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# 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

(Non)equilibrium Molecular Dynamics: Algorithms, Analysis, and Application

# Diffusion dependent Overdamped Langevin dynamics

- **Aim:** Estimation of  $\mathbb{E}_\pi[f] = \int_{\mathbb{T}^d} f(q)\pi(q)dq$ ,  $\pi \propto e^{-\beta V}$   
with the estimator

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- **Challenge:** **Find optimal diffusion coefficient  $\mathcal{D}$  to accelerate convergence**

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## 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 for any initial distribution  $\pi_0$ , the law  $\pi_t$  of the process  $q_t$  satisfies<sup>2</sup>

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

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

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  - 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 Inference<sup>3</sup>:  $\mathcal{D} \equiv (\nabla^2 V)^{-1}$
- Other works<sup>4</sup> suggest  $\mathcal{D} \propto e^{\beta V} \mathbf{I}_d$

<sup>2</sup>Lelièvre/Nier/Pavliotis (2013)

<sup>3</sup>Girolami/Calderhead (2011)

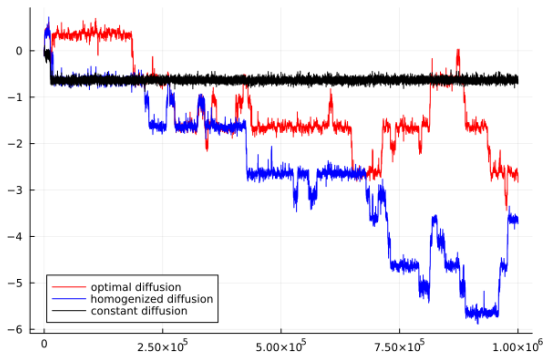
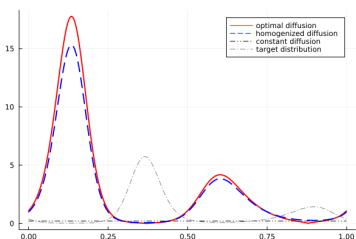
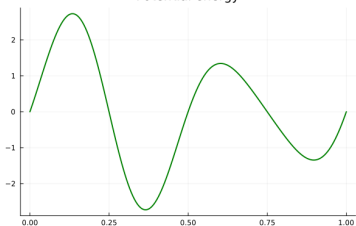
<sup>4</sup>Roberts/Stramer (2002), Lelièvre/Pavliotis/Robin/Santet/Stoltz (In prep.)

# 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



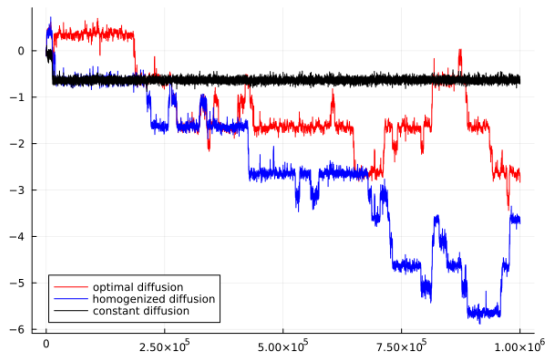
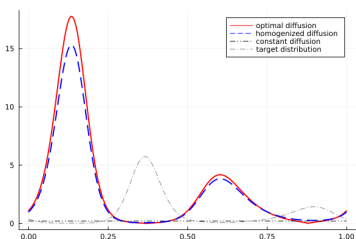
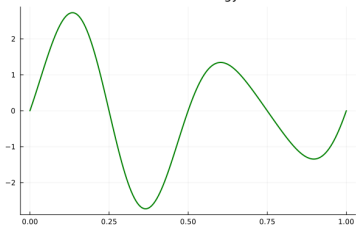
RWMH example trajectories (same noise)

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RWMH example trajectories (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

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

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

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

endowed with

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

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

# Theoretical analysis of the optimization problem

- $V \in \mathcal{C}^\infty(\mathbb{T}^d)$ ,  $V$  and  $\pi$  bounded on  $\mathbb{T}^d$
- $\pi$  satisfies a Poincaré inequality
- $\mathfrak{D}_p^{a,b}$  weakly closed for  $L_\pi^p$
- $\mathcal{D} \mapsto \Lambda(\mathcal{D})$  concave

## 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

- **Differentiability issues** when  $\Lambda(\mathcal{D}_p^*)$  is degenerate (which is expected)  
→ smooth-maximum approach

$$f_\alpha(x_1, \dots, x_n) = \frac{\sum_{i=1}^n x_i e^{\alpha x_i}}{\sum_{i=1}^n e^{\alpha x_i}} \xrightarrow{\alpha \rightarrow +\infty} \max_{1 \leq i \leq n} x_i.$$

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Euler–Lagrange equation

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

and formal limit when  $\alpha \rightarrow +\infty$  leads to

$$\mathcal{D}_p^*(q) = \gamma_p \left| \mathcal{D}_p^*(q) \right|_F^{2-p} e^{\beta(p-1)V(q)} \sum_{i=1}^{N_2} \nabla u_{\mathcal{D}_p^*}^i(q) \otimes \nabla u_{\mathcal{D}_p^*}^i(q)$$

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



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- **Discussion about positivity** (ergodicity issues ?)

# Numerical approximation of the optimization problem

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

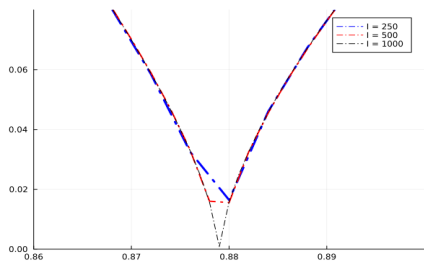
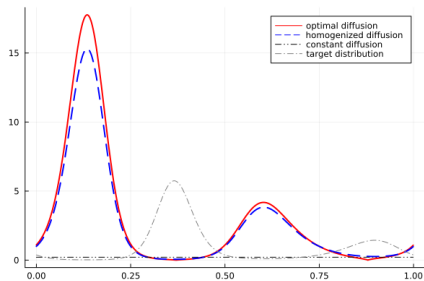
$$\boxed{A(\mathcal{D})u_{\mathcal{D}} = \Lambda(\mathcal{D})Bu_{\mathcal{D}}}$$

with

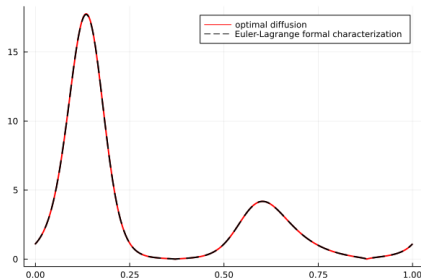
$$A_{i,j}(\mathcal{D}) = \int \nabla \varphi_j^{\top} \mathcal{D} \nabla \varphi_i \, d\pi, \quad B_{i,j} = \int \varphi_j \varphi_i \, d\pi$$

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

# Numerical results - 1

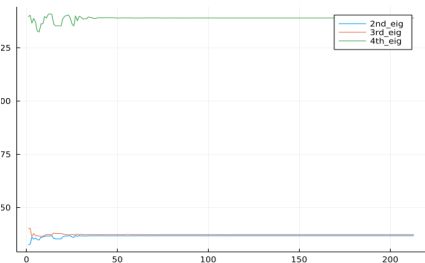
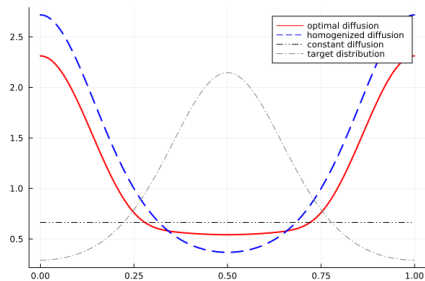


$$V(q) = \sin(4\pi q)(2 + \sin(2\pi q))$$

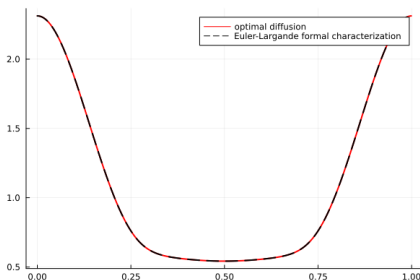


Non-degenerate eigenvalue

# Numerical results - 2



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



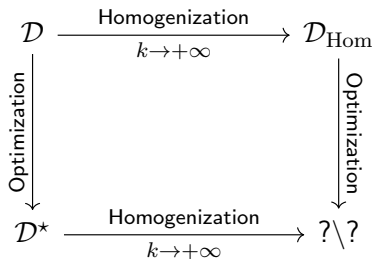
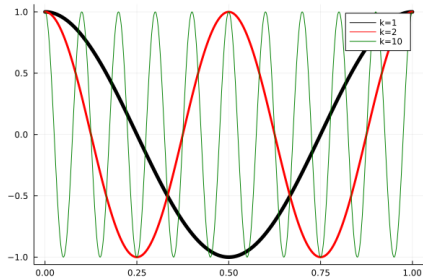
Degenerate eigenvalue

# Optimal diffusion in the homogenized limit

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

**Goal:** Obtain a **good approximation** of the optimal diffusion

- Idea 1: study the asymptotic behaviour of the optimal diffusion in the **homogenized limit**
- Idea 2: optimize the periodic homogenization limit



# 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:

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

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

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

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# Optimization of the homogenized limit

**Goal:** compute

$$\Lambda_{\text{Hom}}^* = \sup_{\mathcal{D} \in \mathfrak{D}_p^{a,b}} \Lambda_{\text{Hom}}(\mathcal{D})$$

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

## 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.

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

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

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# 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

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

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## 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  $\Lambda_{\text{Hom}}^{\star} := \Lambda(\mathcal{D}_{\text{Hom}}^{\star})$ .

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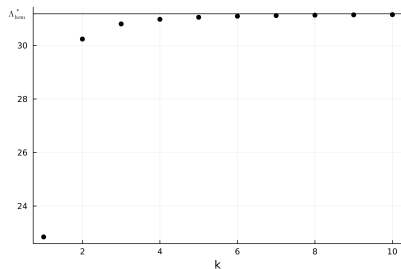
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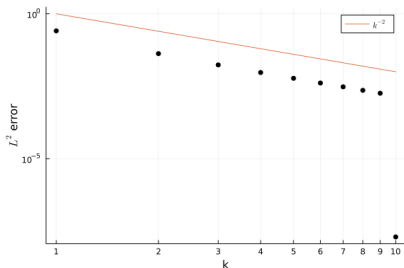
- This implies that a good proxy ( $d = 1$ ) is  $\mathcal{D}_{\text{Hom}}^{\star} = e^{\beta V}$
- In this case,  $\overline{\mathcal{D}} = (\int_{\mathbb{T}} e^{-\beta V})^{-1} := Z^{-1}$ , and

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

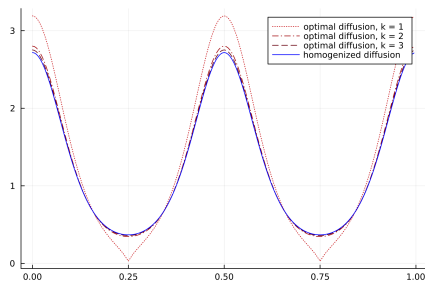
# Numerical results - 3



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

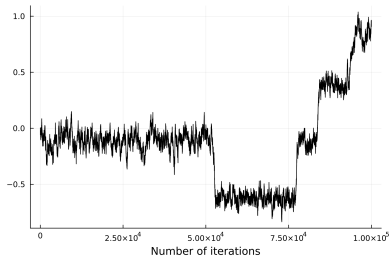


$$V(q) = \cos(4\pi q)$$

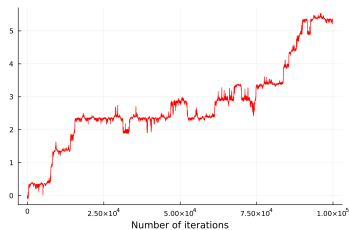


$(\mathcal{D}^{k,*})_{k \geq 1}$  and  $\mathcal{D}_{\text{Hom}}^*$  (rescaled with  $1/k$  unit cell)

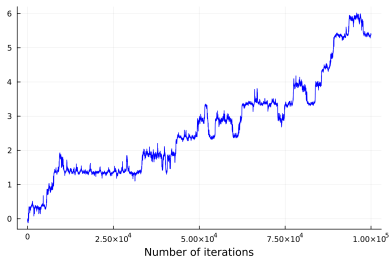
# Numerical results - Application to sampling experiments - 1



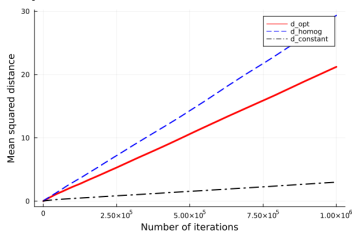
$$V(q) = \sin(4\pi q)(2 + \sin(2\pi q))$$



Constant diffusion coefficient



Optimal diffusion coefficient

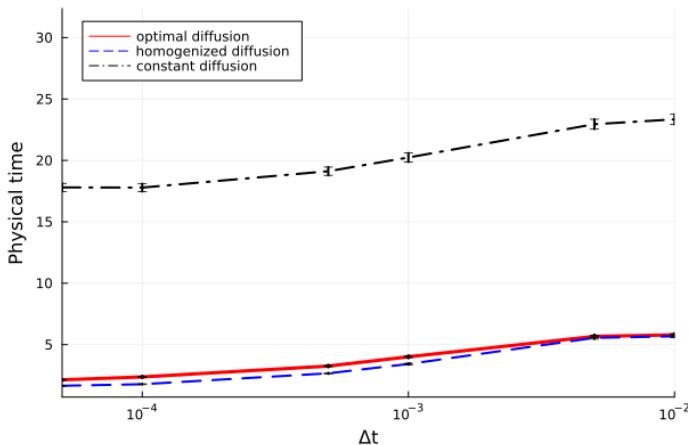


Homogenized diffusion coefficient

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

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- Spectral gap is only **one** criterion: sampling issues when  $\mathcal{D}^*(q) \approx 0$
- Normalization constraint on  $\mathcal{D}$ : which one to choose ?

- Adapt to nonequilibrium dynamics: non-gradient force  $F$ , use biasing scalar function  $\mathcal{E} > 0$

$$dq_t^\eta = \mathcal{E}(q_t^\eta) (-\nabla V(q_t^\eta) + \eta F(q_t^\eta)) dt + \sqrt{2\mathcal{E}(q_t^\eta)} dW_t.$$

- $\mathcal{L}_\mathcal{E}^\eta$  is not self-adjoint: optimize real part of the **spectral gap**
- Antisymmetric part in the gen. eigen. problem, complex eigenvalues

$$(A - \eta M) u_\mathcal{E} = \Lambda(\mathcal{E}) B(\mathcal{E}) u_\mathcal{E}$$

$$A \in \mathcal{S}_d, M \in \mathcal{A}_d, B \in \mathcal{S}_d^{++}$$

- Adapt to QSD: from a metastable state  $A$ , if  $\nu^{\mathcal{D}}$  is a QSD *i.e.*

$$\begin{cases} \mathcal{L}_{\mathcal{D}}^* \nu_{\mathcal{D}} = \lambda(\mathcal{D}) \nu_{\mathcal{D}} & \text{on } A \\ \nu_{\mathcal{D}} = 0 & \text{on } \partial A \end{cases}$$

- Then to accelerate convergence, we maximize  $\lambda_2 - \lambda_1$  which amounts to

$$\max_{\mathcal{D} + \text{proper normalization}} \lambda_2(\mathcal{D})$$

- It is observed numerically that there is indeed an optimum when  $\mathcal{D} \propto e^{\alpha V}$ , with  $\alpha \approx 1.5$  (**normalization constraint effect**)

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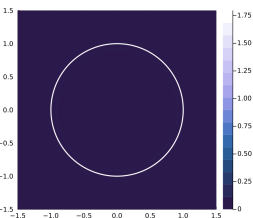
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Thank you !

# Which diffusion coefficient? Anisotropic case

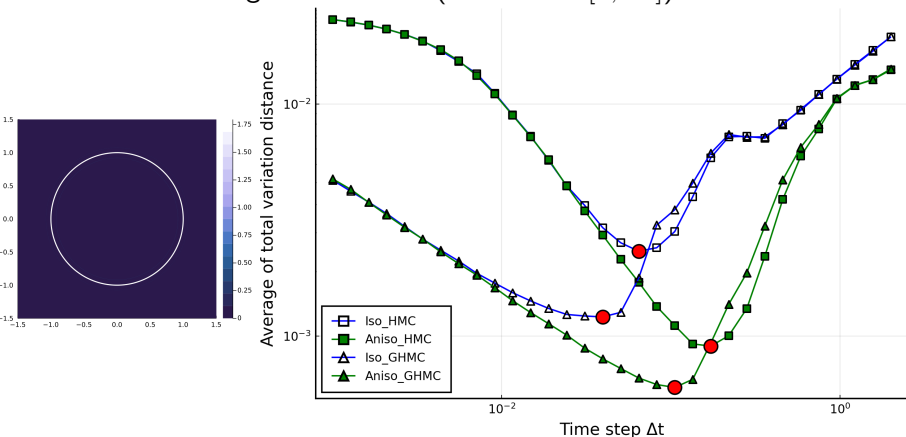
- Anisotropic diffusion coefficient  $\mathcal{D}_{\text{Tan}}(q) = \varepsilon \mathbf{I}_2 + \tilde{q}\tilde{q}^\top / \|q\|^2$ ,  $\tilde{q} = (-y \ x)^\top$
- Isotropic diffusion coefficient  $\mathcal{D}_{\text{One}} \equiv (1 + \varepsilon)\mathbf{I}_2$ ,  $\varepsilon = 0.1$



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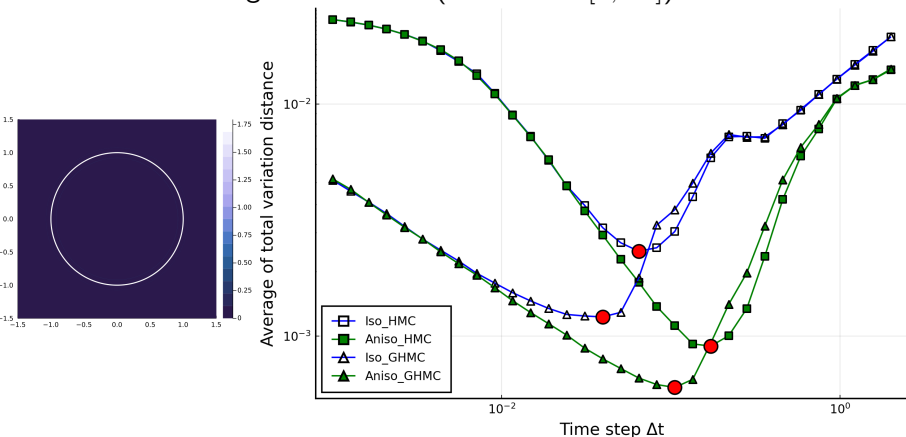
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⇒ Compromise: **small**/**large** time steps (exploration vs rejection)



## 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  $\xi \in \mathbb{R}^d$ ,

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