Concentration Inequalities for Euler Schemes

Florent Malrieu[1] and Denis Talay[2]

[1] IRMAR, UMR 6625, Université Rennes 1, France
florent.malrieu@univ-rennes1.fr
[2] INRIA Sophia-Antipolis, 2004 route des Lucioles, B.P. 93, 06902
Sophia-Antipolis Cedex, France Denis.Talay@sophia.inria.fr

Summary. We establish a Poincaré inequality for the law at time t of the explicit Euler scheme for a stochastic differential equation. When the diffusion coefficient is constant, we also establish a Logarithmic Sobolev inequality for both the explicit and implicit Euler scheme, with a constant related to the convexity of the drift coefficient. Then we provide exact confidence intervals for the convergence of Monte Carlo methods.

1 Poincaré and Logarithmic Sobolev Inequalities

To describe and control the statistical errors of probabilistic numerical methods, one can use better results than limit theorems such as Central Limit Theorems. Indeed, it is worthy having non asymptotic error estimates in order to choose numerical parameters (number of Monte Carlo simulations, or number of particles, or time length of an ergodic simulation) in terms of the desired accuracy and confidence interval. To this end, concentration inequalities are extremely useful and accurate. As reminded in the section 6 below, sufficient conditions for concentration inequalities are Poincaré (or spectral gap) and Logarithmic Sobolev inequalities. Such inequalities consist in bounding from above a variance or an entropy by an energy quantity. We start by defining Poincaré and Logarithmic Sobolev inequalities for measures on $\mathbb{R}^d$.

Remark 1. In what follows, we call "smooth" function a $\mathcal{C}^\infty$ function with polynomial growth.

Definition 1 (Poincaré inequality). *A probability measure μ on $\mathbb{R}^d$ satisfies a Poincaré (or spectral gap) inequality with constant C if*

$$\mathrm{Var}_\mu(f) := \mathbb{E}_\mu(f^2) - (\mathbb{E}_\mu f)^2 \leq C\,\mathbb{E}_\mu\Big(|\nabla f|^2\Big) \tag{1}$$

for all smooth functions f with bounded derivatives.

Definition 2 (Logarithmic Sobolev inequality). *The probability measure μ on $\mathbb{R}^d$ satisfies a Logarithmic Sobolev inequality with constant C if*

$$\mathrm{Ent}_\mu\big(f^2\big) := \int f^2 \log f^2 \, d\mu - \int f^2 \, d\mu \log \int f^2 \, d\mu \le C \, \mathbb{E}_\mu\Big(|\nabla f|^2\Big) \qquad (2)$$

for all smooth functions f bounded derivatives.

The Logarithmic Sobolev inequality implies the Poincaré inequality and a better concentration inequality (see (18) and (19)) below.

One can easily check that the Gaussian measure $\mathcal{N}(m, S)$ on $\mathbb{R}^d$ satisfies a Poincaré (respectively Logarithmic Sobolev) inequality with constant ρ (respectively 2ρ), where ρ is the largest eigenvalue of the covariance matrix S.

We now consider a much less elementary example and we follow [3]. Let (X_t) be a time continuous Markov process with infinitesimal generator $\mathbf{L}$. Set

$$\alpha(s) := P_s\Big[\big(P_{t-s} f\big)^2\Big].$$

As the time derivative of $P_t f$ is $P_t \mathbf{L} f$, one has

$$\alpha'(s) = 2 P_s \boldsymbol{\Gamma} P_{t-s} f, \qquad (3)$$

where

$$\boldsymbol{\Gamma}(f,g) := \frac{1}{2}[\mathbf{L}(fg) - f\mathbf{L}g - g\mathbf{L}f] \quad \text{and} \quad \boldsymbol{\Gamma} f := \boldsymbol{\Gamma}(f,f).$$

Suppose that the semigroup P_t satisfies the commutation relation

$$\exists \rho \in \mathbb{R}, \ \boldsymbol{\Gamma} P_t f \le e^{-2\rho t} P_t \boldsymbol{\Gamma} f. \qquad (4)$$

Then it also satisfies the Poincaré inequality since

$$P_t\big(f^2\big) - \big(P_t f\big)^2 = \alpha(t) - \alpha(0) = \int_0^t \alpha'(s)\, ds \le \frac{1 - e^{-2\rho t}}{\rho} P_t \boldsymbol{\Gamma} f.$$

It now remains to get sufficient conditions for (4). Set

$$\boldsymbol{\Gamma_2} f := \frac{1}{2}[\mathbf{L}(\boldsymbol{\Gamma} f) - 2\boldsymbol{\Gamma}(f, \mathbf{L} f)],$$

and notice that $\alpha''(s) = 4 P_s \boldsymbol{\Gamma_2} P_{t-s} f$. Suppose that the Bakry–Émery criterion with curvature ρ holds, that is,

$$\boldsymbol{\Gamma_2} f \ge \rho \, \boldsymbol{\Gamma} f. \qquad (5)$$

Then $\alpha''(s) \ge 2\rho\alpha'(s)$, from which one can deduce (4).

We end this section by considering the special case of diffusion processes. Let $(X_t)_{t\geq 0}$ be the $\mathbb{R}^d$ valued diffusion process solution of the stochastic differential equation

$$X_t = X_0 + \int_0^t b(X_s)\, ds + \int_0^t \sqrt{2}\sigma(X_s)\, dB_s, \tag{6}$$

where $(B_t)_{t\geq 0}$ is a Brownian motion on $\mathbb{R}^d$, $\sigma(x)$ is a $d \times d$ matrix valued function, and $b(x)$ is a $\mathbb{R}^d$ valued function. A straightforward computation provides

$$\boldsymbol{\Gamma}(f) = |\sigma \nabla f|^2.$$

Using the fact that $\mathbf{L}$ is the generator of a diffusion process, one can prove that the logarithmic Sobolev inequality

$$\mathrm{Ent}_{P_t}\left(f^2\right) \leq \frac{2}{\rho}\left(1 - e^{-2\rho t}\right) P_t(\boldsymbol{\Gamma} f)$$

is implied by the reinforced commutation relation

$$\sqrt{\boldsymbol{\Gamma} P_t f} \leq e^{-\rho t} P_t\Big(\sqrt{\boldsymbol{\Gamma} f}\Big),$$

that is,

$$|\sigma \nabla P_t f| \leq e^{-\rho t} P_t(|\sigma \nabla f|). \tag{7}$$

In addition, one can show that this reinforced commutation relation is equivalent to the Bakry–Émery curvature criterion. In the case of one–dimensional diffusions, this criterion is equivalent to the condition

$$\exists \rho \in \mathbb{R},\ \inf_{x\in\mathbb{R}} \left(\sigma(x)\sigma''(x) + \frac{\sigma'(x)}{\sigma(x)} b(x) - b'(x) \right) \geq \rho. \tag{8}$$

Observe that this condition obviously holds true when σ, σ', σ'', b and b' are bounded functions, and σ is bounded from below by a positive constant.

We now aim to get Poincaré and Logarithmic Sobolev inequalities for approximation schemes of diffusion processes and particle systems for McKean–Vlasov partial differential equations. Complete proofs will appear in [10].

2 Poincaré Inequalities for Multidimensional Euler Schemes

Consider the Euler scheme $(X_n^\gamma)_{n\in\mathbb{N}}$ on $\mathbb{R}^d$ with discretization step γ:

$$X_{n+1}^\gamma := X_n^\gamma + b(X_n^\gamma)\gamma + \sqrt{2}\sigma(X_n^\gamma)(B_{n+1} - B_n). \tag{9}$$

This scheme discretizes (6) and defines a Markov chain on $\mathbb{R}^d$ with transition kernel

$$K(f)(x) := \mathbb{E}\Big[f\Big(x + b(x)\gamma + \sqrt{2\gamma}\sigma(x)Y\Big)\Big],$$

where Y is Gaussian $\mathcal{N}(0, I_d)$. We conjecture that, under appropriate hypotheses on the functions b and σ, the law of X_n^γ satisfies a Poincaré inequality with a constant uniform in $\gamma < 1$ and $1 \le n \le \dfrac{1}{\gamma}$. However, at the time being, we have succeeded to only get a partial version of this result. The extension is in progress.

Proposition 1. *If $d = 1$, suppose that the functions σ and b have continuous and bounded derivatives and σ is bounded. If $d > 1$, suppose in addition that σ is constant. Then, for all $n \in \mathbb{N}$ and all smooth functions f,*

$$K^n\big(f^2\big)(x) - \left(K^n f(x)\right)^2 \le C_{\gamma,n} K^n\Big(|\nabla f|^2\Big)(x).$$

The constant $C_{\gamma,n}$ can be chosen as

$$C_{\gamma,n} = \gamma c \frac{(C_\gamma)^n - 1}{C_\gamma - 1}, \tag{10}$$

where C_γ satisfies

$$\exists C > 0,\ \forall 0 < \gamma < 1,\ C_\gamma^{1/\gamma} \le C.$$

Proof. We mimic the continuous time semigroup argument. Observe that

$$\begin{aligned} K^n(f^2) - (K^n f)^2 &= \sum_{i=1}^n \Big\{K^i\big[(K^{n-i}f)^2\big] - K^{i-1}\Big[\big(K^{n-i+1}f\big)^2\Big]\Big\} \\ &= \sum_{i=1}^n K^{i-1}\Big\{K\big[(K^{n-i}f)^2\big] - \Big[K\big(K^{n-i}f\big)^2\Big]\Big\}. \end{aligned}$$

Therefore,

$$\mathbf{Var}_{K^n}(f) = \sum_{i=1}^n K^{i-1}\mathbf{Var}_K\big(K^{n-i}f\big). \tag{11}$$

Notice that the operator $\mathbf{Var}_K()$ is the discrete time version of the operator $\boldsymbol{\Gamma}$. The kernel K is the Gaussian law with mean $x + b(x)\gamma$ and covariance matrix $2\gamma\sigma(x)\sigma^*(x)$. Thus, since σ is bounded, it satisfies the Poincaré inequality

$$\mathbf{Var}_K(f)(x) \le 2\gamma\, K\Big(|\sigma(x)\nabla f|^2\Big)(x) \le c\gamma\, K\Big(|\nabla f|^2\Big)(x). \tag{12}$$

In addition,

$$\nabla K f(x) = \mathbb{E}[(I_d + \gamma \mathrm{Jac}\ b(x) + \sqrt{\gamma}\mathrm{Jac}\ (\sigma(x)Y))\nabla f(x + \gamma b(x) + \sqrt{\gamma}\sigma(x)Y)].$$

Therefore, the Cauchy–Schwarz inequality leads to

$$|\nabla Kf(x)|^2 \leq \sum_i \mathbb{E}\left(1 + b_i(x)\gamma + \sqrt{\gamma}\sum_{j,k}\frac{\partial\sigma_{ij}}{\partial x_k}(x)Y_j\right)^2 K\Big(|\nabla f|^2\Big)(x),$$

from which the desired result easily follows.

In the next sections we prove that, under the above restrictive hypotheses, we even can get Logarithmic Sobolev inequalities.

3 Logarithmic Sobolev Inequalities for One-Dimensional Euler and Milstein Schemes

The aim of this section is to establish Logarithmic Sobolev inequalities for numerical schemes in dimension one and to make the constants explicit in the inequalities in terms of the curvature of the solution of (6).

The Commutation Relation for the Bernoulli Scheme

Consider the approximation scheme with transition kernel

$$Jf(x) := \mathbb{E}\Big[f(x + \gamma b(x) + \sqrt{2\gamma}\sigma(x)Z)\Big],$$

where the law of Z is the probability measure $\frac{1}{2}\delta_{-1} + \frac{1}{2}\delta_1$. Then $(\sigma(Jf)')(x)$ is equal to

$$\mathbb{E}\Big[\Big(\sigma(x)(1 + \gamma b'(x) + \sqrt{2\gamma}\sigma'(x)Z)\Big)f'\Big(x + \gamma b(x) + \sqrt{2\gamma}\sigma(x)Z\Big)\Big].$$

Thus

$$\sigma(x)(Jf)'(x) = \mathbb{E}\Big[(1 - \alpha_x(\gamma))(\sigma f')\Big(x + \gamma b(x) + \sqrt{2\gamma}\sigma(x)Z\Big)\Big],$$

where

$$\alpha_x(\gamma) := \frac{\sigma(x + \gamma b(x) + \sqrt{2\gamma}\sigma(x)Z) - \sigma(x)(1 + \gamma b'(x) + \sqrt{2\gamma}\sigma'(x)Z)}{\sigma(x + \gamma b(x) + \sqrt{2\gamma}\sigma(x)Z)}.$$

In view of the Taylor formula,

$$\begin{aligned}\sigma\Big(x + \gamma b(x) + \sqrt{2\gamma}\sigma(x)Z\Big) &= \sigma(x) + \sigma'(x)\Big(b(x)\gamma + \sqrt{2\gamma}\sigma(x)Z\Big) \\ &\quad + \sigma''(x)\sigma(x)^2 Z^2\gamma + O(\gamma^{3/2}).\end{aligned}$$

Therefore

$$\alpha_x(\gamma) = \left[\sigma(x)\sigma''(x) + \frac{\sigma'(x)b(x)}{\sigma(x)} - b'(x)\right]\gamma + O(\gamma^{3/2}),$$

since $Z^2 = 1$ almost surely. The curvature criterion (8) leads to

$$\alpha_x(\gamma) \geq \rho\gamma + O(\gamma^{3/2}).$$

Consequently, for all γ small enough it holds that

$$|\sigma(x)(Jf)'(x)| \leq \Big[1 - \rho\gamma + O(\gamma^{3/2})\Big] J(|\sigma f'|)(x).$$

Now, the Bernoulli law satisfies a Logarithmic Sobolev inequality with constant 2 (see [1]). We thus deduce that the iterated kernel J^n of the Bernoulli scheme satisfies a Logarithmic Sobolev inequality with constant

$$\frac{2}{\rho + O(\gamma^{1/2})}\Big(1 - (1 - \rho\gamma + O(\gamma^{3/2}))^{2n}\Big).$$

The Milstein Scheme

The previous result seems surprising since we have used that Bernoulli r.v. satisfy $Z^2 = 1$ a.s. Consider the new Markov chain with kernel

$$Jf(x) := \mathbb{E}\Big[f\Big(x + \gamma b(x) + \sqrt{2\gamma}Z + \sigma'(x)\sigma(x)(Z^2 - 1)\gamma\Big)\Big],$$

where the law of Z is a probability measure with compact support, mean 0 and variance 1. This chain is the one-dimensional Milstein scheme for (6). For a comparison with the Euler scheme, see, e.g. [15]. Similar arguments as above lead to the following result.

Proposition 2. *Let Z have a law with compact support, mean 0 and variance 1 which satisfies a Logarithmic Sobolev inequality with constant c. Then the iterated kernel J^n of the Milstein scheme satisfies a Logarithmic Sobolev inequality with constant*

$$\frac{c}{\rho + O(\gamma^{1/2})}\Big(1 - (1 - \rho\gamma + O(\gamma^{3/2}))^{2n}\Big).$$

4 Logarithmic Sobolev Inequalities for Multidimensional Euler Schemes with Constant Diffusion Coefficient and Potential Drift Coefficient

In this section, we are given a smooth function U and we consider the equation

$$dX_t = \sqrt{2}dB_t - \nabla U(X_t)\,dt.$$

4.1 The Explicit Euler Scheme

Assume in this subsection that ∇U is a uniformly Lipschitz function on $\mathbb{R}^d$. For $U(x) = |x|^2/2$ one gets the Ornstein–Uhlenbeck process. The transition kernel of the explicit Euler scheme is

$$Kf(x) = \mathbb{E}\Big[f\Big(x - \nabla U(x)\gamma + \sqrt{2\gamma}Y\Big)\Big],$$

where Y is a d dimensional Gaussian vector $\mathcal{N}(0, I_d)$.

Let $\lambda \in \mathbb{R}$ be the largest real number such that

$$\langle \text{Hess } U(x)v, v\rangle \geq \lambda |v|^2 \tag{13}$$

for all x and v in $\mathbb{R}^d$. We now assume that $\lambda\gamma < 1$. This technical assumption is not restrictive since the discretization step γ is small.

Theorem 1. *For all $n \in \mathbb{N}$, $x \in \mathbb{R}$ and smooth functions f from $\mathbb{R}^d$ to $\mathbb{R}$,*

$$\text{Ent}_{K^n}\left(f^2\right) \leq D_{\gamma,n} K^n\Big(|\nabla f|^2\Big),$$

where

$$D_{\gamma,n} := \frac{4}{\lambda(2-\lambda\gamma)}\left(1 - (1-\lambda\gamma)^{2n}\right). \tag{14}$$

Remark 2. If λ is equal to 0, $D_{\gamma,n}$ needs to be understood as $4n\gamma$.

Proof. The kernel K satisfies a Logarithmic Sobolev inequality with constant 4γ. Moreover,

$$\nabla Kf(x) = (I_d - \gamma \text{Hess } U(x))K(\nabla f)(x).$$

Therefore

$$|\nabla Kf(x)| \leq (1 - \gamma\lambda)K(|\nabla f|)(x). \tag{15}$$

Observe that

$$\text{Ent}_{K^n}\left(f^2\right) := K^n(f^2 \log f^2) - K^n(f^2)\log K^n(f^2)$$

is equal to

$$\sum_{i=1}^{n} \left\{K^i\left[K^{n-i}(f^2)\log K^{n-i}(f^2)\right] - K^{i-1}\left[K^{n-i+1}(f^2)\log K^{n-i+1}(f^2)\right]\right\}.$$

In the sequel, g_{n-i} will stand for $\sqrt{K^{n-i}(f^2)}$. We have

$$\text{Ent}_{K^n}\left(f^2\right) = \sum_{i=1}^{n} K^{i-1}\left[\text{Ent}_K\left(g_{n-i}^2\right)\right] \leq 4\gamma \sum_{i=1}^{n} K^i\Big(|\nabla g_{n-i}|^2\Big),$$

since K satisfies a Logarithmic Sobolev inequality with constant 4γ. Now, in view of the commutation relation (15), we get

$$|\nabla g_{n-i}|^2 = \frac{\left|\nabla K^{n-i}(f^2)\right|^2}{4K^{n-i}(f^2)} \leq (1-\lambda\gamma)^2 \frac{\left[K\left|\nabla K^{n-i-1}(f^2)\right|\right]^2}{4KK^{n-i-1}(f^2)}$$

for all $1 \leq i \leq n$. Therefore, using Cauchy–Schwarz inequality,

$$\frac{(Kf)^2}{K(g)} \leq K\left(\frac{f^2}{g}\right),$$

from which

$$\frac{\left[K\left|\nabla K^{n-i-1}(f^2)\right|\right]^2}{4KK^{n-i-1}(f^2)} \leq K\left[\frac{\left|\nabla K^{n-i-1}(f^2)\right|^2}{4K^{n-i-1}(f^2)}\right] = K\left[|\nabla g_{n-i-1}|^2\right].$$

A straightforward induction shows that

$$|\nabla g_{n-i}|^2 \leq (1-\lambda\gamma)^{2(n-i)} K^{n-i}\left[|\nabla f|^2\right].$$

Consequently,

$$\begin{aligned}
\mathrm{Ent}_{K^n}\left(f^2\right) &\leq 4\gamma\left[\sum_{i=0}^{n-1}(1-\lambda\gamma)^{2i}\right]K^n\left[|\nabla f|^2\right] = 4\gamma\frac{1-(1-\lambda\gamma)^{2n}}{1-(1-\lambda\gamma)^2}K^n\left[|\nabla f|^2\right] \\
&= \frac{4}{\lambda(2-\lambda\gamma)}\left(1-(1-\lambda\gamma)^{2n}\right)K^n\left[|\nabla f|^2\right],
\end{aligned}$$

which ends the proof.

4.2 The Implicit Euler Scheme

In this subsection we assume that U is a uniformly convex function, that is, there exists $\lambda > 0$ such that

$$\langle \mathrm{Hess}\, U(x)v, v\rangle \geq \lambda|v|^2 \text{ for all } x, v \in \mathbb{R}^d.$$

Since the drift coefficient $-\nabla U$ is not necessarily globally Lipschitz, we consider the implicit Euler scheme

$$X_{n+1}^\gamma = X_n^\gamma - \nabla U\left(X_{n+1}^\gamma\right)\gamma + \sqrt{2\gamma}Y,$$

where Y is a standard Gaussian variable on $\mathbb{R}^d$. Setting

$$\varphi(x) := \left(I + \nabla U(x)\gamma\right)^{-1}(x),$$

the kernel $\overline{K}$ of the implicit Euler scheme is

$$\overline{K}f(x) = \mathbb{E}\Big[f \circ \varphi\Big(x + \sqrt{2\gamma}Y\Big)\Big].$$

Let $\mathcal{N}(x, 2\gamma I)$ be the Gaussian distribution with mean x and covariance matrix $2\gamma I_d$. We have

$$\mathrm{Ent}_{\overline{K}}\big(f^2\big) = \mathrm{Ent}_{\mathcal{N}(x,2\gamma I)}\big((f \circ \varphi)^2\big) \leq 4\gamma \mathbb{E}_{\mathcal{N}(x,2\gamma I)}\Big[|\nabla(f \circ \varphi)|^2\Big].$$

In view of the definition of φ we get

$$\mathrm{Jac}\ \varphi(x) = [I_d + \gamma \mathrm{Hess}\ U(x)]^{-1},$$

and thus

$$\langle \mathrm{Jac}\ \varphi(x)v, v\rangle \leq (1 + \gamma\lambda)^{-1}|v|^2$$

for all v in $\mathbb{R}^d$, from which

$$|\nabla(f \circ \varphi)| = |(\mathrm{Jac}\ \varphi)(\nabla f(\varphi))| \leq \frac{1}{1 + \lambda\gamma}|(\nabla f) \circ \varphi|.$$

Consequently, the kernels $\left(\overline{K}(\cdot)(x)\right)_x$ satisfy a Logarithmic Sobolev inequality with constant $\frac{4\gamma}{1+\lambda\gamma}$.

On the other hand,

$$\nabla \overline{K}f(x) = \mathbb{E}_{\mathcal{N}(x,2\gamma I)}[(\mathrm{Jac}\ \varphi)(\nabla f) \circ \varphi].$$

Then $\overline{K}$ and ∇ satisfy the commutation relation

$$\left|\nabla \overline{K}(f)(x)\right| \leq (1 + \gamma\lambda)^{-1}\overline{K}(|\nabla f|)(x).$$

Obvious adaptations of the proof of Theorem 1 lead to

Theorem 2. *For all $n \in \mathbb{N}$, $x \in \mathbb{R}$ and smooth functions f from $\mathbb{R}^d$ to $\mathbb{R}$ one has*

$$\mathrm{Ent}_{\overline{K}^n}\left(f^2\right) \leq \overline{D}_{\gamma,n}\overline{K}^n\Big(|\nabla f|^2\Big),$$

where

$$\overline{D}_{\gamma,n} = \frac{4(1 + \lambda\gamma)}{\lambda(2 + \lambda\gamma)}\left(1 - \frac{1}{(1 + \lambda\gamma)^{2n}}\right). \tag{16}$$

5 Uniform Logarithmic Sobolev Inequalities for One–Dimensional Euler Schemes with Constant Diffusion Coefficient and Convex Potential Drift Coefficient

Let V be a smooth functions from $\mathbb{R}$ to $\mathbb{R}$. Let $(X_t)_{t\geq 0}$ be the solution of

$$dX_t = \sqrt{2}\, dB_t - V'(X_t)\, dt.$$

Notice that

$$\nabla P_t f(x) = \mathbb{E}^x\left[\nabla f(X_t)\exp\left(-\int_0^t V''(X_s)\,ds\right)\right]. \tag{17}$$

When $V'' \geq \lambda > 0$ we easily get the commutation relation

$$|\nabla P_t f| \leq e^{-\lambda t} P_t(|\nabla f|).$$

We now consider the less obvious case where V'' is supposed nonnegative only.

5.1 Poincaré Inequality for the Diffusion Process

Lemma 1. *Let*

$$D(t,x) := \mathbb{E}^x\left[\exp\left(-2\int_0^t V''(X_s)\,ds\right)\right].$$

Then it exist $t_0 > 0$ such that $D(t_0) := \sup_{x\in\mathbb{R}} D(t_0,x) < 1$.

Proof. One has $D(t+s) \leq D(t)D(s)$ for all $t \geq 0$ and $s \geq 0$. Indeed, for all $t \geq 0$, $s \geq 0$ and $x \in \mathbb{R}$, the Markov property ensures that

$$\begin{aligned}
D(t+s,x) &= \mathbb{E}^x\left[\exp\left(-2\int_0^t V''(X_u)\,du\right)\mathbb{E}^{X_t}\left\{\exp\left(-2\int_0^s V''(X_u)\,du\right)\right\}\right] \\
&= \mathbb{E}^x\left[D(s,X_t)\exp\left(-2\int_0^t V''(X_u)\,du\right)\right] \\
&\leq D(s)\mathbb{E}^x\left[\exp\left(-2\int_0^t V''(X_u)\,du\right)\right] = D(s)D(t,x) \leq D(s)D(t).
\end{aligned}$$

For $x \geq a$, set $\tau_a := \inf\{t \geq 0, X_t^x = a\}$. Then,

$$\begin{aligned}
D(t,x) = \mathbb{E}^x&\left[\mathbb{1}_{\{\tau_a<t\}}\exp\left(-2\int_0^t V''(X_s)\,ds\right)\right] \\
&+ \mathbb{E}^x\left[\mathbb{1}_{\{\tau_a\geq t\}}\exp\left(-2\int_0^t V''(X_s)\,ds\right)\right].
\end{aligned}$$

The second term on the r.h.s. is bounded from above by $\exp(-\lambda t)$. The first one can be bounded from above as follows:

$$\begin{aligned}
&\mathbb{E}^x\left[\mathbb{1}_{\{\tau_a<t\}}\exp\left(-2\int_0^t V''(X_s)\,ds\right)\right] \\
&\qquad = \mathbb{E}^x\left[\mathbb{1}_{\{\tau_a<t\}}e^{-\lambda\tau_a}\mathbb{E}\left\{\exp\left(-2\int_{\tau_a}^t V''(X_s)\,ds\right)\middle|\mathcal{F}_{\tau_a}\right\}\right] \\
&\qquad = \mathbb{E}^x\left[\mathbb{1}_{\{\tau_a<t\}}e^{-\lambda\tau_a}D(t-\tau_a,a)\right] \\
&\qquad = \mathbb{E}^x\left[\mathbb{1}_{\{\tau_a<t/2\}}e^{-\lambda\tau_a}D(t-\tau_a,a)\right] \\
&\qquad\quad + \mathbb{E}^x\left[\mathbb{1}_{\{t/2\leq\tau_a<t\}}e^{-\lambda\tau_a}D(t-\tau_a,a)\right] \\
&\qquad \leq D(t/2,a) + e^{-\lambda t/2}.
\end{aligned}$$

One can easily show that

$$\sup_{x\geq a} D(t,x) \leq D(t/2,a) + e^{-\lambda t/2} + e^{-\lambda t}.$$

The right hand side is bounded from above by 1 for all t large enough. By symmetry, one also has

$$\sup_{|x|\geq a} D(t,x) < 1.$$

Finally, the continuity of $x \mapsto D(t,x)$ ensures that

$$\sup\{D(t,x),\ x \in [-a,a]\} < 1$$

for all $t > 0$, which ends the proof.

Proposition 3. *Assume that V is convex and it exists $a \geq 0$ and $\lambda > 0$ such that* $\sup\{V''(x),\ |x| \geq a\}$. *It then exists $t_0 \geq 0$ such that $D(t_0) < 1$ and*

$$\mathbf{Var}_{P_t(\cdot)(x)}(f) \leq 2t_0\left(1 + \frac{1 - D(t_0)^{t/t_0 - 1}}{1 - D(t_0)}\right) P_t\left(|\nabla f|^2\right)$$

for all $t > t_0$. Moreover, the invariant measure μ of (X_t) satisfies a Poincaré inequality with constant $2t_0(1 + 1/(1 - D(t_0)))$.

Observe that the proposition implies that, for all $t_0 > 0$ and $n \in \mathbb{N}$,

$$|\nabla P_{nt_0} f(x)|^2 \leq D(nt_0) P_{nt_0}\left(|\nabla f|^2\right)(x) \leq D(t_0)^n P_{nt_0}\left(|\nabla f|^2\right)(x).$$

Proof. Let $t_0 > 0$ be as in Lemma 1 and set $K(f)(x) := P_{t_0} f(x)$. Arbitrarily choose $t > 0$. Let n be the integer part of t/t_0. We have

$$\begin{aligned}\mathbf{Var}_{P_t(\cdot)(x)}(f) &= P_t(f^2)(x) - (P_t(f)(x))^2 \\ &= P_{nt_0}\big(\mathbf{Var}_{P_{t-nt_0}}(f)\big) + \mathbf{Var}_{P_{nt_0}}(P_{t-nt_0} f).\end{aligned}$$

Since $t - nt_0 < t_0$, P_{t-nt_0} satisfies a Poincaré inequality with a constant bounded by $2t_0$. Therefore,

$$\mathbf{Var}_{P_t(\cdot)(x)}(f) \leq 2t_0 P_t\left(|\nabla f|^2\right) + \mathbf{Var}_{K^n}(P_{t-nt_0}(f)).$$

Moreover, K^n satisfies the Poincaré inequality

$$\mathbf{Var}_{K^n}(f) =\leq \frac{2t_0(1 - D(t_0)^n)}{1 - D(t_0)} K^n(|\nabla f|^2).$$

In view of the commutation relation $|\nabla P_{t-nt_0}(f)|^2 \leq P_{t-nt_0}(|\nabla f|^2)$, we finally get

$$\mathbf{Var}_{P_t(\cdot)(x)}(f) \leq 2t_0 P_t\left(|\nabla f|^2\right) + \frac{2t_0(1 - D(t_0)^n)}{1 - D(t_0)} K^n P_{t-nt_0}(|\nabla f|^2).$$

5.2 Uniform Poincaré Inequality for the Euler Scheme

We now get a uniform Poincaré inequality for the Euler scheme with kernel

$$K(f)(x) = \mathbb{E}\{f(x - V'(x)\alpha + Y)\},$$

where Y is Gaussian $\mathcal{N}(0, 2\alpha)$. Consider the commutation relation

$$\nabla K^2 f(x) = (1 - \alpha V''(x))\mathbb{E}^x[(1 - \alpha V''(X_1))\nabla f(X_2)].$$

As $1 - \alpha V''(x) \leq 1$, we have

$$\left|\nabla K^2 f(x)\right|^2 \leq \mathbb{E}^x\left[(1 - \alpha V''(X_1))^2\right] K^2(|\nabla f|^2)(x).$$

Since the support of the law of X_1 is the entire real line, for all $x \in \mathbb{R}$, $\mathbb{E}^x\left[(1 - \alpha V''(X_1))^2\right] < 1$. Moreover

$$\sup_{x\in\mathbb{R}} \mathbb{E}^x\left[(1 - \alpha V''(X_1))^2\right] < 1$$

since $V''(y) \geq \lambda > 0$ if $|y| \geq a$. This observation leads to Poincaré inequalities for both K^n and the invariant measure of the Euler scheme; in these inequalities the constants are uniform w.r.t. time.

5.3 Uniform Logarithmic Sobolev Inequality

In view of (17) we have

$$\begin{aligned} |\nabla P_t(f)(x)| &\leq \mathbb{E}^x\left[|f'(X_t)| \exp\left(-\int_0^t V''(X_s)\, ds\right)\right] \\ &= \mathbb{E}\left[|f'(X_t)| \mathbb{E}\left\{\exp\left(-\int_0^t V''(X_s)\, ds\right)\middle| X_0 = x, X_t\right\}\right]. \end{aligned}$$

To get the commutation relation $|\nabla P_t(f)| \leq \rho P_t(|f'|)$, one needs to suppose that the following property holds true:

Property 1. There exists $t_0 > 0$ such that $D(t_0) := \sup_{x,y\in\mathbb{R}} D(t_0, x, y) < 1$, where

$$D(t_0, x, y) := \mathbb{E}\left[\exp\left(-\int_0^{t_0} V''(X_s)\, ds\right)\middle| X_0 = x, X_{t_0} = y\right]$$

for all $t > 0$ and x, y in $\mathbb{R}$.

This property holds true when V'' is nonnegative. We are now trying to relax the convexity condition on V, assuming only that V is strictly convex out of a compact set.

6 Applications

6.1 Monte Carlo Simulations

Poincaré and Logarithmic Sobolev inequalities are important for applications because they provide concentration inequalities for empirical means. The proof of this claim uses a tensorization argument and the Herbst's argument that we now remind.

Theorem 3. *Let μ be a probability measure on $\mathbb{R}^d$. If μ satisfies a spectral gap (respectively Logarithmic Sobolev) inequality with constant C, then the measure $\mu^{\otimes N}$ on $\mathbb{R}^{dN}$ satisfies a spectral gap (respectively Logarithmic Sobolev) inequality with constant C.*

Theorem 4. *If μ satisfies a Logarithmic Sobolev inequality with constant c, then for all Lipschitz functions f with Lipschitz constant ε and all $\lambda > 0$,*

$$K\big(e^{\lambda f}\big) \le e^{c\lambda^2\varepsilon^2/4} e^{\lambda K f}.$$

The Herbst's argument ensures that a measure which satisfies a Logarithmic Sobolev inequality has Gaussian tails (see [9]). One then deduces

Theorem 5. *Let the measure μ on $\mathbb{R}^d$ satisfy the Logarithmic Sobolev inequality* (2) *with constant C. Let $X_1, \dots, X_N$ be i.i.d. random variables with law μ. Then, for all bounded Lipschitz functions on $\mathbb{R}^d$, it holds*

$$\mathbb{P}\left(\left|\frac{1}{N}\sum_{i=1}^{N} f(X_i) - \mathbb{E}(f(X_1))\right| \ge r\right) \le 2e^{-Nr^2/C}. \tag{18}$$

One can also show

Theorem 6. *Assume that the measure μ on $\mathbb{R}^d$ satisfies the Poincaré inequality* (1) *with constant c. Let $X_1, \dots, X_N$ be i.i.d. random variables with law μ. Then, for all bounded Lipschitz functions on $\mathbb{R}^d$ with Lipschitz constant α, it holds*

$$\mathbb{P}\left(\left|\frac{1}{N}\sum_{i=1}^{N} f(X_i) - \mathbb{E}(f(X_1))\right| \ge r\right) \le 2\exp\left(-\frac{N}{K}\min\left(\frac{r}{\alpha}, \frac{r^2}{\alpha^2}\right)\right). \tag{19}$$

6.2 Ergodic Simulations

Let $(Y_n)_n$ be a Markov chain on $\mathbb{R}^d$ with transition kernel K such that, for all smooth functions f,

$$|\nabla K f|(x) \le \alpha K(|\nabla f|)(x), \tag{20}$$

for some $\alpha < 1$. For example, fix $t_0 > 0$ and set $K = P_{t_0}$, where (P_t) is the semi-group of the diffusion

$$dX_t = dB_t - \nabla U(X_t)\,dt$$

with Hess $U(x) \geq \rho I$ and $\rho > 0$. One can then choose $\alpha = e^{-\rho t_0}$. Alternatively, K can be chosen as the transition kernel of the implicit Euler scheme which discretizes (X_t). Using Herbst's argument one can show

Proposition 4. *For all 1-Lipschitz functions f on $\mathbb{R}^d$,*

$$\mathbb{P}_x\left(\left|\frac{1}{N}\sum_{i=1}^{N} f(Y_i) - \int f\,d\mu\right| \geq r + \frac{d_x}{N}\right) \leq 2\exp\left(-\frac{N(1-\alpha)^2}{c}r^2\right), \tag{21}$$

where $d_x = \dfrac{\alpha}{1-\alpha}\mathbb{E}_x(|x - X_1|)$.

6.3 Stochastic Particle Methods for McKean–Vlasov Equations

Consider the McKean–Vlasov equation

$$\frac{\partial}{\partial t}P_t = \frac{1}{2}\sum_{i,j=1}^{d}\frac{\partial^2}{\partial x_i \partial x_j}(a_{ij}[x, P_t]P_t) - \sum_{i=1}^{d}\frac{\partial}{\partial x_i}(b_i[x, P_t]P_t), \tag{22}$$

where P_t is a probability measure on $\mathbb{R}^d$ and, for some functions b and σ,

$$\begin{aligned} b[x, p] &= \int_{\mathbb{R}^d} b(x, y)\,p(dy), \\ \sigma[x, p] &= \int_{\mathbb{R}^d} \sigma(x, y)\,p(dy), \\ a[x, p] &= \sigma[x, p]\sigma[x, p]^* \end{aligned}$$

for all x in $\mathbb{R}^d$ and all probability measures p. The functions b and σ are the *interaction kernels*. This equation has been introduced by [13] and then widely studied from both probabilistic and analytic points of view (see, e.g., [14] for a review). Under appropriate conditions one can show that P_t is the marginal law at time t of the law of the solution of the nonlinear stochastic differential equation

$$\begin{cases} \overline{X}_t = \overline{X}_0 + \int_0^t \sigma\left[\overline{X}_s, Q_s\right] dB_s + \int_0^t b\left[\overline{X}_s, Q_s\right] ds, \\ \mathcal{L}(\overline{X}_t) = Q_t, \end{cases}$$

where $\mathcal{L}(\overline{X}_t)$ stands for the law of $\overline{X}_t$: one thus has $P_t = Q_t$. This probabilistic interpretation suggests to consider the stochastic particle system in mean field interaction

$$\begin{cases} dX_t^{i,N} = \dfrac{1}{N}\sum_{j=1}^{N}\sigma(X_t^{i,N}, X_t^{j,N})dB_t^i + \dfrac{1}{N}\sum_{j=1}^{N} b(X_t^{i,N}, X_t^{j,N})\,dt, \\ X_0^{i,N} = X_0^i, \quad i = 1, \ldots, N, \end{cases}$$

where $(B^i_\cdot)_i$ are independent Brownian motions on $\mathbb{R}^d$. One aims to approximate P_t by the empirical measure μ_t^N of the particle system:

$$\mu_t^N = \frac{1}{N}\sum_{i=1}^{N} \delta_{X_t^{i,N}}.$$

The convergence of the particle system to the nonlinear process has been deeply studied (see [14]). Suppose now that σ is constant (for the same reason as in section 2). It can also be shown that the law of the particle system at time t satisfies a Logarithmic Sobolev inequality with a constant which does not depend on the number of particles. However the corresponding confidence intervals are not fully satisfying for numerical purposes since the particle system needs to be discretized in time to be simulated. The convergence rate of the Euler scheme in terms of N and the discretization step are studied in [6, 7, 2, 5]. Refining the proof of Theorem 1 by precisely expliciting the diffusion matrix of the particle system, one can also show that the Euler scheme satisfies a spectral gap inequality with a constant independent of N:

Proposition 5. *Suppose that the coefficient b is a bounded Lipschitz function, and σ is constant. Then the Euler scheme for the above particle system satisfies*

$$\mathbb{P}\left(\left|\frac{1}{N}\sum_{i=1}^{N} f\left(X_t^{\gamma,i,N}(x)\right) - \mathbb{E}f\left(X_t^{\gamma,i,N}(x)\right)\right| \geq r\right) \leq 2\exp\left(-\frac{N}{C_t^\gamma}r^2\right)$$

for all Lipschitz functions f with Lipschitz constant equal to 1 and all $r \geq 0$,

We again conjecture that, when the diffusion kernel is not constant, under appropriate conditions the particle system and the corresponding discretizated system satisfy a Poincaré inequality. Then the above inequality would still hold true with $\min(r, r^2)$ instead of r^2.

We now consider the granular media equation:

$$\frac{\partial u}{\partial t} = \operatorname{div}\left[\nabla u + u(\nabla V + \nabla W * u)\right],$$

where $*$ stands for the convolution and V and W are convex potentials on $\mathbb{R}^d$. This equation in $\mathbb{R}$ with $V = |x|^2/2$ and $W = |x|^3$ has been introduced by [4] to describe the evolution of media composed of many particles colliding inelastically in a thermal bath. One can show that the solution u_t of the nonlinear partial differential equation converges to an equilibrium distribution u_∞. Indeed, define the generalized relative entropy as

$$\eta(u) = \int u\log u + \int uV + \frac{1}{2}\iint W(x-y)u(x)u(y).$$

One has

Theorem 7 ([8]). *If V is uniformly convex, i.e.* Hess $V \geq \lambda I$ *and W is even and convex then*

$$\eta(u_t) - \eta(u_\infty) \leq K e^{-2\lambda t}$$

where u_∞ is the unique minimizer of η or equivalently the unique solution of

$$u_\infty = \frac{1}{Z} \exp\left(-V(x) - W * u_\infty(x)\right),$$

with

$$Z = \int \exp\left(-V(x) - W * u_\infty(x)\right) dx.$$

The granular media equations can be viewed as McKean–Vlasov equations. The particle system well defined and the propagation of chaos result holds uniformly in time (see [11]):

$$\mathbb{E}\Big(\Big|X_t^{i,N} - \overline{X}_t^i\Big|\Big) \leq \frac{c}{\sqrt{N}},$$

where the $\overline{X}^i$'s are independent copies of the solution of the nonlinear equation. As the interaction kernels are not globally Lipschitz, one needs to use the implicit Euler scheme to discretize the particle system. Let $(Y_n^{N,\gamma})_{n\in\mathbb{N}}$ be this implicit Euler scheme with discretization step γ. We have (see [12]):

Theorem 8. *There exists $c > 0$ such that*

$$\mathbb{P}\left(\left|\frac{1}{N}\sum_{i=1}^{N} f(Y_t^{i,N,\gamma}) - \int f\, du_\infty\right| \geq r + c\sqrt{\gamma} + \frac{c}{\sqrt{N}} + ce^{-\lambda t}\right) \leq 2e^{-N\lambda r^2/2}$$

for all Lipschitz functions f with Lipschitz constant 1.

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