

# Nonparametric estimation of McKean-Vlasov SDEs via deconvolution

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joint work with

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# Plan of this talk

1. Interacting particle system associated to McKean-Vlasov SDE
2. Assumptions and probabilistic properties
3. Estimation procedure
4. Convergence rates
5. On Fourier transforms

# 1. Introduction

Consider an interacting particle system: an  $\mathbb{R}^N$ -valued stochastic process

$$(X_t^1, \dots, X_t^N)_{t \geq 0}$$

defined by

$$dX_t^i = -V'(X_t^i)dt - \frac{1}{N} \sum_{j=1}^N W'(X_t^i - X_t^j)dt + dB_t^i, \quad i = 1, \dots, N, \quad t \geq 0,$$

where

- ▶  $X_0^1, \dots, X_0^N$  are i.i.d. random variables with a common law  $\bar{\Pi}_0$ ,
- ▶  $(B_t^1)_{t \geq 0}, \dots, (B_t^N)_{t \geq 0}$  are independent standard Brownian motions, independent of  $X_0^1, \dots, X_0^N$ ,
- ▶  $V, W : \mathbb{R} \rightarrow \mathbb{R}$  are called respectively confinement, interaction potentials.

Our objective is to estimate  $W'$  from

$$X_T^1, \dots, X_T^N$$

when  $N, T \rightarrow \infty$ .

Let  $(\bar{X}_t)_{t \geq 0}$  be the solution of the McKean-Vlasov SDE:

$$d\bar{X}_t = -V'(\bar{X}_t)dt - W' * \bar{\Pi}_t(\bar{X}_t)dt + dB_t, \quad t \geq 0,$$

where

- ▶  $\bar{\Pi}_t$  denotes the law of  $\bar{X}_t$ ,
- ▶  $*$  denotes convolution:

$$W' * \bar{\Pi}_t(x) = \int_{\mathbb{R}} W'(x - y) \bar{\Pi}_t(dy), \quad x \in \mathbb{R},$$

- ▶  $(B_t)_{t \geq 0}$  is a standard Brownian motion, independent of  $\bar{X}_0$ .

## Nonparametric estimation:

- ▶ Hoffmann, Liu 2023+, Belomestny, P., Podolskij 2023, Della Maestra, Hoffmann 2022, Lu, Maggioni, Tang 2021, Li, Lu, Maggioni, Tang, Zhang 2021

Recall the McKean-Vlasov SDE

$$d\bar{X}_t = -V'(\bar{X}_t)dt - W' * \bar{\Pi}_t(\bar{X}_t)dt + dB_t, \quad t \geq 0.$$

Assume that

$$V(x) = 0, \quad W(x) = \sum_{j=1}^J \alpha_j x^{2j} + \beta(x), \quad x \in \mathbb{R},$$

for some known  $J \in \mathbb{N}$  and unknown  $\alpha_1 > 0$ ,  $\alpha_j \geq 0$ ,  $1 < j < J$ ,  $\alpha_J > 0$  and unknown even  $\beta \in C^2(\mathbb{R})$  with bounded, integrable  $\beta'$  such that

$$\inf_{x \in \mathbb{R}} W''(x) =: \lambda > 0.$$

### Proposition (Belomestny, P., Podolskij 2023)

Assume that for some  $p > 0$ ,

$$\limsup_{x \rightarrow \infty} x^{2p} \int_{|y| > x} |\beta'(y)|^2 dy < \infty.$$

and let  $\beta'$  be entire and of the first order and type less than  $\vartheta > 0$ , i.e.  $|\beta'(z)| \leq A \exp(\vartheta|z|)$ ,  $z \in \mathbb{C}$ , for some  $A > 0$  and let  $\vartheta \leq \lambda^{\frac{1}{2}}$ . Choose an arbitrary  $r_T^N \rightarrow 0$  as  $N, T \rightarrow \infty$  in the estimation procedure. Set

$$N_T^{-1} := N^{-1} + \exp(-\lambda T)$$

Then

$$\mathbb{E} \left[ \int_{\mathbb{R}} |(\beta')_T^N(x) - \beta'(x)|^2 dx \right] \lesssim (r_T^N)^{-2} (\log N_T)^{-\frac{p}{j}},$$

where  $\lesssim$  stands for the inequality up to a constant.

Examples:

$$\beta(x) = \frac{1 - \cos(bx)}{x^2}, \quad b > 0, \quad \beta(x) = \frac{\sin^{2k}(x)}{x^{2k}}, \quad k \in \mathbb{N}.$$

### Theorem (Belomestny, P., Podolskij 2023)

Let  $X_T^1, \dots, X_T^N$  be i.i.d. from the invariant law  $\Pi = \Pi_\beta$  of  $(\bar{X}_t)_{t \geq 0}$ ,  $\mathcal{F}$  a specific class of functions  $f : \mathbb{R} \rightarrow \mathbb{R}$  in accordance with estimation procedure and  $p > \frac{1}{2}$ . Then there exists  $C > 0$  such that

$$\inf_{(\beta')_N} \sup_{\beta \in \mathcal{F}} \Pi_\beta^{\otimes N} (\|(\beta')_N - \beta'\|_2^2) > C(\log N)^{-\frac{p}{J}} > 0.$$

**Remark.** The classical deconvolution problem:

$$Y_i = X_i + \varepsilon_i, \quad i = 1, \dots, N,$$

where  $(X_i)_{i \in \mathbb{N}}$ ,  $(\varepsilon_i)_{i \in \mathbb{N}}$  are independent sequences of i.i.d. random variables with densities  $f_X$ ,  $f_\varepsilon$  respectively. If for  $p > \frac{1}{2}$ ,

$$\int_{\mathbb{R}} |\mathcal{F}f_X(z)|^2 |z|^{2p} dz \leq C, \quad |\mathcal{F}f_\varepsilon(z)| \asymp \exp(-C|z|^{2J}), \quad |z| \rightarrow \infty,$$

then the minimax rate for the estimation of  $f_X$  is  $(\log N)^{-\frac{p}{J}}$ .

## 2. Assumptions and probabilistic properties

Assume that

- ▶  $V(x) = \frac{\alpha}{2}x^2 + \tilde{V}(x)$ ,  $x \in \mathbb{R}$ , where  $\alpha > 0$  is unknown, whereas  $\tilde{V}$  is known and either

A1  $\tilde{V} = 0$  or

A2  $\tilde{V}$  is even with continuous bounded derivatives up to some integer  $M \geq 2$ ,

moreover,  $\inf_{x \in \mathbb{R}} V''(x) =: C_V > 0$ ,

- ▶  $W \in C^2(\mathbb{R})$  is unknown, even with bounded, integrable  $W'$  and bounded  $W''$  such that  $\inf_{x \in \mathbb{R}} W''(x) =: -C_W < 0$  and

$$\lambda := C_V - 2C_W > 0,$$

- ▶ initial law  $\bar{\Pi}_0$  admits a density  $\pi_0$  and for all  $a \in \mathbb{R}$ ,

$$\int_{\mathbb{R}} \exp(ax)\pi_0(x)dx < \infty, \quad \int_{\mathbb{R}} \log(\pi_0(x))\pi_0(x)dx < \infty.$$



## Uniform in time propagation of chaos property:

### Proposition

Let  $p \in \mathbb{N}$ . Then for all  $N \in \mathbb{N}$ ,  $i = 1, \dots, N$  and  $t \geq 0$ ,

$$\mathbb{E}[|X_t^i - \bar{X}_t^i|^{2p}] \leq \frac{C}{N^p},$$

where  $(\bar{X}_t^i)_{t \geq 0}$  starting at  $\bar{X}_0^i = X_0^i$  and driven by  $(B_t^i)_{t \geq 0}$ ,  $i = 1, \dots, N$ , are independent copies of  $(\bar{X}_t)_{t \geq 0}$ .

- ▶ A version of results<sup>1,2</sup>

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<sup>1</sup>Cattiaux P., Guillin, A., Malrieu, F. Probabilistic approach for granular media equations in the non-uniformly convex case. *Probab. Theory Related Fields* 140:19–40, 2008.

<sup>2</sup>Malrieu, F. Convergence to equilibrium for granular media equations and their Euler schemes. *Ann. Appl. Probab.* 13(2):540–560, 2003.

Combined with **exponential convergence to equilibrium** for  $\bar{\Pi}_t$  as  $t \rightarrow \infty$ <sup>3</sup>:

### Theorem

Denote by  $\Pi$  the invariant law of  $(\bar{X}_t)_{t \geq 0}$  and

$$\Pi_T^N := \frac{1}{N} \sum_{i=1}^N \delta_{X_T^i}.$$

Then

$$\mathbb{E}[W_1^2(\Pi_T^N, \Pi)] \leq C \left( \frac{1}{N} + \exp(-\lambda T) \right) =: \frac{1}{N_T},$$

where  $W_1$  denotes the Wasserstein 1-distance, i.e.

$$W_1(\mu, \nu) := \inf_{X \sim \mu, Y \sim \nu} \mathbb{E}[|X - Y|],$$

where the infimum is taken over all couplings  $(X, Y)$  of random variables  $X$  and  $Y$  with respective laws  $\mu$  and  $\nu$ .

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<sup>3</sup>Carrillo, J.A., McCann, R.J, Villani, C. Kinetic equilibration rates for granular media and related equations: entropy dissipation and mass transportation estimates. Rev. Mat. Iberoamericana 19(3):971-1018, 2003.

The invariant law  $\Pi$  admits a density

$$\pi(x) = \frac{1}{Z} \exp(-2V(x) - 2W * \pi(x))$$

with a normalizing constant

$$Z := \int_{\mathbb{R}} \exp(-2V(x) - 2W * \pi(x)) dx < \infty.$$

### Lemma

Then, for any  $x \in \mathbb{R}$ ,

$$\exp(-C_0 x^2) \lesssim \pi(x) \lesssim \exp(-C_V x^2)$$

with  $C_0 := \sup_{x \in \mathbb{R}} |V''(x)|$ . Moreover, let  $n \geq 1$  under A1 and  $1 \leq n \leq M$  under A2. Then

$$|\pi^{(n)}(x)| \lesssim (1 + |x|)^n \exp(-C_V x^2)$$

### 3. Estimation procedure

Step 1. We estimate

$$l(x) := (\log \pi(x))' = \frac{\pi'(x)}{\pi(x)} = -2V'(x) - 2W' * \pi(x)$$

by

$$l_T^N(x) := \frac{(\pi')_T^N(x)}{\pi_T^N(x)} \mathbf{1}(\pi_T^N(x) > \delta),$$

with

$$\pi_T^N(x) := (Nh_0)^{-1} \sum_{i=1}^N K(h_0^{-1}(x - X_T^i)),$$
$$(\pi')_T^N(x) := (Nh_1^2)^{-1} \sum_{i=1}^N K'(h_1^{-1}(x - X_T^i)),$$

where

- ▶  $K$  is a smooth kernel of order  $m$ , i.e.  $\mathbf{m}_0 = 1$ ,  $\mathbf{m}_1 = 0$ , ...,  $\mathbf{m}_{m-1} = 0$ ,  $\mathbf{m}_m \neq 0$ , where  $\mathbf{m}_k = \int_{\mathbb{R}} x^k K(x) dx$ , moreover,  $m \geq 2$  under A1 or  $2 \leq m \leq M$  under A2.
- ▶  $h_0 = h_{T,0}^N \rightarrow 0$ ,  $h_1 = h_{T,1}^N \rightarrow 0$  and  $\delta = \delta_T^N \rightarrow 0$  as  $N, T \rightarrow \infty$ .

Step 2. In

$$l(x) = -2\alpha x - 2\tilde{V}'(x) - 2W' * \pi(x)$$

we have that

$$W' * \pi(x) \rightarrow 0$$

as  $|x| \rightarrow \infty$  since  $W'$  is integrable.

We define a minimum contrast estimator for  $\alpha$ :

$$\alpha_T^N := \arg \min_{\alpha \in \mathbb{R}} \int_{\mathbb{R}} (l_T^N(x) - 2\alpha x - 2\tilde{V}'(x))^2 \frac{1}{U} w\left(\frac{x}{U}\right) dx,$$

where

- ▶  $w$  is a weight function with support  $[\epsilon, 1]$  for some  $\epsilon \in (0, 1)$ ,
- ▶  $U = U_T^N \rightarrow \infty$  as  $N, T \rightarrow \infty$ .

Step 3. We estimate

$$\Psi(x) = -W' * \pi(x)$$

by

$$\Psi_T^N(x) = \frac{1}{2} (l_T^N(x) + 2\alpha_T^N x + 2\tilde{V}'(x)) \mathbf{1}(|x| \leq \epsilon U).$$

Step 4<sup>4,5</sup>. We use

$$\mathcal{F}\Psi(z) = -\mathcal{F}W'(z)\mathcal{F}\pi(z), \quad z \in \mathbb{R} =: \mathcal{L}_0,$$

where

$$\mathcal{F}\phi(z) := \int_{\mathbb{R}} \phi(t) \exp(izt) dt.$$

Choose entire functions  $\rho_T^N$  such that for all  $z \in \mathcal{L}_0$  it holds  $|\mathcal{F}(\Pi_T^N)(z) + \rho_T^N(z)| \geq r_T^N > 0$ , where  $r_T^N \rightarrow 0$  as  $N, T \rightarrow \infty$ . Then, we define the estimator  $(W')_T^N$  via

$$\mathcal{F}(W')_T^N(z) := -\frac{\mathcal{F}\Psi_T^N(z)}{\mathcal{F}\Pi_T^N(z) + \rho_T^N(z)}, \quad z \in \mathcal{L}_0,$$

**Remark.** Actually, we consider deconvolution on  $\mathcal{L}_a := \{y + ia : y \in \mathbb{R}\}$  for some  $a \geq 0$ .

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<sup>4</sup>Johannes, J. Deconvolution with unknown error distribution. Ann. Statist. 37(5A) 2301-2323, 2009.

<sup>5</sup>Belomestny, D., Goldenshluger, A. Density deconvolution under general assumptions on the distribution of measurement errors. Ann. Statist. 49(2):615-649, 2021.

## 4. Convergence rates

### Proposition

Let

$$h_0 := N_T^{-\frac{1}{2(m+1)}}, \quad h_1 := N_T^{-\frac{1}{2(m+2)}}, \quad \delta := \frac{c_0}{2} \exp(-C_0 U^2),$$

and  $U \geq 1$ . Then

$$\sup_{|x| \leq U} \mathbb{E}[|l_T^N(x) - l(x)|^2]^{\frac{1}{2}} \lesssim \exp(C_0 U^2) (N_T^{-\frac{m}{2(m+2)}} + U N_T^{-\frac{m}{2(m+1)}}).$$

## Theorem

In the setting of the above proposition it holds that

$$\mathbb{E} \left[ \int_{\mathbb{R}} |\Psi_T^N(x) - \Psi(x)|^2 dx \right]^{\frac{1}{2}} \lesssim U^{\frac{1}{2}} \sup_{|x| \leq U} \mathbb{E}[|l_T^N(x) - l(x)|^2]^{\frac{1}{2}} \\ + \frac{\exp(-C_V(\frac{\epsilon U}{2})^2)}{\frac{\epsilon U}{2}} + \left( \int_{|x| > \frac{\epsilon U}{2}} |W'(x)|^2 dx \right)^{\frac{1}{2}}.$$

## Corollary

In the setting of previous theorem, moreover, assume that for some  $C > C_V$ ,

$$\limsup_{y \rightarrow \infty} \exp(2Cy^2) \int_{|x| > y} |W'(x)|^2 dx < \infty.$$

Let  $C_0 U^2 := \frac{(1-\gamma)m}{2(m+2)} \log N_T$ , where  $\gamma := \frac{\epsilon^2 C_V}{\epsilon^2 C_V + 4C_0}$ . Then

$$\mathbb{E} \left[ \int_{\mathbb{R}} |\Psi_T^N(x) - \Psi(x)|^2 dx \right]^{\frac{1}{2}} \lesssim (\log N_T)^{\frac{1}{4}} N_T^{-\frac{\gamma m}{2(m+2)}}.$$



## Theorem

In the setting of previous corollary, moreover, assume that

$$\int_{\mathcal{L}_{\pm a}} \left| \frac{\mathcal{F}W'(z)}{\mathcal{F}\pi(z)} \right|^2 dz < \infty$$

and let

$$r_T^N := \exp\left(\frac{a\epsilon}{2}U\right)(\log N_T)^{\frac{1}{4}} N_T^{-\frac{\gamma m}{4(m+2)}}$$

where, recall,  $C_0 U^2 = \frac{(1-\gamma)m}{2(m+2)} \log N_T$  and  $\gamma = \frac{\epsilon^2 C_V}{\epsilon^2 C_V + 4C_0}$ . Then

$$\mathbb{E} \left[ \int_{\mathbb{R}} |(W')_T^N(x) - W'(x)|^2 dx \right]^{\frac{1}{2}} \lesssim r_T^N.$$

Remarks:

- ▶ polynomial convergence rate,
- ▶  $m \leq M$  under A2.

## 5. On Fourier transforms

### Theorem

Denote the order of  $\mathcal{F}\pi$  by  $\rho$ . Then  $\rho \leq 2$ . Moreover, denote by  $\rho_1$  the critical exponent of the sequence of zeros  $(a_j)_{j \in \mathbb{N}}$  of  $\mathcal{F}\pi$ . In addition, assume that either  $\rho_1 < \rho$  or  $\rho_1 = \rho < 2$ . Then there exist  $C > 0$  and a family of positive numbers  $(r_j)_{j \in \mathbb{N}}$  such that, for all  $z \in \mathbb{C}$  outside of  $\cup_{j \geq 1} B_{r_j}(a_j)$ , it holds that

$$|\mathcal{F}\pi(z)| \gtrsim \exp(-C|z|^2).$$

- ▶ The proof uses Gaussian tails of  $\pi$ , Hadamard's factorization theorem
- ▶ Examples of  $W'$ : Hermite functions

**Example.** Under A2, moreover, assume that  $W, V$  are infinitely differentiable respectively on  $\mathbb{R}, \mathbb{R}_0$ ,  $V^{(n)}$ ,  $2 \leq n \leq M + 2$ , are bounded on  $\mathbb{R}_0$  and there exist

$$V^{(M+1)}(0-) \neq V^{(M+1)}(0+).$$

It provides that

$$\pi(x) = \frac{1}{Z} \exp(-2V(x) - 2W * \pi(x))$$

is infinitely differentiable on  $\mathbb{R}_0$  and there exist

$$\pi^{(M+1)}(0-) \neq \pi^{(M+1)}(0+).$$

Then, iteratively integrating by parts we obtain

$$\mathcal{F}\pi(z) = \frac{1}{(-iz)^{M+1}} (I_-(z) + I_+(z)),$$

where

$$I_-(z) := \int_{-\infty}^0 \exp(izx) \pi^{(M+1)}(x) dx, \quad I_+(z) := \int_0^{\infty} \exp(izx) \pi^{(M+1)}(x) dx.$$

If we integrate by parts once more, then

$$I_+(z) = \frac{1}{iz} \left( -\pi^{(M+1)}(0+) - \int_0^\infty \exp(izx) \pi^{(M+2)}(x) dx \right).$$

By Riemann's lemma, the last integral tends to zero and so

$$I_+(z) := -\frac{1}{iz} \pi^{(M+1)}(0+) + o\left(\frac{1}{z}\right)$$

as  $z \rightarrow \infty$ . Clearly an analogous reasoning applies to  $I_-(z)$ . It yields that for all large enough  $z$ ,

$$|\mathcal{F}\pi(z)| \geq \frac{C}{|z|^{M+2}}.$$

## References

- ▶ Amorino, C., Belomestny, D., Pilipauskaitė, V., Podolskij, M., Zhou, S.-Y. Polynomial rates via deconvolution for nonparametric estimation in McKean-Vlasov SDEs. Preprint arXiv:2401.04667.
- ▶ Belomestny, D., Pilipauskaitė, V., Podolskij, M. Semiparametric estimation of McKean-Vlasov SDEs. *Ann. Inst. H. Poincaré Probab. Statist.* 59(1): 79-96, 2023.

Thank you for your attention