

Concentration analysis of multivariate elliptic diffusions

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Some known concentration results for Markov processes

Let X be a nice ergodic Markov processes with semigroup $(P_t)_{t \geq 0}$, invariant distribution μ and generator L on $\mathbb{L}^2(\mu)$ (endowed with inner product $\langle f, g \rangle_\mu = \int fg d\mu$) and denote

$$\mathbb{C}_v(f, T, x) := \mathbb{P}^\nu \left(\left| \frac{1}{T} \int_0^T f(X_t) dt - \mu(f) \right| > x \right), \quad f \in \mathbb{L}^2(\mu), x, T > 0.$$

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Bounds have been mostly studied with two approaches (*Lyapunov vs. Poincaré* [BCG08]):

1. Functional inequalities:

- Poincaré inequality (PI):

$$\text{Var}_\mu(g) := \mu(g^2) - \mu(g)^2 \leq -C_P \langle Lg, g \rangle_\mu, \quad g \in D(L).$$

$$\text{Implies: } \|P_t f - \mu(f)\|_{\mathbb{L}^2(\mu)} \leq e^{-2t/C_P} \|f - \mu(f)\|_{\mathbb{L}^2(\mu)}$$

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- log-Sobolev inequality (LS): $(P_t)_{t \geq 0}$ symmetric and

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2. Mixing assumptions:

$$(\alpha(v, \varphi)) : \quad \alpha_v(t) := \sup_{s \geq 0} \sup_{A \in \sigma(X_u, u \leq s), B \in \sigma(X_u, u \geq s+t)} |\mathbb{P}^v(A \cap B) - \mathbb{P}^v(A)\mathbb{P}^v(B)| \leq \varphi(t) \xrightarrow[t \rightarrow \infty]{} 0.$$

For reasonable v implied by ergodicity of P_t , i.e., $\|P_t(x, \cdot) - \mu\|_{\text{TV}} \leq CV(x)\varphi(t)$

Some known concentration results for Markov processes

[Lez01] Suppose $\nu \ll \mu$, $d\nu/d\mu \in \mathbb{L}^2(\mu)$ and $\|f\|_\infty < \infty$. If μ satisfies (PI) then we have the Bernstein inequality (BI)

$$\mathbb{C}_\nu(f, T, x) \leq 2 \left\| \frac{d\nu}{d\mu} \right\|_{\mathbb{L}^2(\mu)} \exp \left(- \frac{T x^2}{2(\sigma^2(f) + 2C_P \|f\|_\infty x)} \right),$$

where $\sigma^2(f) = \lim_{t \rightarrow \infty} t^{-1} \text{Var}_{\mathbb{P}^\mu} (\int_0^t f(X_s) ds)$

[GGW14] If μ satisfies (LS), $\mu(f) = 0$ and $\mu(\exp(\lambda_\pm f^\pm)) < \infty$ for some $\lambda_\pm > 0$ then we have the (BI)

$$\mathbb{C}_\nu(f, T, x) \leq 2 \left\| \frac{d\nu}{d\mu} \right\|_{\mathbb{L}^2(\mu)} \exp \left(- \frac{T x^2}{2(\sigma^2(f) + C_P(\Lambda^*)^{-1}(2C_{LS}/C_P)x)} \right),$$

w. $\Lambda^* = \Lambda_+^* \vee \Lambda_-^*$ and Λ_\pm^* Legendre transf. of $[0, \lambda_\pm]$ $\exists s \mapsto \Lambda_\pm(s) := \log \mu(\exp(s(\pm f)))$.

[CG08] If $(\alpha(\mu, \varphi))$ with $\varphi(t) = c \exp(-t^{\frac{1-q}{1+q}})$, $q \in [0, 1)$ [$q = 0$: exponential mixing, $q \in (0, 1)$: subexponential mixing] and $\|f\|_\infty < \infty$, then for any $x \geq C(c, q)/\sqrt{T}$, it holds

$$\mathbb{C}_\mu(f, T, x) \leq 2 \exp \left(-c(q) \left(\frac{x\sqrt{T}}{\|f\|_\infty} \right)^{1-q} \right).$$

Martingale approximation for diffusions

- Let X be a (weak) solution to the SDE

$$dX_t = b(X_t) dt + \sigma(X_t) dW_t,$$

$b \in \text{Lip}_{\text{loc}}(\mathbb{R}^d; \mathbb{R}^d)$, $\sigma \in \text{Lip}(\mathbb{R}^d; \mathbb{R}^{d \times d})$ and bounded, $a := \sigma\sigma^\top$ s.t. $\lambda_- \mathbb{I} \leq a(x) \leq \lambda_+ \mathbb{I}$, $\forall x$

- Let $L = b^\top \nabla + \sum_{i,j} a_{i,j} \partial_{x_i} \partial_{x_j}$ and suppose that for given $f: \mathbb{R}^d \rightarrow \mathbb{R}$ the **Poisson equation** $Lg = f$ has some sufficiently regular solution $L^{-1}[f]$
- By Itô's formula: $L^{-1}[f](X_t) - L^{-1}[f](X_0) = \int_0^t LL^{-1}[f](X_s) ds + \int_0^t (\nabla L^{-1}[f](X_s))^\top \sigma(X_s) dW_s$ and hence

$$\int_0^t f(X_s) ds = \underbrace{\int_0^t (-\nabla L^{-1}[f](X_s))^\top \sigma(X_s) dW_s}_{(\text{loc.}) \text{ martingale}} + \underbrace{L^{-1}[f](X_t) - L^{-1}[f](X_0)}_{\text{remainder}}$$

- If we have some control on $L^{-1}[f]$, $\nabla L^{-1}[f]$ we can use martingale approximation for derivation of concentration bounds
- employed in case $d = 1$ for **exponentially ergodic** diffusions in [AWS21; GP07] and for $d \geq 1$ and **periodic drift** [NR20] in the context of drift estimation

Poisson equation under subexponential drift assumptions

Assume $\|b(x)\| \lesssim 1 + \|x\|^\kappa$ and for some $q \in (-1, 1)$, $\tau, A > 0$,

$$\langle b(x), x/\|x\| \rangle \leq -\tau \|x\|^{-q}, \quad \|x\| > A. \quad (\mathcal{D}(q))$$

[PV01; BRS18] If $\mu(f) = 0$ and $|f(x)| \lesssim 1 + \|x\|^n$, then for $L^{-1}[f](x) := -\int_0^\infty P_t f(x) dt$ we have $L^{-1}[f] \in \mathcal{W}_{loc}^{2,p}(\mathbb{R}^d)$ for any $p > 1$, $L^{-1}[f]$ solves the Poisson equation and

$$|L^{-1}[f](x)| \lesssim 1 + \|x\|^{n+1+q}, \quad \|\nabla L^{-1}[f](x)\| \lesssim 1 + \|x\|^{n+\kappa+1+q}.$$

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Let $\|\nu\|_f := \sup_{|g| \leq f} |\nu(g)|$ for some $f \geq 1$ and (Ψ_1, Ψ_2) be either pairs of inverse Young functions (i.e., $xy \leq \Psi_1^{-1}(x) + \Psi_2^{-1}(y)$) or (Id, Id) or (Id, Id) .

Proposition [DFG09; AWST22]

Given $(\mathcal{D}(q))$ we have

$$\|P_t(x, \cdot) - \mu\|_{TV} \leq C(q_+) \exp(\iota \|x\|^{1-q_+}) \exp\left(-\iota' t^{\frac{1-q_+}{1+q_+}}\right) \quad \text{and} \quad \int_{\mathbb{R}^d} \exp(\iota \|x\|^{1-q_+}) \mu(dx) < \infty.$$

Moreover, for $\gamma \geq 1 + q$, $r_{\gamma,q}(t) \sim (1+t)^{(\gamma-(1+q))/(1+q)}$, $f_{\gamma,q}(x) \sim 1 + \|x\|^{\gamma-(1+q)}$,

$$(\Psi_1(r_{\gamma,q}(t)) \vee 1) \|P_t(x, \cdot) - \mu\|_{1 \vee \Psi_2 \circ f_{\gamma,q}} \leq C(\Psi)(1 + \|x\|^\gamma).$$

Continuous-time concentration result

Theorem [AWST22]

Assume $(\mathcal{D}(q))$, $\|b(x)\| \lesssim 1 + \|x\|^\kappa$ and $|f(x)| \leq \mathfrak{L}(1 + \|x\|^\eta)$. Let

$$\rho(\eta, \kappa, q) := \begin{cases} 1/(1 - q_+), & \eta = 0 \\ \frac{1}{2} + \frac{\eta + \kappa + 1 + q}{1 - q_+}, & \eta > 0. \end{cases}$$

Then, there exists a constant $c > 0$ s.t. for any $x \geq 2/\sqrt{T}$,

$$\mathbb{C}_\mu(f, T, x) := \mathbb{P}^\mu \left(\left| \frac{1}{T} \int_0^T f(X_t) dt - \mu(f) \right| > x \right) \leq \exp \left(- c \left(\frac{x\sqrt{T}}{\mathfrak{L}} \right)^{1/\rho(\eta, \kappa, q)} \right).$$

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Poincaré, $\eta = 0$	log-Sobolev, $\eta \leq 2$	subexponential, $\eta > 0$
$\frac{\log(1/\delta)}{\varepsilon}$	$\frac{\log(1/\delta)}{\varepsilon}$	$\frac{\log(1/\delta)^{2\rho(\eta, \kappa, q)}}{\varepsilon^2}$

Table 1: Order of sufficient sample length $\Psi(\varepsilon, \delta)$ s.t. **(ε, δ) -PAC-bound** $\mathbb{P}^\mu(|\mu_T(f) - \mu(f)| \leq \varepsilon) \geq 1 - \delta$ holds for $T \geq \Psi(\varepsilon, \delta)$

Discrete-time concentration result

Let observations $(X_{k\Delta})_{k=1,\dots,n}$ be given for some $\Delta \leq 1$. Define $\mathbb{H}_{n,\Delta}(f) := \frac{1}{\sqrt{n\Delta}} \mathbb{G}_{n,\Delta}(f)$, where

$$\mathbb{G}_{n,\Delta}(f) \coloneqq \frac{1}{\sqrt{n\Delta}} \sum_{k=1}^n f(X_{k\Delta}) \Delta.$$

Then for $\mathbb{G}_t(f) \coloneqq t^{-1/2} \int_0^T f(X_t) dt$, $f = \tilde{f} - \mu(\tilde{f})$, $\Phi_k(t) \coloneqq \int_t^{k\Delta} (L\tilde{f}(X_s) - \mu(L\tilde{f})) ds$,
 $\omega_k(t) \coloneqq \int_t^{k\Delta} \nabla \tilde{f}(X_s)^\top \sigma(X_s) dW_s$,

$$\sqrt{n\Delta} (\mathbb{G}_{n,\Delta}(f) - \mathbb{G}_{n\Delta}(f)) = \mu(L\tilde{f}) \frac{n\Delta^2}{2} + \sum_{k=1}^n \int_{(k-1)\Delta}^{k\Delta} \Phi_k(t) dt + \sum_{k=1}^n \int_{(k-1)\Delta}^{k\Delta} \omega_k(t) dt.$$

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Then for $\mathbb{H}_t(f) := t^{-1} \int_0^T f(X_t) dt$, $f = \tilde{f} - \mu(\tilde{f})$, $\Phi_k(t) := \int_t^{k\Delta} (L\tilde{f}(X_s) - \mu(L\tilde{f})) ds$, $\omega_k(t) := \int_t^{k\Delta} \nabla \tilde{f}(X_s)^\top \sigma(X_s) dW_s$,

$$n\Delta(\mathbb{H}_{n,\Delta}(f) - \mathbb{H}_{n\Delta}(f)) = \mu(L\tilde{f}) \frac{n\Delta^2}{2} + \sum_{k=1}^n \int_{(k-1)\Delta}^{k\Delta} \Phi_k(t) dt + \sum_{k=1}^n \int_{(k-1)\Delta}^{k\Delta} \omega_k(t) dt.$$

Theorem [AWST22]

Assume $(\mathcal{D}(q))$, $\|b(x)\| \lesssim 1 + \|x\|^\kappa$, $f \in C^2(\mathbb{R}^d; \mathbb{R})$ s.t. $\|D^k f(x)\| \lesssim 1 + \|x\|^{\eta_k}$, $k = 0, 1, 2$. Define $\alpha := (\kappa + \eta_1) \vee \eta_2$, and let $\tilde{\gamma} > 1 + q$, $r > 1$, s.t. $\tilde{\gamma} - (1 + q) > r(\alpha \vee (1 + q)/(r - 1))$. Then, for $p \geq 2$,

$$\|\mathbb{H}_{n,\Delta}(f) - \mu(f)\|_{L^p(\mathbb{P}^\mu)} \leq \mathfrak{D} \left(\Delta + \sqrt{\frac{\Delta}{n}} p^{\frac{\max\{(\tilde{\gamma} + 2\alpha + 1 - q_+)/2, \eta_1 + 1 - q_+\}}{1 - q_+}} + \frac{1}{\sqrt{n\Delta}} p^{\frac{1}{2} + \frac{\eta_1 + \kappa + 1 + q}{1 - q_+}} \right) := \Phi(n, \Delta, p),$$

and

$$\mathbb{P}^\mu \left(|\mathbb{H}_{n,\Delta}(f) - \mu(f)| > e\Phi(n, \Delta, x) \right) \leq e^{-x}, \quad x \geq 2.$$

Application

MCMC for moderately heavy tailed targets

- Langevin diffusion

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

has invariant density $\pi(x) \propto \exp(-U(x)) \rightsquigarrow$ sampling from π by numerical approximation of X ,
e.g., Euler scheme

$$\vartheta_{n+1}^{(\Delta)} = \vartheta_n^{(\Delta)} - \Delta \nabla U(\vartheta_n^{(\Delta)}) + \sqrt{2\Delta} \xi_{n+1}, \quad \vartheta_0^{(\Delta)} \sim X_0, \quad (\xi_n) \underset{\text{iid}}{\sim} \mathcal{N}(0, \mathbb{I}_d)$$

- abundant literature on sampling precision in TV or Wasserstein distance for U **strongly convex** or modifications thereof [Dal17; DK19; DM17; DMM19] $\rightsquigarrow \pi(x) dx$ **sub-Gaussian**
- Assume instead that for some $q \in (0, 1)$

$$\langle \nabla U(x), x/\|x\| \rangle \geq \tau \|x\|^{-q}, \quad \|x\| > A. \quad (\mathcal{U}(q))$$

$$\rightsquigarrow \exists \lambda > 0 : \int_{\mathbb{R}^d} \exp(\lambda \|x\|^{\tilde{q}}) \pi(x) dx < \infty \iff \tilde{q} \leq 1 - q$$

\rightsquigarrow prototypical example: $\pi(x) \propto \exp(-\beta \|x\|^{1-q})$ outside some ball around the origin

Convergence guarantees

Proposition [AWST22]

Assume $(\mathcal{U}(q))$ and that ∇U is bounded. Let $f \in C^2(\mathbb{R}^d)$ s.t. $\|D^k f(x)\| \lesssim 1 + \|x\|^{\eta_k}$, $k = 0, 1, 2$, and consider the burn-in estimator

$$\mathbb{H}_{n,m,\Delta}(f) \coloneqq \mathbb{H}_{n,\Delta}(f) \circ \theta_m = \frac{1}{n} \sum_{k=m+1}^{n+m} f(X_{k\Delta}).$$

Then we have the following approximation guarantees:

	step length Δ	sample size n	burn-in m
ε -prec. sampling	$\frac{\varepsilon^2}{d(\log(\mathfrak{C}/\varepsilon))^{(1-q)/(1+q)}}$	$\frac{d(\log(\mathfrak{C}/\varepsilon))^{2(1-q)/(1+q)}}{\varepsilon^2}$	—
(ε, δ) -PAC bound	$\frac{(\delta\varepsilon)^2}{d(\log(1/\delta))^{2(\eta_0+(q+3)/2)/(1-q)}}$	$\frac{d\mathfrak{D}^2(\log(1/\delta))^{(4(\eta_0+(q+3)/2)/(1-q)}}{\delta^2\varepsilon^4}$	$\frac{d(\log(1/\delta))^{2(\eta_0+q+2)/(1-q)}}{(\delta\varepsilon)^2}$

Table 2: Order of sufficient sampling frequency Δ , sample size n and burn-in m for (ε, δ) -PAC bounds and sampling within ε -TV margin

- we provide concentration inequalities for subexponentially ergodic diffusions and polynomially bounded functions given continuous observations
- Concentration inequalities for sampled chains are derived from the continuous observation result
- we demonstrate implications on sufficient sample sizes for MCMC for moderately heavy tailed targets

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Thank you for your attention!

C. Aeckerle-Willems and C. Strauch. "Concentration of scalar ergodic diffusions and some statistical implications". In: *Ann. Inst. Henri Poincaré Probab. Stat.* (2021), to appear.

C. Aeckerle-Willems, C. Strauch, and L. Trottner. *Concentration analysis of multivariate elliptic diffusion processes*. 2022.

D. Bakry, P. Cattiaux, and A. Guillin. "Rate of convergence for ergodic continuous Markov processes: Lyapunov versus Poincaré". In: *J. Funct. Anal.* 254.3 (2008), pp. 727–759. ISSN: 0022-1236.

V. I. Bogachev, M. Röckner, and S. V. Shaposhnikov. "The Poisson equation and estimates for distances between stationary distributions of diffusions". In: *J. Math. Sci. (N.Y.)* 232.3, Problems in mathematical analysis. No. 92 (Russian) (2018), pp. 254–282. ISSN: 1072-3374.

P. Cattiaux and A. Guillin. "Deviation bounds for additive functionals of Markov processes". In: *ESAIM Probab. Stat.* 12 (2008), pp. 12–29. ISSN: 1292-8100.

A. S. Dalalyan. "Theoretical guarantees for approximate sampling from smooth and log-concave densities". In: *J. R. Stat. Soc. Ser. B. Stat. Methodol.* 79.3 (2017), pp. 651–676. ISSN: 1369-7412.

R. Douc, G. Fort, and A. Guillin. "Subgeometric rates of convergence of f -ergodic strong Markov processes". In: *Stochastic Process. Appl.* 119.3 (2009), pp. 897–923. ISSN: 0304-4149.

A. S. Dalalyan and A. Karagulyan. "User-friendly guarantees for the Langevin Monte Carlo with inaccurate gradient". In: *Stochastic Process. Appl.* 129.12 (2019), pp. 5278–5311. ISSN: 0304-4149.

A. Durmus and E. Moulines. "Nonasymptotic convergence analysis for the unadjusted Langevin algorithm". In: *Ann. Appl. Probab.* 27.3 (2017), pp. 1551–1587. ISSN: 1050-5164.

A. Durmus, S. Majewski, and B. a. Miasojedow. "Analysis of Langevin Monte Carlo via convex optimization". In: *J. Mach. Learn. Res.* 20 (2019), Paper No. 73, 46. ISSN: 1532-4435.

F. Gao, A. Guillin, and L. Wu. "Bernstein-type concentration inequalities for symmetric Markov processes". In: *Theory Probab. Appl.* 58.3 (2014), pp. 358–382. ISSN: 0040-585X.

L. Galtchouk and S. Pergamenshchikov. "Uniform concentration inequality for ergodic diffusion processes". In: *Stochastic Process. Appl.* 117.7 (2007), pp. 830–839. ISSN: 0304-4149.

P. Lezaud. "Chernoff and Berry-Esséen inequalities for Markov processes". In: *ESAIM Probab. Statist.* 5 (2001), pp. 183–201. ISSN: 1292-8100.

R. Nickl and K. Ray. "Nonparametric statistical inference for drift vector fields of multi-dimensional diffusions". In: *Ann. Statist.* 48.3 (2020), pp. 1383–1408. ISSN: 0090-5364.

E. Pardoux and A. Y. Veretennikov. "On the Poisson equation and diffusion approximation. I". In: *Ann. Probab.* 29.3 (2001), pp. 1061–1085. ISSN: 0091-1798.