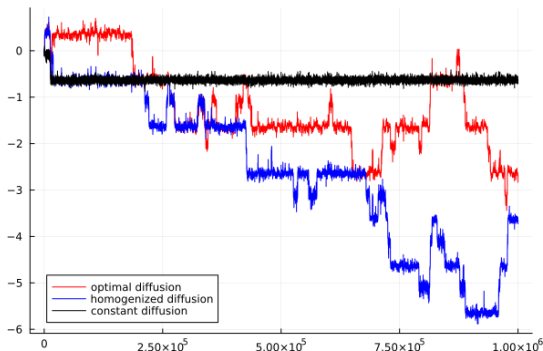
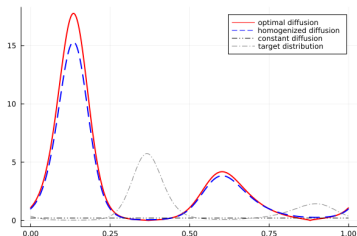
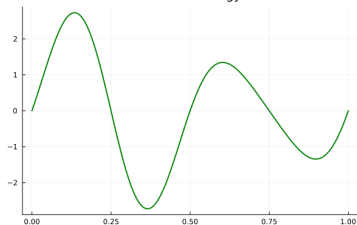


Which diffusion coefficient? Metastability case

• Example with $V(q) = \sin(4\pi q)(2 + \sin(2\pi q))$

$\mathcal{D}_{\text{opt}}, \mathcal{D}_{\text{exp}} = e^{\beta V}, \mathcal{D}_{\text{cst}} = a \in \mathbb{R}$ (all three normalized in $L^2(\pi)$)

Potential energy



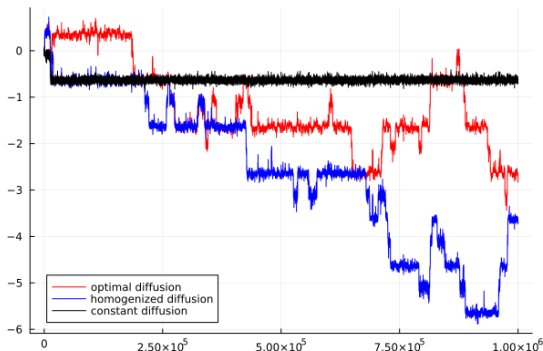
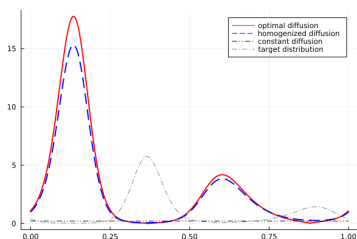
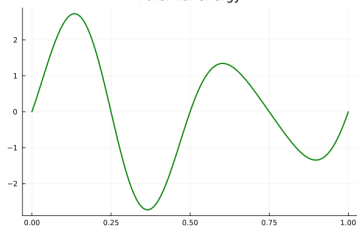
Typical trajectory (same noise)

Which diffusion coefficient? Metastability case

- Example with $V(q) = \sin(4\pi q)(2 + \sin(2\pi q))$

$$\mathcal{D}_{\text{opt}}, \mathcal{D}_{\text{exp}} = e^{\beta V}, \mathcal{D}_{\text{cst}} = a \in \mathbb{R} \text{ (all three normalized in } L^2(\pi))$$

Potential energy



Typical trajectory (same noise)

- 'Optimal' \mathcal{D} helps to cross energy barriers (if $V \uparrow$, then $\mathcal{D} \uparrow$)

Formulation of the optimization problem

- Using $\mathcal{L}_{\mathcal{D}} = -\beta^{-1}\nabla^*\mathcal{D}\nabla$ on $L^2(\pi)$, the **spectral gap** of $-\beta\mathcal{L}_{\mathcal{D}}$ is

$$\Lambda(\mathcal{D}) = \min_{u \in H^1(\mathbb{T}^d) \setminus \{0\}} \left\{ \frac{\int_{\mathbb{T}^d} \nabla u^\top \mathcal{D} \nabla u \, d\pi}{\int_{\mathbb{T}^d} u^2 \, d\pi} \mid \int_{\mathbb{T}^d} u \, d\pi = 0 \right\}$$

Formulation of the optimization problem

- Using $\mathcal{L}_{\mathcal{D}} = -\beta^{-1} \nabla^* \mathcal{D} \nabla$ on $L^2(\pi)$, the **spectral gap** of $-\beta \mathcal{L}_{\mathcal{D}}$ is

$$\Lambda(\mathcal{D}) = \min_{u \in H^1(\mathbb{T}^d) \setminus \{0\}} \left\{ \frac{\int_{\mathbb{T}^d} \nabla u^\top \mathcal{D} \nabla u \, d\pi}{\int_{\mathbb{T}^d} u^2 \, d\pi} \mid \int_{\mathbb{T}^d} u \, d\pi = 0 \right\}$$

- L^p constraints on \mathcal{D} :

$$\mathfrak{D}_p^{a,b} = \left\{ \mathcal{D} \in L^\infty(\mathbb{T}^d, \mathcal{M}_{a,b}) \mid \|\mathcal{D}\|_{L^\infty} \leq 1 \right\}$$

endowed with the norm

$$\|\mathcal{D}\|_{L^p_\pi} = \left(\int_{\mathbb{T}^d} |\mathcal{D}(q)|_F^p e^{-\beta p V(q)} \, dq \right)^{1/p}$$

$\mathcal{D} \in L^p_\pi(\mathbb{T}^d, \mathcal{M}_{a,b})$ for $1 \leq p \leq +\infty$, $a, b \geq 0$ if

$e^{-\beta V(q)} \mathcal{D}(q) \in \mathcal{M}_{a,b} = \left\{ M \in \mathcal{S}_d^+ \mid \forall \xi \in \mathbb{R}^d, a |\xi|^2 \leq \xi^\top M \xi \leq b^{-1} |\xi|^2 \right\}$ a.e.

Theoretical analysis of the optimization problem

- $V \in \mathcal{C}^\infty(\mathbb{T}^d)$
- $\mathcal{D} \mapsto \Lambda(\mathcal{D})$ concave
- $\mathfrak{D}_p^{a,b}$ weakly closed for the L_π^p norm

V and π bounded on $\mathbb{T}^d \Rightarrow \pi$ satisfies a Poincaré inequality

Theorem [Existence of a maximizer]

For any $p \in [1, +\infty]$, there exists

$$\mathcal{D}_p^* = \arg \max_{\mathcal{D} \in \mathfrak{D}_p^{a,b}} \Lambda(\mathcal{D})$$

The maximizer is such that

- $\|\mathcal{D}\|_{L_\pi^p} = 1$;
- For any open set $\Omega \subset \mathbb{T}^d$, there exists $q \in \Omega$ such that $\mathcal{D}_p^*(q) \neq 0$

Maximizer characterization

Euler–Lagrange equation:

$$\left. \frac{d}{dt} \Lambda \left(\mathcal{L}_{\mathcal{D}_p^* + t\delta\mathcal{D}} \right) \right|_{t=0} + \gamma \left. \frac{d}{dt} \left\| \mathcal{D}_p^* + t\delta\mathcal{D} \right\|_{L^p_\pi}^p \right|_{t=0} = 0$$

leads to ($s_p \geq 0$)

$$\mathcal{D}_p^*(q) \propto \left(\sum_{i=1}^{N_2} \nabla u_{\mathcal{D}_p^*}^i(q) \otimes \nabla u_{\mathcal{D}_p^*}^i(q) \right)^{s_p}$$

with $\left(u_{\mathcal{D}_p^*}^i \right)_{1 \leq i \leq N_2}$ eigenvectors associated to $\Lambda(\mathcal{D}_p^*)$

Numerical approximation of the optimization problem

- Piecewise constant approximation for \mathcal{D} on \mathbb{T}^d
- \mathbb{P}_1 Finite Elements approximation to compute $(\Lambda(\mathcal{D}), u_{\mathcal{D}})$:

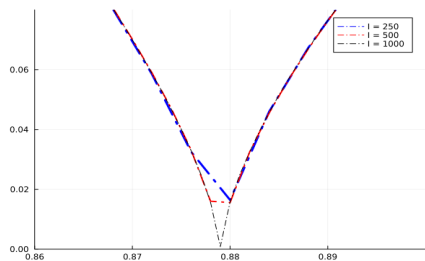
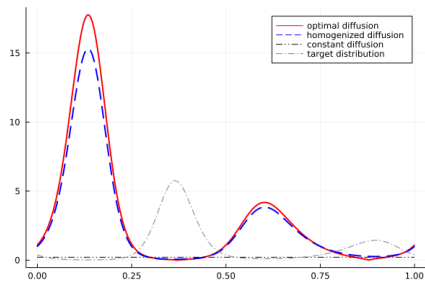
$$A(\mathcal{D})u_{\mathcal{D}} = \Lambda(\mathcal{D})Bu_{\mathcal{D}}$$

with

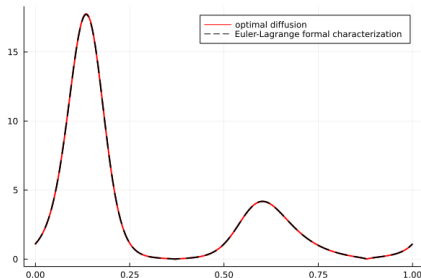
$$A_{i,j}(\mathcal{D}) = \int \nabla \varphi_j^{\top} \mathcal{D} \nabla \varphi_i \, d\pi, \quad B_{i,j} = \int \varphi_j \varphi_i \, d\pi$$

- **Generalized eigenvalue problem:** A sym., B pos. def. sym.

Numerical results - 1

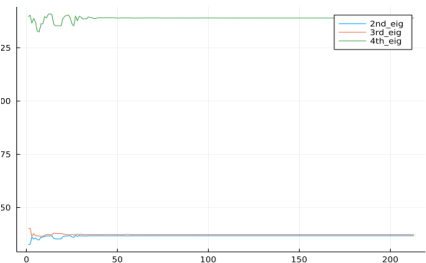
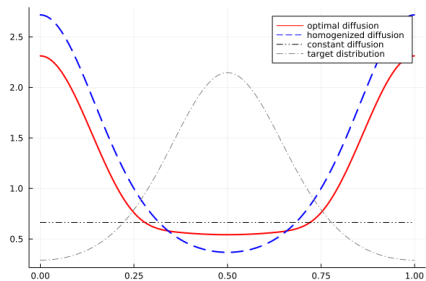


$$V(q) = \sin(4\pi q)(2 + \sin(2\pi q))$$

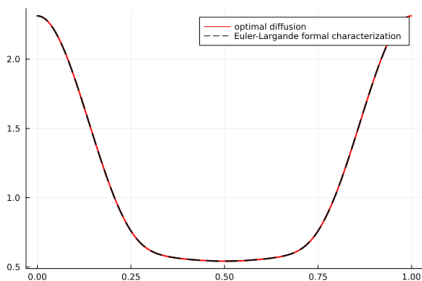


Non-degenerate eigenvalue

Numerical results - 2



$$V(q) = \cos(2\pi q)$$



Degenerate eigenvalue

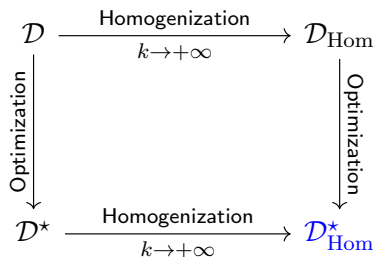
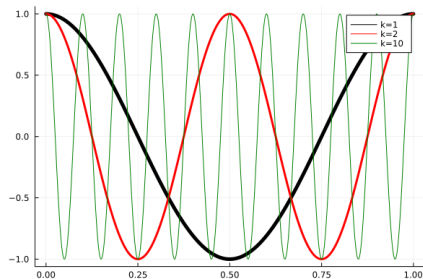
Optimal diffusion in the homogenized limit

- Previous procedure only helpful in **low dimensions**
- Need to solve a **high-dimensional generalized eigenvalue problem**

Optimal diffusion in the homogenized limit

- Previous procedure only helpful in **low dimensions**
- Need to solve a **high-dimensional generalized eigenvalue problem**

Idea: use **homogenization theory** to obtain a good approximation



Optimization of the homogenized limit

Goal: compute

$$\Lambda_{\text{Hom}}^* = \Lambda(\mathcal{D}_{\text{Hom}}^*)$$

$$\begin{array}{ccc} \mathcal{D} & \xrightarrow[k \rightarrow +\infty]{\text{Hom.}} & \mathcal{D}_{\text{Hom}} \\ \text{Opt.} \downarrow & & \downarrow \text{Opt.} \\ \mathcal{D}^* & \xrightarrow[k \rightarrow +\infty]{\text{Hom.}} & \mathcal{D}_{\text{Hom}}^* \end{array}$$

Theorem [Analytic expression]

- **Linear constraint:** For a fixed $M \in \mathcal{S}_d^{++}$, under the constraint, $\int_{\mathbb{T}^d} \mathcal{D} \, d\pi = M$,

$$\mathcal{D}_{\text{Hom}}^*(q) = M/\pi(q)$$

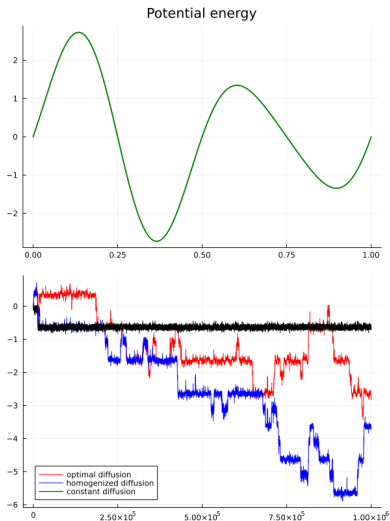
is a maximizer.

- **L_{π}^p constraint, $d = 1$:** Under the constraint $\|\mathcal{D}\|_{L_{\pi}^p} \leq 1$,

$$\mathcal{D}_{\text{Hom}}^*(q) = e^{\beta V(q)}$$

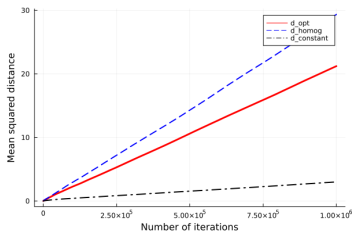
is a maximizer.

Numerical results - Application to sampling experiments - 1



Typical trajectories

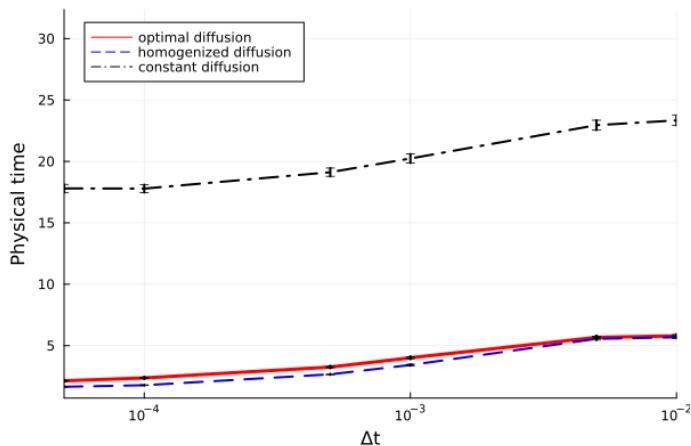
$$V(q) = \sin(4\pi q)(2 + \sin(2\pi q))$$



Mean square distance (averaged)

Numerical results - Application to sampling experiments - 2

Diffusion coefficient	Constant	Homogenized	Optimal
Spectral gap	2.16	10.57	11.23



Transition times between the two wells, $N_{\text{transitions}} = 10^5$

Conclusion

- Using a position-dependant diffusion coefficient can help **sample rare events, cross energy barriers**, etc.
- Optimization problem can be solved numerically in **low dimensions**

Conclusion

- Using a position-dependant diffusion coefficient can help **sample rare events, cross energy barriers**, etc.
- Optimization problem can be solved numerically in **low dimensions**
- In high-dimension, use **free energy F** and coordinate reaction ξ :

$$\mathcal{D}(q) \propto e^{\beta F(\xi(q))}$$

- Good approximation with **homogenization procedure**: $\mathcal{D}_{\text{Hom}}^* = e^{\beta V}$

Conclusion

- Using a position-dependant diffusion coefficient can help **sample rare events, cross energy barriers**, etc.
- Optimization problem can be solved numerically in **low dimensions**
- In high-dimension, use **free energy F** and coordinate reaction ξ :

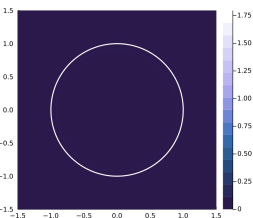
$$\mathcal{D}(q) \propto e^{\beta F(\xi(q))}$$

- Good approximation with **homogenization procedure**: $\mathcal{D}_{\text{Hom}}^* = e^{\beta V}$

Thank you !

Which diffusion coefficient? Anisotropic case

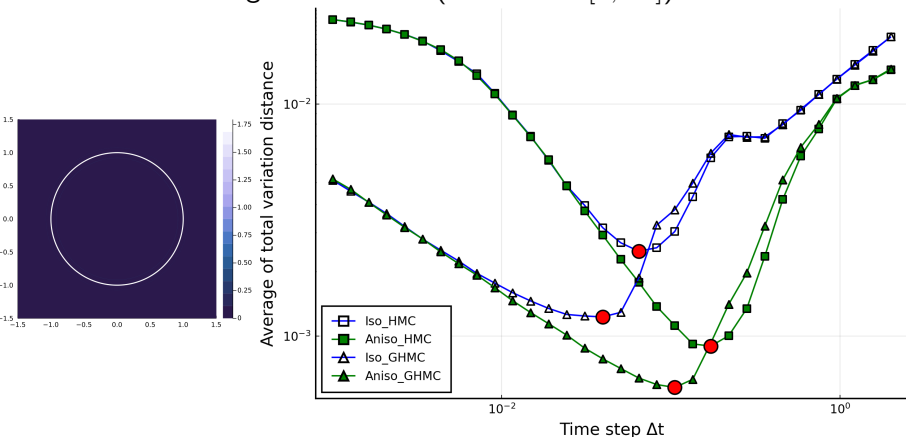
- Anisotropic diffusion coefficient $\mathcal{D}_{\text{Tan}}(q) = \varepsilon \mathbf{I}_2 + \tilde{q}\tilde{q}^\top / \|q\|^2$, $\tilde{q} = (-y \ x)^\top$
- Isotropic diffusion coefficient $\mathcal{D}_{\text{One}} \equiv (1 + \varepsilon)\mathbf{I}_2$, $\varepsilon = 0.1$



Which diffusion coefficient? Anisotropic case

- Anisotropic diffusion coefficient $\mathcal{D}_{\text{Tan}}(q) = \varepsilon \mathbf{I}_2 + \tilde{q}\tilde{q}^\top / \|\tilde{q}\|^2$, $\tilde{q} = (-y \ x)^\top$
- Isotropic diffusion coefficient $\mathcal{D}_{\text{One}} \equiv (1 + \varepsilon)\mathbf{I}_2$, $\varepsilon = 0.1$

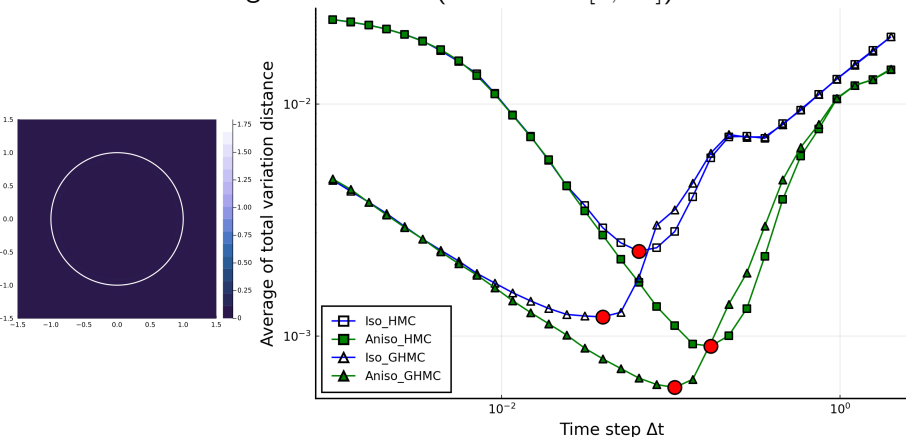
Computing: after fixed number of iterations, distance to the invariant measure of the angle distribution (uniform on $[0, 2\pi]$)



Which diffusion coefficient? Anisotropic case

- **Anisotropic diffusion coefficient** $\mathcal{D}_{\text{Tan}}(q) = \varepsilon \mathbf{I}_2 + \tilde{q}\tilde{q}^\top / \|\tilde{q}\|^2$, $\tilde{q} = (-y \ x)^\top$
- **Isotropic diffusion coefficient** $\mathcal{D}_{\text{One}} \equiv (1 + \varepsilon)\mathbf{I}_2$, $\varepsilon = 0.1$

Computing: after fixed number of iterations, distance to the invariant measure of the angle distribution (uniform on $[0, 2\pi]$)



⇒ Compromise: **small**/**large** time steps (exploration vs rejection)

Periodic homogenization procedure

- Decrease the period: $(\mathbb{Z}/k)^d$ -periodic functions $V_{\#,k}(q) = V(kq)$ and $\mathcal{D}_{\#,k}(q) = \mathcal{D}(kq)$
- Write the spectral gap problem:

$$\Lambda_{\#,k}(\mathcal{D}) = \min_{u \in H^1(\mathbb{T}^d) \setminus \{0\}} \left\{ \frac{\int_{\mathbb{T}^d} \nabla u^\top \mathcal{D}_{\#,k} \nabla u e^{-\beta V_{\#,k}}}{\int_{\mathbb{T}^d} u^2 e^{-\beta V_{\#,k}}} \mid \int_{\mathbb{T}^d} u e^{-\beta V_{\#,k}} = 0 \right\}$$

⁵See for instance Allaire, *Shape Optimization by the Homogenization Method* (2002)

Periodic homogenization procedure

- Decrease the period: $(\mathbb{Z}/k)^d$ -periodic functions $V_{\#,k}(q) = V(kq)$ and $\mathcal{D}_{\#,k}(q) = \mathcal{D}(kq)$
- Write the spectral gap problem:

$$\Lambda_{\#,k}(\mathcal{D}) = \min_{u \in H^1(\mathbb{T}^d) \setminus \{0\}} \left\{ \frac{\int_{\mathbb{T}^d} \nabla u^\top \mathcal{D}_{\#,k} \nabla u e^{-\beta V_{\#,k}}}{\int_{\mathbb{T}^d} u^2 e^{-\beta V_{\#,k}}} \mid \int_{\mathbb{T}^d} u e^{-\beta V_{\#,k}} = 0 \right\}$$

- Use **H-convergence**:⁵ $\exists \overline{\mathcal{D}} \in \mathfrak{D}_p^{a,b}$, $\Lambda_{\#,k}(\mathcal{D}) \xrightarrow{k \rightarrow +\infty} \Lambda_{\text{Hom}}(\mathcal{D})$ with

$$\Lambda_{\text{Hom}}(\mathcal{D}) := \min_{u \in H^1(\mathbb{T}^d) \setminus \{0\}} \left\{ \frac{\int_{\mathbb{T}^d} \nabla u^\top \overline{\mathcal{D}} \nabla u}{\int_{\mathbb{T}^d} u^2} \mid \int_{\mathbb{T}^d} u = 0 \right\}$$

- $\overline{\mathcal{D}}$ can be expressed using \mathcal{D} and corrector functions appearing in the H-convergence procedure

⁵See for instance Allaire, *Shape Optimization by the Homogenization Method* (2002)

Definition [H -convergence]

A sequence $(\mathcal{A}^k)_{k \geq 1} \subset L^\infty(\mathbb{T}^d, \mathcal{M}_{a,b})$ H -converges to $\bar{\mathcal{A}} \in L^\infty(\mathbb{T}^d, \mathcal{M}_{a,b})$ if, for any $f \in H^{-1}(\mathbb{T}^d)$ such that $\langle f, \mathbf{1} \rangle_{H^{-1}, H^1} = 0$, the sequence $(u^k)_{k \geq 1} \subset H^1(\mathbb{T}^d)$ of solutions to

$$\begin{cases} -\operatorname{div}(\mathcal{A}^k \nabla u^k) = f & \text{on } \mathbb{T}^d, \\ \int_{\mathbb{T}^d} u^k(q) dq = 0 \end{cases}$$

satisfies in the limit $k \rightarrow +\infty$,

$$\begin{cases} u^k \rightharpoonup u & \text{weakly in } H^1(\mathbb{T}^d), \\ \mathcal{A}^k \nabla u^k \rightharpoonup \bar{\mathcal{A}} \nabla u & \text{weakly in } L^2(\mathbb{T}^d)^d, \end{cases}$$

where $u \in H^1(\mathbb{T}^d)$ is the solution of the homogenized problem

$$\begin{cases} -\operatorname{div}(\bar{\mathcal{A}} \nabla u) = f & \text{on } \mathbb{T}^d, \\ \int_{\mathbb{T}^d} u(q) dq = 0 \end{cases}$$

Definition [Correctors]

If $\mathcal{A} = \mathcal{D} \exp(-\beta V)$, $(w_i)_{1 \leq i \leq d} \subset H^1(\mathbb{T}^d)$ is the family of unique solutions to the problem

$$\begin{cases} -\operatorname{div}(\mathcal{A}(e_i + \nabla w_i)) = 0, \\ \int_{\mathbb{T}^d} w = 0 \end{cases}$$

Then for any $\xi \in \mathbb{R}^d$,

$$\xi^\top \overline{\mathcal{D}} \xi = \xi^\top \left(\int_{\mathbb{T}^d} \mathcal{D}(q) d\pi \right) \xi - \int_{\mathbb{T}^d} \nabla w_\xi^\top \mathcal{D} \nabla w_\xi d\pi.$$

Homogenization of the optimal diffusion

Goal: optimize for a given $k \geq 1$, then let $k \rightarrow +\infty$

- Recall the oscillating potential $V_{\#,k}(q) = V(kq)$. Let $\mathcal{D}_{\#,k,p}^{a,b} \equiv \mathcal{D}_p^{a,b}$ but defined with $V_{\#,k}$ instead of V .

- Let

$$\Lambda^k(\mathcal{D}) = \min_{u \in H^1(\mathbb{T}^d) \setminus \{0\}} \left\{ \frac{\int_{\mathbb{T}^d} \nabla u^\top \mathcal{D} \nabla u e^{-\beta V_{\#,k}}}{\int_{\mathbb{T}^d} u^2 e^{-\beta V_{\#,k}}} \mid \int_{\mathbb{T}^d} u e^{-\beta V_{\#,k}} = 0 \right\}$$

and

$$\Lambda^{k,\star} = \max_{\mathcal{D} \in \mathcal{D}_{\#,k,p}^{a,b}} \Lambda^k(\mathcal{D})$$

Homogenization of the optimal diffusion

Goal: optimize for a given $k \geq 1$, then let $k \rightarrow +\infty$

- Recall the oscillating potential $V_{\#,k}(q) = V(kq)$. Let $\mathfrak{D}_{\#,k,p}^{a,b} \equiv \mathfrak{D}_p^{a,b}$ but defined with $V_{\#,k}$ instead of V .

- Let

$$\Lambda^k(\mathcal{D}) = \min_{u \in H^1(\mathbb{T}^d) \setminus \{0\}} \left\{ \frac{\int_{\mathbb{T}^d} \nabla u^\top \mathcal{D} \nabla u e^{-\beta V_{\#,k}}}{\int_{\mathbb{T}^d} u^2 e^{-\beta V_{\#,k}}} \mid \int_{\mathbb{T}^d} u e^{-\beta V_{\#,k}} = 0 \right\}$$

and

$$\Lambda^{k,\star} = \max_{\mathcal{D} \in \mathfrak{D}_{\#,k,p}^{a,b}} \Lambda^k(\mathcal{D})$$

Lemma

There exists a maximizer $\mathcal{D}^{k,\star} \in \mathfrak{D}_p^{a,b}$ such that, denoting by $\mathcal{D}_{\#,k}^{k,\star}(q) = \mathcal{D}^{k,\star}(kq)$,

$$\Lambda^k(\mathcal{D}_{\#,k}^{k,\star}) = \Lambda^{k,\star}$$

Commutation between Homogenization and Optimization

$$\begin{array}{ccc} \Lambda(\mathcal{D}) & \xrightarrow[k \rightarrow +\infty]{\text{Hom.}} & \Lambda_{\text{Hom}}(\mathcal{D}) \\ \text{Opt.} \downarrow & & \downarrow \text{Opt.} \\ \Lambda^{k,\star} & \xrightarrow[k \rightarrow +\infty]{\text{Hom.}} & \Lambda_{\text{Hom}}^{\star} \end{array}$$

Theorem

The sequence $(\Lambda^{k,\star})_{k \geq 1}$ converges to $\Lambda_{\text{Hom}}^{\star} := \Lambda(\mathcal{D}_{\text{Hom}}^{\star})$.

Commutation between Homogenization and Optimization

$$\begin{array}{ccc} \Lambda(\mathcal{D}) & \xrightarrow[k \rightarrow +\infty]{\text{Hom.}} & \Lambda_{\text{Hom}}(\mathcal{D}) \\ \text{Opt.} \downarrow & & \downarrow \text{Opt.} \\ \Lambda^{k,\star} & \xrightarrow[k \rightarrow +\infty]{\text{Hom.}} & \Lambda_{\text{Hom}}^{\star} \end{array}$$

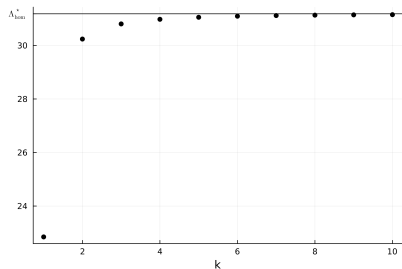
Theorem

The sequence $(\Lambda^{k,\star})_{k \geq 1}$ converges to $\Lambda_{\text{Hom}}^{\star} := \Lambda(\mathcal{D}_{\text{Hom}}^{\star})$.

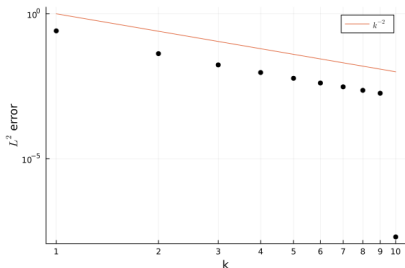
- This implies that a good proxy ($d = 1$) is $\mathcal{D}_{\text{Hom}}^{\star} = e^{\beta V}$
- In this case, $\overline{\mathcal{D}} = (\int_{\mathbb{T}} e^{-\beta V})^{-1} := Z^{-1}$, and

$$\Lambda_{\text{Hom}}^{\star} = 4\pi^2 Z^{-1}$$

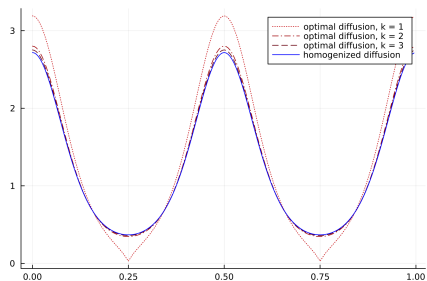
Numerical results - 3



$(\Lambda^{k,*})_{k \geq 1}$ converges to Λ_{Hom}^*



$$V(q) = \cos(4\pi q)$$



$(\mathcal{D}^{k,*})_{k \geq 1}$ and $\mathcal{D}_{\text{Hom}}^*$ (rescaled with $1/k$ unit cell)