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# Long run convergence of discrete-time interacting particle systems of the McKean-Vlasov type

Pascal Bianchi, Walid Hachem and Victor Priser

March 25, 2024

## Abstract

We consider a discrete time system of  $n$  coupled random vectors, a.k.a. interacting particles. The dynamics involves a vanishing step size, some random centered perturbations, and a mean vector field which induces the coupling between the particles. We study the doubly asymptotic regime where both the number of iterations and the number  $n$  of particles tend to infinity, without any constraint on the relative rates of convergence of these two parameters. We establish that the empirical measure of the interpolated trajectories of the particles converges in probability, in an ergodic sense, to the set of recurrent McKean-Vlasov distributions. A first application example is the granular media equation, where the particles are shown to converge to a critical point of the Helmholtz energy. A second example is the convergence of stochastic gradient descent to the global minimizer of the risk, in a wide two-layer neural networks using random features.

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## 1 Introduction

Given two integers  $n, d > 0$ , consider the iterative algorithm defined as follows. Starting with the  $n$ -uple  $(X_0^{1,n}, \dots, X_0^{n,n})$  of random variables  $X_0^{i,n} \in \mathbb{R}^d$ , the algorithm generates at the iteration  $k + 1$  for  $k \in \mathbb{N}$  the  $n$ -uple of  $\mathbb{R}^d$ -valued random variables  $(X_k^{1,n}, \dots, X_k^{n,n})$ , referred to as the *particles*, according to the dynamics:

$$X_{k+1}^{i,n} = X_k^{i,n} + \frac{\gamma_{k+1}}{n} \sum_{j=1}^n b(X_k^{i,n}, X_k^{j,n}) + \sqrt{2\gamma_{k+1}} \xi_{k+1}^{i,n} + \gamma_{k+1} \zeta_{k+1}^{i,n}, \quad (1)$$

for each  $i \in [n]$  where  $[n] := \{1, \dots, n\}$ . In this equation, the function  $b : \mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{R}^d$  is a continuous vector field,  $(\gamma_k)_k$  is a vanishing sequence of deterministic positive step sizes, and  $((\xi_k^{i,n})_{i \in [n]})_{k \in \mathbb{N}^*}$  and  $((\zeta_k^{i,n})_{i \in [n]})_{k \in \mathbb{N}^*}$  are  $\mathbb{R}^{d \times n}$ -valued random noise sequences in the time parameter  $k$ . We assume that for each  $n$ , the  $n$ -uple  $(X_0^{1,n}, \dots, X_0^{n,n})$  is exchangeable, and that the same holds for the  $n$ -uple of sequences  $((\xi_k^{1,n})_{k \in \mathbb{N}^*}, \dots, (\xi_k^{n,n})_{k \in \mathbb{N}^*})$  and  $((\zeta_k^{1,n})_{k \in \mathbb{N}^*}, \dots, (\zeta_k^{n,n})_{k \in \mathbb{N}^*})$ . Defining, for each  $n > 0$ , the filtration  $(\mathcal{F}_k^n)_{k \in \mathbb{N}}$  as

$$\mathcal{F}_k^n := \sigma((X_0^{i,n})_{i \in [n]}, ((\xi_\ell^{i,n})_{i \in [n]})_{\ell \leq k}, ((\zeta_\ell^{i,n})_{i \in [n]})_{\ell \leq k}), \quad (2)$$

we furthermore assume that for each  $n$ , the sequence  $((\xi_k^{i,n})_{i \in [n]})_k$  is a  $(\mathcal{F}_k^n)_k$ -martingale increment sequence *i.e.*,  $\mathbb{E}(\xi_{k+1}^{i,n} | \mathcal{F}_k^n) = 0$ . Finally, we assume that  $\mathbb{E}(\xi_{k+1}^{i,n} (\xi_{k+1}^{j,n})^T | \mathcal{F}_k^n) = \sigma^2 \mathbf{1}_{i=j} I_d$  for some  $\sigma^2 \geq 0$ .

The aim of the paper is to characterize the asymptotic behavior of the empirical measure of the particles

$$\mu_k^n := \frac{1}{n} \sum_{i=1}^n \delta_{X_k^{i,n}} \quad (3)$$

in the regime where both the time index  $k$  and the number of particles  $n$  tend to infinity (denoted hereinafter as  $(k, n) \rightarrow (\infty, \infty)$ ), without any constraint on the relative rates of convergence of these two parameters. To this end, we consider for each  $i \in [n]$  the random continuous process  $\bar{X}^{i,n} : [0, \infty) \rightarrow \mathbb{R}^d, t \mapsto \bar{X}_t^{i,n}$  defined as the piecewise linear interpolation of the particles  $(X_k^{i,n})_k$ . Specifically, writing

$$\tau_k := \sum_{j=1}^k \gamma_j \quad (4)$$

for each  $k \in \mathbb{N}$ , we define:

$$\forall t \in [\tau_k, \tau_{k+1}), \quad \bar{X}_t^{i,n} := X_k^{i,n} + \frac{t - \tau_k}{\gamma_{k+1}} (X_{k+1}^{i,n} - X_k^{i,n}). \quad (5)$$

The interpolated processes  $\bar{X}^{i,n}$ , for  $i \in [n]$ , are elements of the set  $\mathcal{C}$  of the  $[0, \infty) \rightarrow \mathbb{R}^d$  continuous functions, equipped with the topology of uniform convergence on compact intervals. This paper studies the empirical measure of these processes:

$$m^n := \frac{1}{n} \sum_{i=1}^n \delta_{\bar{X}^{i,n}}. \quad (6)$$

For each  $n$  and each  $p \geq 1$ ,  $m^n$  is a random variable on  $\mathcal{P}_2(\mathcal{C})$ , where  $\mathcal{P}_2(\mathcal{C})$  is the set of Borel probability measures on  $\mathcal{C}$ , such that their restrictions to compactly supported functions admit a finite second order moment. The space  $\mathcal{P}_2(\mathcal{C})$  is naturally equipped with the metric  $W_2$  of Wasserstein convergence over functions of compact intervals. Our aim is to analyse the convergence in probability, of the shifted random measures

$$\Phi_t(m^n) = \frac{1}{n} \sum_{i=1}^n \delta_{\bar{X}_{t+}^{i,n}},$$

when both  $n$  and  $t$  converge to infinity with arbitrary relative rates, where for every  $m \in \mathcal{P}_2(\mathcal{C})$ ,  $\Phi_t(m) \in \mathcal{P}_2(\mathcal{C})$  is defined by  $\Phi_t(m)(f) = \int f(x(t + \cdot)) dm(x)$  for every bounded continuous function  $f$  on  $\mathcal{C}$ . Under mild assumptions on the vector field  $b$ , and some moment assumptions on the iterates and on the noise sequence  $((\zeta_k^{i,n})_{i \in [n]})_k$ , ensuring that the effect of the latter becomes negligible in our asymptotic regime, we establish the following result, which we explain hereafter.

**Main theorem (informal).** The sequence  $(\Phi_t(m^n))$  ergodically converges in probability as  $(t, n) \rightarrow (\infty, \infty)$  to the set of *recurrent McKean-Vlasov distributions*.

Let us explain what the terms *McKean-Vlasov distribution*, *recurrent*, and *ergodic convergence* mean in this paper. Here, a McKean-Vlasov distribution  $\rho$  is defined as the law of a  $\mathbb{R}^d$ -valued process  $(X_t : t \in \mathbb{R})$  satisfying the following condition: for every smooth function  $\phi$ , the process

$$\phi(X_t) - \int_0^t L(\rho_s)(\phi)(X_s) ds$$

is a martingale, where  $\rho_t$  the marginal law of  $X_t$ , and where the linear operator  $L(\rho_t)$  associates to  $\phi$  the function  $L(\rho_t)(\phi)$  given by:

$$x \mapsto \langle b(x, \rho_t), \nabla \phi(x) \rangle + \sigma^2 \Delta \phi(x),$$

where  $\Delta$  is the Laplacian, and where we use the slightly abusive notation  $b(x, \rho_t) := \int b(x, y) d\rho_t(y)$ .

A McKean-Vlasov distribution  $\rho$  is said recurrent if, for some sequence  $(t_k) \rightarrow \infty$ ,  $\rho = \lim_{k \rightarrow \infty} \Phi_{t_k}(\rho)$ . The  $W_2$ -closure of the set of recurrent McKean-Vlasov distributions will be referred to as the *Birkhoff center*, and denoted by BC, following the terminology used for general dynamical systems.

Finally, by *ergodic convergence*, we refer to the fact that the time-averaged Wasserstein distance between the measures  $\Phi_t(m^n)$  and the Birkhoff center converges to zero. Our main theorem can thus be written more precisely:

$$\frac{1}{t} \int_0^t W_2(\Phi_s(m^n), \text{BC}) ds \xrightarrow{(n,t) \rightarrow (\infty, \infty)} 0, \quad \text{in probability.}$$

The Birkhoff center can be characterized in a useful way, provided that one is able to show the existence of a *Lyapunov function*, namely a function  $F$  on  $\mathcal{P}_2(\mathcal{C})$  such that, for every McKean-Vlasov distribution  $\rho$ ,  $F(\Phi_t(\rho))$  is non-increasing in the variable  $t$ . Indeed, in such a situation, the Birkhoff center is included in the subset  $\Lambda$  of McKean-Vlasov distributions which satisfy the property that  $t \mapsto F(\Phi_t(\rho))$  is constant whenever  $\rho \in \Lambda$ . We provide two important examples of McKean-Vlasov distribution admitting useful Lyapunov functions.

**Granular media.** Our first example corresponds to the scenario where the vector field  $b$  takes the form:

$$b(x, y) = -\nabla V(x) - \nabla U(x - y),$$

where  $V$  and  $U$  denote two real differentiable functions on  $\mathbb{R}^d$ , whose gradients satisfy some linear growth condition. In this case, a Lyapunov function exists, which can be expressed as a function of the so-called *Helmholtz energy*. As a consequence of our main result, we establish that, when  $\sigma > 0$ , the empirical measures  $(\mu_k^n)$  converge ergodically in probability as  $(k, n) \rightarrow (\infty, \infty)$  to the set  $\mathcal{S}$  of critical points of the Helmholtz energy, namely:

$$\frac{\sum_{l=1}^k \gamma_l W_2(\mu_k^n, \mathcal{S})}{\sum_{l=1}^k \gamma_l} \xrightarrow{(n,k) \rightarrow (\infty, \infty)} 0, \quad \text{in probability.}$$

where, this time,  $W_2$  represents the classical Wasserstein distance, and where  $\mathcal{S}$  is the set of probability measures  $\mu$  on  $\mathbb{R}^d$  which admit a second order moment and a density  $d\mu/d\mathcal{L}^d$  w.r.t. the Lebesgue measure, and such that:

$$\nabla V(x) + \int \nabla U(x - y) d\mu(y) + \sigma^2 \nabla \log \frac{d\mu}{d\mathcal{L}^d}(x) = 0,$$

for  $\mu$ -almost every  $x$ . Our result hold under mild assumptions, and does not require the rather classical strong convexity or doubling conditions on  $U$  and/or  $V$ .

**Stochastic gradient descent (SGD) in two layer neural networks.** An other archetypal example where a useful Lyapunov function exists is encountered in the field of Machine Learning, when studying the convergence of the popular SGD algorithm. As an illustration, we consider the problem of optimizing the coefficients of the output layer of a two layer network, assuming that the coefficients of the first/hidden layer are sampled, once for all, from a given iid distribution. This scenario is known as the *random features* setting. It captures the asymptotic regime of networks where the width  $n$  of the hidden layer goes to infinity, and the ability of the network to reach near perfect reconstruction of a target function, under some hypotheses. More specifically, the output of the neural network for an arbitrary input  $x$  of dimension  $q$  is assumed to have the form:

$$h(x; \mathbf{a}, \mathbf{w}_0^n) := \frac{1}{n} \sum_{i=1}^n a^i \varphi(x, w_0^{i,n}),$$

where  $n$  is the number of neurons at the output of the hidden layer,  $\mathbf{a} = (a^1, \dots, a^n)$  are the coefficients of the output layer,  $\mathbf{w}_0 = (w_0^{1,n}, \dots, w_0^{n,n})$  are (random but fixed)  $\mathbb{R}^{d-1}$ -vectors of the hidden layer, and  $\varphi$  is a real bounded continuous function. We consider the regularized risk minimization problem:

$$\min_{\mathbf{a} \in \mathbb{R}^n} \int (h(x; \mathbf{a}, \mathbf{w}_0^n) - y)^2 d\nu(x, y) + \frac{\lambda}{n} \|\mathbf{a}\|^2, \quad (7)$$

where  $\nu$  is a probability measure on  $\mathbb{R}^q \times \mathbb{R}$ , and where  $\lambda > 0$  is a regularization parameter. We assume that the distribution  $\nu$  is unknown by the observer, but that iid random samples  $(x_{k+1}^n, y_{k+1}^n)_{k \in \mathbb{N}}$  with distribution  $\nu$  are revealed during the iterations of the algorithm. For a fixed  $n$  and a learning rate set to  $n\gamma_k$ , the SGD iterations generate a sequence  $(a_k^{1,n}, \dots, a_k^{n,n})$  of random variables. Defining the particles as  $X_k^{i,n} := (a_k^{i,n}, w_0^{i,n})$  for each  $i \in [n]$ , it turns out that the SGD iterations can be casted into the form of Eq. (1), for a well chosen vector field  $b$ . In this case, the variables  $(\zeta_{k+1}^{1,n}, \dots, \zeta_{k+1}^{n,n})$  of Eq. (1) are centered random perturbations whose first components represent the difference between the stochastic gradient derived from the new sample  $(x_{k+1}^n, y_{k+1}^n)$  and the true gradient of the objective (7). Potentially, we also include the case where a random additive noise of variance  $\sigma^2$ , scaled by  $\sqrt{2\gamma_k}$ , is artificially added at each iteration to each of the variables  $(a_k^{1,n}, \dots, a_k^{n,n})$ , in the flavor of a Langevin algorithm. We establish that a Lyapunov function exists, which is built upon the map  $\mathcal{R}_\sigma$  given by:

$$\begin{aligned} \mathcal{R}_\sigma(\mu) := & \frac{1}{2} \int \left( \int a \varphi(x, w) d\mu(a, w) - y \right)^2 d\nu(x, y) + \frac{\lambda}{2} \int a^2 d\mu(a, w) \\ & + \sigma^2 \int \log \left( \frac{d\mu(\cdot | w)}{d\mathcal{L}^1}(a) \right) d\mu(a, w), \end{aligned}$$

for every probability  $\mu$  on  $\mathbb{R} \times \mathbb{R}^{d-1}$  which admits second order moments. Here,  $\mu(da|w)$  is the conditional distribution obtained from the disintegration of  $\mu$  w.r.t. its marginal in the variable  $w$ , and  $\frac{d\mu(\cdot | w)}{d\mathcal{L}^1}$  represents its density w.r.t. the Lebesgue measure on  $\mathbb{R}$  (setting  $\mathcal{R}_\sigma(\mu) = +\infty$  when no such density exist). Specifically, a Lyapunov function can be expressed as the function which, to every McKean-Vlasov distribution, associates the value  $\mathcal{R}_\sigma(\rho_\epsilon)$  for an arbitrary  $\epsilon > 0$ . By further studying the subset  $\Lambda$  of McKean-Vlasov distributions on which this Lyapunov function is constant, we obtain our main corollary. Given some prescribed distribution  $\varpi$  for the fixed parameters  $w_0^{i,n}$ , the empirical measure  $\mu_k^n$  of the points  $(a_k^{i,n}, w_0^{i,n})$  for  $i \in [n]$ , converges ergodically in probability to the unique minimizer of the risk  $\mathcal{R}_\sigma(\mu)$  among all probability measures  $\mu$  with the prescribed marginal  $\mu(\cdot \times \mathbb{R}^{d-1}) = \varpi$ .

**Contributions.** Compared to existing works, our contributions are threefolds. First, our results hold under mild assumptions on the vector field  $b$  aside from continuity and linear growth, whereas most of the existing works (see below) rely on stronger conditions, such as Lipschitz, doubling or even global boundedness conditions. Second, we address the case of discrete time systems, whereas the continuous time model is more often considered in the literature. Discrete time algorithms are important in applications, such as neural networks, transformers, MonteCarlo

simulations or numerical solvers. In particular, stability results are more difficult to establish in this setting. Finally, our result focus on a double limit  $(k, n) \rightarrow (\infty, \infty)$ . At the exception of some papers listed below, the results of the same kind generally consider the case, where the time window is fixed, while the number of particles growth to infinity, ignoring long time convergence, or assume certain constraints on the relative rate of convergence of the two variables.

**About the literature.** The first results addressing the limiting behavior of a finite system of particles, are provided in the setting of the propagation of chaos. These results are reviewed in [CD22]. Such results can be applied to a large class of particle systems, where the interacting term  $b$  can take various forms [MRC87, Oel84, Szn84, ELL21]. In our case, if we disregard the transition from continuous to discrete time, such results typically establish the convergence to zero of the expectation of the squared Wassertein distance between the empirical measure of the particles, on some fixed time interval  $[0, T]$ , and a McKean-Vlasov distribution with the same initial measure. Under classical assumptions, the convergence holds at rate  $1/n$ , where  $n$  is the number of particles, but with a constant that is growing exponentially with  $T$ . This type of result behaves poorly in the long run, and achieving the double limit in both the time and the number of particles, becomes unattainable. By imposing additional assumptions, [Mal01, BGM10, CGM08, BRTV98, DEGZ20] obtain a bound which is uniform in time, and thus make the double asymptotic regime explicit. However, these works require strong assumptions on the vector field  $b$ . For instance, as pointed out in [DMT19], uniform propagation of chaos over time can only be achieved when a unique McKean-Vlasov stationary distribution exists, which [Tug13] has shown is not always the case. In that sense, our assumptions are weaker, as they allow for the existence of multiple stationary distributions for the McKean-Vlasov distribution.

Few works address discrete-time particle systems. The paper [Mal03] uses an implicit Euler scheme for the granular media case, assuming that the potential function is zero and the interaction is strongly convex. The contribution of the paper [Ver06] is the closest to the present one, as it consider an equation very close to Eq. (1). However, this paper assumes that  $b$  is globally bounded. Moreover, it does not address the convergence in probability of the empirical measure of the particles, but rather the convergence of its expectation. Lastly, an other paper which is close to our work is [BS00]. This paper is not specific to the case of McKean-Vlasov processes. In particular, it does not consider a system of particles, and does not consider double limits. However, it establishes, in the same spirit as ours, the ergodic convergence of the empirical measure of a so-called weak asymptotic pseudotrajectory, to the Birkhoff center of a flow on a metric space.

Finally, let us review some applications of our model. Particle systems are historically motivated by statistical physics. However, in the last decades, particle systems have found utility in many models: neural networks, Markov Chain Monte Carlo theory, mathematical biology, mean fields game, etc. A well-known model in statistical physics is the granular media [Vil06]. This model is widely studied as it has the nice property of being a gradient system, and uniform in time propagation of chaos works well in this model. This model can also be described by a gradient flow [AGS08]. In Markov Chain Monte Carlo theory, the Stein Variational Gradient Descent estimates a target distribution with a particle system [LW16, SSR22], and the convergence of this algorithm remains an open question. Wide Neural Networks can also be represented by particle systems. We can obtain a convergence result to the minimizers of the risk when the time and the number of particles grow to infinity [CB18]. Here, the authors establish the convergence to the gradient descent in continuous time and in the double asymptotic regime. The paper [MMN18] establishes the convergence of a noisy stochastic gradient descent when the number of iterations depends on the number of particles, see also [RVE22, SS20]. The case where the parameters of the hidden layer are random but fixed along the optimization process, is also known as the random features model [RR07, CRR18].

## 2 The setting

We begin by introducing some notations and by recalling some definitions.

### 2.1 Notations

**General notations.** We denote by  $\langle \cdot, \cdot \rangle$  and  $\|\cdot\|$  the inner product and the corresponding norm in a Euclidean space. We use the same notation in an infinite dimensional space, to denote the standard dual pairing and the operator norm.

For  $k \in \mathbb{N} \cup \{\infty\}$ , we denote by  $C^k(\mathbb{R}^d, \mathbb{R}^q)$  the set of functions which are continuously differentiable up to the order  $k$ . We denote by  $C_c(\mathbb{R}^d, \mathbb{R})$  the set of  $\mathbb{R}^d \rightarrow \mathbb{R}$  continuous functions with compact support. Given  $p \in \mathbb{N}^* \cup \{\infty\}$ , we denote as  $C_c^p(\mathbb{R}^d, \mathbb{R})$  the set of compactly supported  $\mathbb{R}^d \rightarrow \mathbb{R}$  functions which are continuously differentiable up to the order  $p$ .

We denote by  $\mathcal{C}$  the set of the  $[0, \infty) \rightarrow \mathbb{R}^d$  continuous functions. It is well-known that the space  $\mathcal{C}$  endowed with the topology of the uniform convergence on the compact intervals of  $[0, \infty)$  is a Polish space.

**Random variables.** The notation  $f_{\#}\mu$  stands for the pushforward of the measure  $\mu$  by the map  $f$ , that is,  $f_{\#}\mu = \mu \circ f^{-1}$ .

For  $t \geq 0$ , we define the projections  $\pi_t$  and  $\pi_{[0,t]}$  as  $\pi_t : (\mathbb{R}^d)^{[0,\infty)} \rightarrow \mathbb{R}^d, x \mapsto x_t$  and  $\pi_{[0,t]} : (\mathbb{R}^d)^{[0,\infty)} \rightarrow (\mathbb{R}^d)^{[0,t]}, x \mapsto (x_u : u \in [0, t])$ .

Let  $p \geq 1$ . For  $\rho \in \mathcal{P}_p(\mathcal{C})$ , we denote

$$\rho_t := (\pi_t)_{\#}\rho.$$

Let  $(\Omega, \mathcal{F}, \mathbb{P})$  be a probability space. We say that a collection  $A$  of random variables on  $\Omega \rightarrow E$  is *tight* in  $E$ , if the family  $\{X_{\#}\mathbb{P} : X \in A\}$  is weak $\star$ -relatively compact in  $\mathcal{P}(E)$  *i.e.*, has a weak $\star$  compact closure in  $\mathcal{P}(E)$ .

We say that a  $n$ -uple of random variables  $(X_1, \dots, X_n)$  is *exchangeable*, if its distribution is invariant by any permutation on  $[n]$ .

Let  $\mathbb{T}$  represent either  $\mathbb{N}$  or  $[0, +\infty)$ . Let  $(U_t^n : t \in \mathbb{T}, n \in \mathbb{N})$  be a collection of random variables on a metric space  $(E, d)$ . We say that  $(U_t^n)$  converges in probability to  $U$  as  $(t, n) \rightarrow (\infty, \infty)$  if, for every  $\epsilon > 0$ , the net  $(\mathbb{P}(d(U_t^n, U) > \epsilon) : t \in \mathbb{T}, n \in \mathbb{N})$  converges to zero as  $t$  and  $n$  both converge to  $\infty$ . We denote this by  $U_t^n \xrightarrow[(t,n) \rightarrow (\infty, \infty)]{\mathbb{P}} U$ . Moreover, assuming that the collection of random variables  $(U_t^n : t \in \mathbb{T}, n \in \mathbb{N})$  are real valued, we say that the latter collection is *uniformly integrable* if:

$$\lim_{a \rightarrow \infty} \sup_{t \in \mathbb{T}, n \in \mathbb{N}^*} \mathbb{E} [ |U_t^n| \mathbb{1}_{|U_t^n| > a} ] = 0.$$

Finally, for any  $d \in \mathbb{N}^*$ ,  $\mathcal{L}^d$  stands for the Lebesgue measure on  $\mathbb{R}^d$ .

## 2.2 Spaces of probability measures

Let  $(E, d)$  denote a Polish space. If  $\mathcal{A} \subset E$  is a subset, we define  $d(x, \mathcal{A}) := \inf\{d(x, y) : y \in \mathcal{A}\}$ , with  $\inf \emptyset = \infty$ . We say that a net  $(\mu_\alpha)$  converges to  $\mathcal{A}$  if  $d(x_\alpha, \mathcal{A}) \rightarrow_\alpha 0$ .

We denote by  $\mathcal{P}(E)$  the set of probability measures on the Borel  $\sigma$ -algebra  $\mathcal{B}(E)$ . We equip  $\mathcal{P}(E)$  with the weak $\star$  topology. Note that  $\mathcal{P}(E)$  is a Polish space. We denote by  $d_L$  the Levy-Prokhorov distance on  $\mathcal{P}(E)$ , which is compatible with the weak $\star$  topology. We define the *intensity* of a random variable  $\rho : \Omega \rightarrow \mathcal{P}(E)$ , as the measure  $\mathbb{I}(\rho) \in \mathcal{P}(E)$  that satisfies

$$\forall A \in \mathcal{F}, \quad \mathbb{I}(\rho)(A) := \mathbb{E}(\rho(A)).$$

**Lemma 1** ([MRC87]). *A sequence  $(\rho_n)$  of random variables on  $\mathcal{P}(E)$  is tight if and only if the sequence  $(\mathbb{I}(\rho_n))$  is weak $\star$ -relatively compact.*

Let  $p \geq 1$ . If  $E$  is a Banach space, we define

$$\mathcal{P}_p(E) := \{\mu \in \mathcal{P}(E) : \int \|x\|^p d\mu(x) < \infty\}.$$

We define the Wasserstein distance of order  $p$  on  $\mathcal{P}_p(E)$  by

$$W_p(\mu, \nu) := \left( \inf_{\zeta \in \Pi(\mu, \nu)} \int \|x - y\|^p d\zeta(x, y) \right)^{1/p}, \quad (8)$$

where  $\Pi(\mu, \nu)$  is the set of measures  $\zeta \in \mathcal{P}(E \times E)$ , such that  $\zeta(\cdot \times E) = \mu$  and  $\zeta(E \times \cdot) = \nu$ . We denote by  $\Pi_p^0(\mu, \nu)$  the set of optimal transport maps *i.e.*, the set of measures  $\zeta \in \Pi(\mu, \nu)$  achieving the infimum in Eq. (8). The set  $\mathcal{P}_p(E)$  is endowed with the distance  $W_p$ . Define:

$$\mathcal{P}_p(\mathcal{C}) = \{\rho \in \mathcal{P}(\mathcal{C}) : \forall T > 0, \int \sup_{t \in [0, T]} \|x_t\|^p d\rho(x) < \infty\}.$$

For every  $\rho, \rho' \in \mathcal{P}_p(\mathcal{C})$ , we define:

$$W_p(\rho, \rho') = \sum_{n=1}^{\infty} 2^{-n} (1 \wedge W_p((\pi_{[0,n]})_{\#}\rho, (\pi_{[0,n]})_{\#}\rho')).$$

We equip  $\mathcal{P}_p(\mathcal{C})$  with the distance  $W_p$ . We say that a subset  $\mathcal{A} \subset \mathcal{P}_p(\mathcal{C})$  has *uniformly integrable  $p$ -moments* if the following condition holds:

$$\forall T > 0, \quad \lim_{a \rightarrow \infty} \sup_{\rho \in \mathcal{A}} \int \mathbf{1}_{\sup_{t \in [0, T]} \|x_t\| > a} \left( \sup_{t \in [0, T]} \|x_t\|^p \right) d\rho(x) = 0. \quad (p\text{-UI})$$

In the same way, a sequence  $(\rho_n)$  has uniformly integrable  $p$ -moments if the condition (p-UI) holds for the sequence  $(\rho_n)$  in place of  $\mathcal{A}$ . Following the same lines as [Vil09, Th. 6.18] and [AGS08, Prop. 7.1.5], we obtain the following lemma. The proof is provided in Appendix A.1.

**Proposition 1.** *i) The space  $\mathcal{P}_p(\mathcal{C})$  is Polish.*

*ii) A subset  $\mathcal{A} \subset \mathcal{P}_p(\mathcal{C})$  is relatively compact if and only if, it is weak\*-relatively compact in  $\mathcal{P}(\mathcal{C})$ , and if  $\mathcal{A}$  has uniformly integrable  $p$ -moments.*

Finally, we will also consider  $\mathcal{P}_p(\mathcal{C})$ -valued sequences of random variables. Therefore, the following extension of Lemma 1, will be useful. It is established in Appendix A.2.

**Lemma 2.** *Let  $(\rho_n)$  be a sequence of random variables valued in  $\mathcal{P}_p(\mathcal{C})$ . Assume that  $(\mathbb{I}(\rho_n))$  is relatively compact in  $\mathcal{P}_p(\mathcal{C})$ . Then,  $(\rho_n)$  is tight in  $\mathcal{P}_p(\mathcal{C})$ .*

## 2.3 Spaces of McKean-Vlasov measures

Consider a non-negative number  $\sigma^2$  and a vector field  $b : \mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{R}^d$  satisfying the following assumption:

**Assumption 1.** *The vector field  $b : \mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{R}^d$  is continuous. Moreover, there exists  $C > 0$  such that for all  $x, y \in \mathbb{R}^d$ ,*

$$\|b(x, y)\| \leq C(1 + \|x\| + \|y\|).$$

For every  $\mu \in \mathcal{P}_1(\mathbb{R}^d)$ , we define  $b(x, \mu) := \int b(x, y) d\mu(y)$ , with a slight abuse of notations. We define  $L(\mu)$  which, to every test function  $\phi \in C_c^2(\mathbb{R}^d, \mathbb{R})$ , associates the function  $L(\mu)(\phi)$  given by

$$L(\mu)(\phi)(x) = \langle b(x, \mu), \nabla \phi(x) \rangle + \sigma^2 \Delta \phi(x). \quad (9)$$

Let  $(X_t : t \in [0, \infty))$  be the canonical process on  $\mathcal{C}$ . Denote by  $(\mathcal{F}_t^X)_{t \geq 0}$  the natural filtration (*i.e.*, the filtration generated by  $\{X_s : 0 \leq s \leq t\}$ ).

**Definition 1.** *Let  $p \geq 1$ . We say that a measure  $\rho \in \mathcal{P}_p(\mathcal{C})$  belongs to the class  $\mathcal{V}_p$  if, for every  $\phi \in C_c^2(\mathbb{R}^d, \mathbb{R})$ ,*

$$\phi(X_t) - \int_0^t L(\rho_s)(\phi)(X_s) ds$$

*is a  $(\mathcal{F}_t^X)_{t \geq 0}$ -martingale on the probability space  $(\mathcal{C}, \mathcal{B}(\mathcal{C}), \rho)$ . We denote by  $\mathcal{V}_p$  the set of such measures.*

In the sequel, it will be convenient to work with the following equivalent characterization. The martingale property implies that every measure  $\rho \in \mathcal{V}_p$  satisfies  $G(\rho) = 0$ , for every function  $G : \mathcal{P}_p(\mathcal{C}) \rightarrow \mathbb{R}$  of the form:

$$G(\rho) := \int \left( \phi(x_t) - \phi(x_s) - \int_s^t L(\rho_u)(\phi)(x_u) du \right) \prod_{j=1}^r h_j(x_{v_j}) d\rho(x), \quad (10)$$

where  $r \in \mathbb{N}$ ,  $\phi \in C_c^2(\mathbb{R}^d, \mathbb{R})$ ,  $h_1, \dots, h_r \in C_c(\mathbb{R}^d, \mathbb{R})^r$ ,  $0 \leq v_1 \leq \dots \leq v_r \leq s \leq t$ , are arbitrary. We denote by  $\mathcal{G}_p$  the set of such mappings  $G$ . Assumption 1 ensures that these mappings are well defined. By Def. 1, every  $\rho \in \mathcal{V}_p$  is a root of all  $G \in \mathcal{G}_p$ . As a matter of fact, a measure  $\rho \in \mathcal{P}_p(\mathcal{C})$



belongs to the set  $V_p$ , if and only if  $G(\rho) = 0$  for every  $G$  of the form (10). In other words, Def. 1 is equivalent to the following identity:

$$V_p = \bigcap_{G \in \mathcal{G}_p} G^{-1}(\{0\}). \quad (11)$$

The following lemma is proved in Appendix A.3.

**Lemma 3.** *Let Assumption 1 hold true. Every  $G \in \mathcal{G}_p$  is a continuous function on  $\mathcal{P}_p(\mathcal{C}) \rightarrow \mathbb{R}$ .*

The following result is a consequence of Lemma 3 and Prop. 1.

**Proposition 2.** *Under Assumption 1,  $V_p$  is a closed subset of  $\mathcal{P}_p(\mathcal{C})$ . Moreover, equipped with the trace topology of  $\mathcal{P}_p(\mathcal{C})$ ,  $V_p$  is a Polish space.*

*Proof.* For all  $\rho_n \in V_p \rightarrow \rho_\infty$  in  $\mathcal{P}_p(\mathcal{C})$ , it holds by Lemma 3 that  $G(\rho_\infty) = 0$  for all  $G \in \mathcal{G}_p$ , which shows that  $\rho_\infty \in V_p$  by (11). Hence,  $V_p$  is closed. A closed subset of a Polish space is also Polish. By Prop. 1,  $V_p$  is Polish.  $\square$

## 2.4 Dynamical systems

Recall the definition of the shift  $\Theta_t(x) = x_{t+}$  defined on  $\mathcal{C}$ . Let us equip the space  $V_p$  assumed nonempty with the trace topology of  $\mathcal{P}_p(\mathcal{C})$ , making it a Polish space (see Prop. 2). With this at hand, one can readily check that the function  $\Phi : [0, \infty) \times V_p \rightarrow V_p$  defined as  $(t, \rho) \mapsto \Phi_t(\rho) = (\Theta_t)_{\#}\rho$  is a semi-flow on the space  $(V_p, \mathcal{W}_p)$ , in the sense that  $\Phi$  is continuous,  $\Phi_0(\cdot)$  coincides with the identity, and  $\Phi_{t+s} = \Phi_t \circ \Phi_s$  for all  $t, s \geq 0$ , see [Ben99] for a nice exposition of the concepts related to semi-flows. The omega limit set of  $\rho \in V_p$  for this semi-flow is the set  $\omega(\rho)$  defined by:

$$\omega(\rho) := \bigcap_{t>0} \overline{\{\Phi_s(\rho) : s > t\}}.$$

Equivalently,  $\omega(\rho)$  is the set of  $\mathcal{W}_p$ -limits of sequences of the form  $(\Phi_{t_n}(\rho))$  where  $t_n \rightarrow \infty$ . A point  $\rho \in V_p$  is called recurrent if  $\rho \in \omega(\rho)$ . The Birkhoff center  $\text{BC}_p$  is defined as the closure of the set of recurrent points:

$$\text{BC}_p := \overline{\{\rho \in V_p : \rho \in \omega(\rho)\}}.$$

We say that a nonempty set  $A_p \subset V_p$  is invariant for  $\Phi$  if  $\Phi_t(A_p) = A_p$  for each  $t \geq 0$ .

Consider a non-empty set  $\Lambda \subset V_p$ .

**Definition 2.** *Consider the semi-flow  $\Phi$ . A lower semi-continuous function  $F : V_p \rightarrow \mathbb{R}$  is called a Lyapunov function for the set  $\Lambda$  if, for every  $\rho \in V_p$  and every  $t > 0$ ,  $F(\Phi_t(\rho)) \leq F(\rho)$ , and  $F(\Phi_t(\rho)) < F(\rho)$  whenever  $\rho \notin \Lambda$ .*

The following result is standard.

**Proposition 3.** *Let  $p > 0$ . If  $F$  is a Lyapunov function for the set  $\Lambda$ , then  $\text{BC}_p \subset \overline{\Lambda}$ .*

*Proof.* The limit  $\ell := \lim_{t \rightarrow \infty} F(\Phi_t(\rho))$  is well-defined because  $F(\Phi_t(\rho))$  is non increasing. Consider a recurrent point  $\rho \in V_p$ , say  $\rho = \lim_n \Phi_{t_n}(\rho)$ . Clearly  $F(\rho) \geq F(\Phi_{t_n}(\rho)) \geq \ell$ . Moreover, by lower semicontinuity of  $F$ ,  $\ell = \lim_n F(\Phi_{t_n}(\rho)) \geq F(\rho)$ . Therefore,  $\ell$  is finite, and  $F(\rho) = \ell$ . This implies that  $t \mapsto F(\Phi_t(\rho))$  is constant. By definition, this in turn implies  $\rho \in \Lambda$ , which concludes the proof.  $\square$

## 3 Main results

### 3.1 Interpolated process and weak\* limits

Let  $(\Omega, \mathcal{F}, \mathbb{P})$  be a probability space. Let  $d > 0$  be an integer. For each  $n \in \mathbb{N}^*$ , consider the random sequence (1) starting with the  $n$ -uple  $(X_0^{1,n}, \dots, X_0^{n,n})$  of random variables  $X_0^{i,n} \in \mathbb{R}^d$ , with  $((\xi_k^{i,n})_{i \in [n]})_{k \in \mathbb{N}^*}$  and  $((\zeta_k^{i,n})_{i \in [n]})_{k \in \mathbb{N}^*}$  being  $\mathbb{R}^{d \times n}$ -valued random noise sequences. For each of integer  $n > 0$ , define the filtration  $(\mathcal{F}_k^n)_{k \in \mathbb{N}}$  as in Eq. (2) or, more generally, as any filtration such that the following random variables

$$(X_0^{i,n})_{i \in [n]}, ((\xi_\ell^{i,n})_{i \in [n]})_{\ell \leq k}, ((\zeta_\ell^{i,n})_{i \in [n]})_{\ell \leq k}$$

belong to  $\mathcal{F}_k^n$ . Consider the following assumptions:

**Assumption 2.** The sequence  $(\gamma_k)$  is a non-negative deterministic sequence satisfying

$$\lim_{k \rightarrow \infty} \gamma_k = 0, \text{ and } \sum_k \gamma_k = +\infty.$$

**Assumption 3.** The following hold true.

i) For each  $n$ , the  $n$  triplets  $((X_0^{i,n}, (\zeta_k^{i,n})_{k \in \mathbb{N}}, (\xi_k^{i,n})_{k \in \mathbb{N}})_{i \in [n]}$  is exchangeable as a  $n$ -uple of  $\mathbb{R}^d \times (\mathbb{R}^d)^\mathbb{N} \times (\mathbb{R}^d)^\mathbb{N}$ -valued random variables.

ii) It holds that  $\sup_{k,n} \mathbb{E} \|\xi_k^{1,n}\|^4 < \infty$ . Furthermore, for each  $n > 0$ , and each  $i, j$ ,

$$\mathbb{E} \left[ \xi_{k+1}^{1,n} \middle| \mathcal{F}_k^n \right] \text{ and } \mathbb{E} \left[ \xi_{k+1}^{i,n} \left( \xi_{k+1}^{j,n} \right)^T \middle| \mathcal{F}_k^n \right] = \sigma^2 \mathbf{1}_{i=j} I_d,$$

for some number  $\sigma^2 \geq 0$ .

iii) For each  $k$ , and each  $n$ , it holds that  $\mathbb{E} \|\zeta_k^{1,n}\| < \infty$ , and

$$\lim_{(k,n) \rightarrow (\infty, \infty)} \mathbb{E} \left\| \mathbb{E} \left[ \zeta_{k+1}^{1,n} \middle| \mathcal{F}_k^n \right] \right\| = 0.$$

**Remark 1.** Assumption 3-(i) holds under the stronger assumption that the  $n$ -uple  $(X_0^{1,n}, \dots, X_0^{n,n})$  is exchangeable,  $(\xi_k^{i,n})_{i \in [n], k \in \mathbb{N}}$  is an i.i.d. sequence independent of  $(X_0^{i,n})_{i \in [n]}$ , and  $\zeta_k^{1,n} = 0$  for every  $k$ .

**Assumption 4.** We assume either:

i)  $\sup_{k,n} \mathbb{E} [\|X_k^{1,n}\|^2 + \|\zeta_k^{1,n}\|^2] < \infty$ ,

or the stronger condition:

ii) The collections of r.v.  $(\|X_k^{1,n}\|^2 : k \in \mathbb{N}, n \in \mathbb{N}^*)$ , and  $(\|\zeta_k^{1,n}\|^2 : k \in \mathbb{N}, n \in \mathbb{N}^*)$  are uniformly integrable.

Recalling the definitions of the interpolated processes  $\bar{X}^{i,n}$  in (5), and the definition of the occupation measure  $m^n$  in (6), we shall consider the *shifted* occupation measure

$$\Phi_t(m^n) = \frac{1}{n} \sum_{i=1}^n \delta_{\Theta_t(\bar{X}^{i,n})},$$

for each  $n \in \mathbb{N}^*$  and each  $t \in (0, +\infty)$ . Note that  $\Phi_t(m^n)$  is a r.v. on  $\mathcal{P}_p(\mathcal{C})$ . We refer to the set

$$\mathcal{M} := \underset{(t,n) \rightarrow (\infty, \infty)}{\text{acc}} \left( \{(\Phi_t(m^n))_{\#} \mathbb{P}\} \right) \quad (12)$$

as the set of accumulation points of the probability distributions of  $\Phi_t(m^n)$  as  $(t, n) \rightarrow (\infty, \infty)$ . In other words,  $\mathcal{M}$  is the set of measures  $M \in \mathcal{P}(\mathcal{P}_p(\mathcal{C}))$  for which there is a sequence  $(t_n, \varphi_n)_n$  on  $(0, \infty) \times \mathbb{N}^*$ , such that  $t_n \rightarrow_n \infty$ ,  $\varphi_n \rightarrow_n \infty$ , and  $(\Phi_{t_n}(\#m^{\varphi_n}))$  converges in distribution to  $M$ .

The following two results show that the collection  $(\Phi_t(m^n))$  of random variables is tight (proven in Section 5.1), and that their limits in distribution are supported by the set of McKean-Vlasov distributions (proven in Section 5.2):

**Proposition 4.** Let  $1 \leq p < 2$ , and let Assumptions 1, 2, 3, and 4-(i) hold true. Then, the collection of shifted occupation measures  $\{\Phi_t(m^n) : t \geq 0, n \in \mathbb{N}^*\}$  is tight in  $\mathcal{P}_p(\mathcal{C})$ . If Assumption 4-(ii) additionally holds, the result remains valid when  $p = 2$ .

**Proposition 5.** Let  $1 \leq p < 2$ , and let Assumptions 1, 2, 3, and 4-(i) hold true. Then,  $\mathbf{V}_p$  is a nonempty closed set, and for every  $M \in \mathcal{M}$ , it holds that  $M(\mathbf{V}_p) = 1$ . If Assumption 4-(ii) additionally holds, the result remains valid when  $p = 2$ .

### 3.2 Ergodic convergence

We provide the proof of the following theorem in Section 5.3.

**Theorem 1.** *Let  $1 \leq p < 2$ , and let Assumptions 1, 2, 3, and 4-(i) hold true. Then,*

$$\frac{1}{t} \int_0^t W_p(\Phi_s(m^n), \text{BC}_p) ds \xrightarrow[(t,n) \rightarrow (\infty, \infty)]{\mathbb{P}} 0.$$

*If Assumption 4-(ii) additionally holds, the result remains valid when  $p = 2$ .*

Recall the definition  $\mu_k^n := \frac{1}{n} \sum_{i=1}^n \delta_{X_k^{i,n}}$ . The proof of the following corollary is provided in Section 5.4.

**Corollary 1.** *Let  $1 \leq p < 2$ , and let Assumptions 1, 2, 3, and 4-(i) hold true. Assumptions 1, 3, and 4-(i) hold true. Then,*

$$\frac{\sum_{l=1}^k \gamma_l W_p(\mu_l^n, (\pi_0)_\#(\text{BC}_p))}{\sum_{l=1}^k \gamma_l} \xrightarrow[(k,n) \rightarrow (\infty, \infty)]{\mathbb{P}} 0.$$

*If Assumption 4-(ii) additionally holds, the statements remains valid also when  $p = 2$ .*

## 4 Examples

### 4.1 Granular media

The proofs of the results relative to this section are provided in Section 6.

In this paragraph, we review some properties of the set  $\mathbf{V}_2$  of McKean-Vlasov processes, in the case where

$$b(x, y) := -\nabla V(x) - \nabla U(x - y), \quad (13)$$

where  $V, U : \mathbb{R}^d \rightarrow \mathbb{R}$  are two functions satisfying the following assumption.

**Assumption 5** (Granular media). *The functions  $V, U$  belong to  $C^1(\mathbb{R}^d, \mathbb{R})$ . Moreover, there exists  $\lambda, C, \beta > 0$ , such that for every  $x \in \mathbb{R}^d$ , the following hold:*

- i)  $\langle x, \nabla V(x) \rangle \geq \lambda \|x\|^2 - C$ ,
- ii)  $U(x) = U(-x)$ , and  $\langle x, \nabla U(x) \rangle \geq -C$ ,
- iii)  $\|\nabla V(x)\| + \|\nabla U(x)\| \leq C(1 + \|x\|)$ ,
- iv)  $\|\nabla V(x) - \nabla V(y)\| + \|\nabla U(x) - \nabla U(y)\| \leq C(\|x - y\|^\beta \vee \|x - y\|)$ , for every  $(x, y) \in (\mathbb{R}^d)^2$ .

Under Assumptions 5, the vector field  $b$  satisfies Assumption 1. We will see later, as a byproduct of Th. 2, that the set  $\mathbf{V}_2$  of McKean-Vlasov distributions associated to the field  $b$  in Eq. (13), is non empty. The following central result provides a central properties of the elements of  $\mathbf{V}_2$ .

**Proposition 6.** *Let Assumption 5 hold true, and let  $b$  be defined by (13). Assume  $\sigma > 0$ . Consider  $\rho \in \mathbf{V}_2$ . Then, for every  $t > 0$ ,  $\rho_t$  admits a density  $x \mapsto \varrho(t, x)$  in  $C^1(\mathbb{R}^d, \mathbb{R})$  w.r.t. the Lebesgue measure. For every  $t > 0$ , the functional*

$$H(\rho_t) := \sigma^2 \int \log \varrho(t, x) \varrho(t, x) dx + \int V d\rho_t + \frac{1}{2} \iint U(x - y) d\rho_t(y) d\rho_t(x) \quad (14)$$

*is finite, and satisfies for every  $t_2 > t_1 > 0$ ,*

$$H(\rho_{t_2}) - H(\rho_{t_1}) = - \int_{t_1}^{t_2} \int \|v_t(x)\|^2 \varrho(t, x) dx dt, \quad (15)$$

*where  $v_t$  is the vector field defined for every  $x \in \mathbb{R}^d$  by:*

$$v_t(x) := -\nabla V(x) - \int \nabla U(x, y) d\rho_t(y) - \sigma^2 \nabla \log \varrho(t, x). \quad (16)$$

Define  $\mathcal{P}_2^r(\mathbb{R}^d)$  as the set of measures  $\mu \in \mathcal{P}_2(\mathbb{R}^d)$  which admits a continuously differentiable density w.r.t. the Lebesgue measure  $\mathcal{L}^d$ , which we denote by  $d\mu/d\mathcal{L}^d$ . Define:

$$\mathcal{S} := \{\mu \in \mathcal{P}_2^r(\mathbb{R}^d) : \nabla V + \int \nabla U(\cdot - y) d\mu(y) + \sigma^2 \nabla \log \frac{d\mu}{d\mathcal{L}^d} = 0 \mu\text{-a.e.}\}. \quad (17)$$

Finally, for every  $\epsilon \geq 0$ , define:

$$\Lambda_\epsilon := \{\rho \in \mathcal{V}_2 : \exists \mu \in \mathcal{S}, \forall t \geq \epsilon, \rho_t = \mu\}. \quad (18)$$

**Proposition 7.** *We posit the assumptions of Prop. 6. For every  $\epsilon > 0$ , the function  $\rho \mapsto H(\rho_\epsilon)$  is real valued on  $\mathcal{V}_2$ , lower semicontinuous, and is a Lyapunov function for the set  $\Lambda_\epsilon$ . Moreover,*

$$\text{BC}_2 \subset \overline{\Lambda}_0.$$

We consider the iterations:

$$X_{k+1}^{i,n} = X_k^{i,n} - \frac{\gamma_{k+1}}{n} \sum_{j \in [n]} \nabla U(X_k^{i,n} - X_k^{j,n}) - \gamma_{k+1} \nabla V(X_k^{i,n}) + \sqrt{2\gamma_{k+1}} \xi_k^{i,n}, \quad (19)$$

for each  $i \in [n]$ . This is a special case of Eq. (1) with  $b(x, y)$  given by Eq. (13) and  $\zeta_k^{i,n} = 0$  for all  $k$ . For simplicity, Assumption 3 will be replaced by the following stronger assumption:

**Assumption 6.** *The  $n$ -tuple  $(X_0^{1,n}, \dots, X_0^{n,n})$  is exchangeable and satisfies  $\sup_n \mathbb{E}(\|X_0^{1,n}\|^4) < \infty$ . Moreover,  $(\xi_k^{i,n})_{i \in [n], k \in \mathbb{N}}$  are i.i.d. centered random variables, with variance  $\sigma^2 I_d$ , and such that  $\mathbb{E}(\|\xi_1^{1,1}\|^4) < \infty$ .*

The next proposition implies that the condition ii) in Assumption 4 holds.

**Proposition 8.** *Let Assumptions 2, 5 and 6 be satisfied. Then,*

$$\sup_{n \in \mathbb{N}^*, k \in \mathbb{N}} \mathbb{E} \left[ \|X_k^{1,n}\|^4 \right] < \infty.$$

Putting Assumptions 2, 5 and 6 together, the hypotheses of Th. 1 are satisfied for  $p = 2$ .

**Theorem 2.** *Let Assumptions 2, 5 and 6 be satisfied. Assume  $\sigma > 0$ . Then, the set  $\mathcal{S}$  given by Eq. (17) is non empty, and furthermore,*

$$\frac{\sum_{l=1}^k \gamma_l W_2(\mu_l^n, \mathcal{S})}{\sum_{l=1}^k \gamma_l} \xrightarrow[(k,n) \rightarrow (\infty, \infty)]{\mathbb{P}} 0.$$

*Proof.* Use Cor. 1 with  $p = 2$ , together with Prop. 7. □

## 4.2 Random features

Consider two integers  $q \geq 1, d \geq 2$ . For any fixed  $n$ -uple  $\mathbf{w} = (w^1, \dots, w^n)$  of  $\mathbb{R}^{d-1}$ -valued vectors, we consider the following regularized risk minimization problem:

$$\min_{\mathbf{a} \in \mathbb{R}^n} R(\mathbf{a}, \mathbf{w}) := \frac{1}{2} \int (h(x; \mathbf{a}, \mathbf{w}) - y)^2 d\nu(x, y) + \frac{\lambda}{2n} \|\mathbf{a}\|^2, \quad (20)$$

where  $\nu \in \mathcal{P}_2(\mathbb{R}^q \times \mathbb{R})$ ,  $\lambda > 0$  is a regularization parameter, and where for every  $x \in \mathbb{R}^q$ , every  $\mathbf{a} = (a^1, \dots, a^n)$  in  $\mathbb{R}^n$ ,

$$h(x; \mathbf{a}, \mathbf{w}) = \frac{1}{n} \sum_{i=1}^n a^i \varphi(x, w^i),$$

where  $\varphi : \mathbb{R}^q \times \mathbb{R}^{d-1} \rightarrow \mathbb{R}$  is a function, referred to as the feature map. In the sequel, we consider the process of searching for a minimizer of (20), when the coefficients  $\mathbf{w}$  are set to an iid sample  $\mathbf{w}_0^n := (w_0^{1,n}, \dots, w_0^{n,n})$  of  $n$  random variables on  $\mathbb{R}^{d-1}$ , following a prescribed distribution. We consider the stochastic gradient descent (SGD) on the  $\mathbf{a}$ -parameter, obtained by randomly selecting, at

time  $k$ , a sample  $(x_{k+1}^n, y_{k+1}^n)$  according to the distribution  $\nu$ . Denoting by  $\mathbf{a}_k^n = (a_k^{1,n}, \dots, a_k^{n,n})$  the updated parameters, we consider the iterations:

$$\mathbf{a}_{k+1}^n = \mathbf{a}_k^n - \gamma_{k+1} n \nabla_{\mathbf{a}} \left[ \frac{1}{2} (h(x_{k+1}^n; \mathbf{a}_k^n, \mathbf{w}_0^n) - y_{k+1}^n)^2 + \frac{\lambda \|\mathbf{a}_k^n\|^2}{2n} \right] + \sqrt{2\gamma_{k+1}} \tilde{\boldsymbol{\xi}}_{k+1}^n, \quad (21)$$

where  $\tilde{\boldsymbol{\xi}}_{k+1}^n = (\tilde{\xi}_{k+1}^{1,n}, \dots, \tilde{\xi}_{k+1}^{n,n})$  are centered iid random variables with variance  $\sigma^2 \geq 0$ , where  $\gamma_{k+1} n$  is the learning rate, and  $\nabla_{\mathbf{a}}$  stands for the gradient w.r.t. variable  $\mathbf{a}$ . In the algorithm given by Eq. (21), only the parameter  $\mathbf{a}$  is updated, while the parameter  $\mathbf{w}$  is set once for all, at the initialization step. In this setting, the values  $(\varphi(x, w_0^{i,n}))_{i \in [n]}$  are referred to as the random features associated with an input  $x$ . Note that the learning rate  $\gamma_{k+1} n$  is chosen in order to vanish with  $k$ , but also to scale with parameter  $n$ . Due to the presence of the term  $\sqrt{2\gamma_{k+1}} \tilde{\boldsymbol{\xi}}_{k+1}^n$ , the iterations (21) should be considered as a noisy version of the classical SGD, in the flavor of a Langevin algorithm. The standard SGD case is obtained by setting  $\sigma = 0$ . The following assumption summarizes the stated conditions on the above random variables.

**Assumption 7.** *The following holds.*

- i) *The r.v.  $(\tilde{\xi}_k^{i,n} : k \in \mathbb{N}^*, i \in [n], n \in \mathbb{N}^*)$  are real iid, centered, random variables with variance  $\sigma^2 \geq 0$ , and satisfy  $\mathbb{E}((\tilde{\xi}_1^{1,1})^4) < \infty$ .*
- ii) *The r.v.  $((x_k^{i,n}, y_k^{i,n}) : k \in \mathbb{N}^*, i \in [n], n \in \mathbb{N}^*)$  are iid, with distribution  $\nu \in \mathcal{P}(\mathbb{R}^d \times \mathbb{R})$ .*
- iii) *The r.v.  $(a_0^{i,n} : i \in [n], n \in \mathbb{N}^*)$  are iid real r.v., and satisfy  $\mathbb{E}((a_0^{1,1})^4) < \infty$ .*
- iv) *The r.v.  $(w_0^{i,n} : i \in [n], n \in \mathbb{N}^*)$  are iid, and satisfy  $\mathbb{E}((w_0^{1,1})^2) < \infty$ .*
- v) *The families of r.v. respectively mentioned in the four above points i–iv are independent.*

Eq. (21) can be expanded, for every  $i \in [n]$ , as:

$$a_{k+1}^{i,n} = (1 - \frac{\lambda \gamma_{k+1}}{n}) a_k^{i,n} + \frac{\gamma_{k+1}}{n} \sum_{j=1}^n (y_{k+1}^n - a_k^{j,n} \varphi(x_{k+1}^n, w_0^{j,n})) \varphi(x_{k+1}^n, w_0^{i,n}) + \sqrt{2\gamma_{k+1}} \tilde{\xi}_{k+1}^{i,n}.$$

We introduce the following vector field for every  $(a, w), (a', w') \in \mathbb{R} \times \mathbb{R}^{d-1}$ :

$$\begin{aligned} \tilde{b}((a, w), (a', w')) &:= \int (y - a' \varphi(x, w')) \varphi(x, w) d\nu(x, y) - \lambda a \\ &= Q(w) - a' K(w, w') - \lambda a, \end{aligned}$$

where we set:

$$\begin{aligned} K(w, w') &:= \int \varphi(x, w) \varphi(x, w') d\nu(x, y) \\ Q(w) &:= \int y \varphi(x, w) d\nu(x, y). \end{aligned}$$

Then, the SGD iterations can be written as:

$$a_{k+1}^{i,n} = a_k^{i,n} + \gamma_{k+1} \frac{1}{n} \sum_{j=1}^n \tilde{b}((a_k^{i,n}, w_0^{i,n}), (a_k^{j,n}, w_0^{j,n})) + \gamma_{k+1} \tilde{\xi}_{k+1}^{i,n} + \sqrt{2\gamma_{k+1}} \tilde{\xi}_{k+1}^{i,n},$$

where  $\tilde{\xi}_{k+1}^{i,n}$  is the random perturbation given by:

$$\tilde{\xi}_{k+1}^{i,n} := \frac{1}{n} \sum_{j=1}^n \left[ (y_{k+1}^n - a_k^{j,n} \varphi(x_{k+1}^n, w_0^{j,n})) \varphi(x_{k+1}^n, w_0^{i,n}) - \tilde{b}((a_k^{i,n}, w_0^{i,n}), (a_k^{j,n}, w_0^{j,n})) \right].$$

The above iterations can be casted into the general form (1), by setting  $X_k^{i,n} := (a_k^{i,n}, w_0^{i,n})$ , along with  $b((a, w), (a', w')) := (\tilde{b}((a, w), (a', w')), 0)$ ,  $\zeta_{k+1}^{i,n} := (\tilde{\xi}_{k+1}^{i,n}, 0)$  and  $\xi_{k+1}^{i,n} := (\tilde{\xi}_{k+1}^{i,n}, 0)$ . Consequently, Th. 1 can be used in order to characterize the long run convergence of the occupation measure of the updated parameters. We define  $\mathcal{F}_k^n$  as the  $\sigma$ -field generated by the r.v.  $a_0^{i,n}, w_0^{i,n}$  and  $(x_l^n, y_l^n, \xi_l^{1,n}, \dots, \xi_l^{n,n})$  for  $l \in [k]$ . Note that  $(\zeta_k^{1,n}, \dots, \zeta_k^{n,n})$  is  $\mathcal{F}_k^n$ -measurable.

**Remark 2.** Although the particles  $X_k^{i,n} = (a_k^{i,n}, w_0^{i,n})$  satisfy Eq. (1), the notable difference with the model considered in Section 3 lies in the fact that the variables  $\xi_{k+1}^{1,n}$  here satisfy:

$$\mathbb{E}(\xi_{k+1}^{1,n} (\xi_{k+1}^{1,n})^T | \mathcal{F}_k^n) = \sigma^2 \text{diag}(1, 0, \dots, 0),$$

whereas our results have been proven under the assumption that  $\mathbb{E}(\xi_{k+1}^{1,n} (\xi_{k+1}^{1,n})^T | \mathcal{F}_k^n) = \sigma^2 I_d$ . This difference is minor, and our results can be extended without any difficulty to the former case. The most important modification lies in the definition of the McKean-Vlasov distribution  $\mathbb{V}_p$  in Def. (1), where one should replace the Laplacian term  $\Delta\phi(x)$  in the definition (9) of  $L$  by the second order partial derivative w.r.t. the first component. This gives rise to the definition:

$$L^{(\sigma^2, \mathbf{0})}(\mu)(\phi)(a, w) = \langle b(a, w), \mu \rangle, \nabla\phi(x) + \sigma^2 \partial_a^2 \phi(a, w). \quad (22)$$

To avoid any confusion, we now denote by  $\mathbb{V}_p^{(\sigma^2, \mathbf{0})}$  the set of McKean-Vlasov distributions defined as in Def. (1), replacing  $L$  by  $L^{(\sigma^2, \mathbf{0})}$ , and we denote by  $\text{BC}_p^{(\sigma^2, \mathbf{0})}$  the corresponding Birkhoff center.

**Assumption 8.** The following holds.

i) The function  $\varphi$  is bounded and continuous.

ii)  $\int y^4 d\nu(x, y) < \infty$ .

**Proposition 9.** Let Assumptions 2, 7 and 8 hold true. Then,  $\sup_{n,k} \mathbb{E}((a_k^{1,n})^4 + (\tilde{\zeta}_k^{i,n})^4) < \infty$ .

*Proof.* The proof is provided in Section 7.1.  $\square$

We denote by  $\tilde{\pi} : (a, w) \mapsto w$  the projection  $\mathbb{R} \times \mathbb{R}^{d-1} \rightarrow \mathbb{R}^{d-1}$  on the last  $d-1$  components. Due to Prop. 9, the conditions of application of Th. 1 are satisfied. As a consequence of Th. 1, the set  $\text{BC}_2^{(\sigma^2, \mathbf{0})}$  is non empty. Moreover, as the marginal distribution of the particles w.r.t. the  $w$ -variable is a constant, fixed once for all to the distribution of  $w_0^{1,1}$ , we obtain the following result. As long as Assumptions 2 and 8 hold true, for every  $\varpi \in \mathcal{P}_2(\mathbb{R}^{d-1})$ , there exists  $\rho \in \text{BC}_2^{(\sigma^2, \mathbf{0})}$  such that  $\tilde{\pi}_\# \rho_t = \varpi$  for all  $t \geq 0$ .

For every  $\mu \in \mathcal{P}_2(\mathbb{R} \times \mathbb{R}^{d-1})$ , define:

$$\mathcal{R}_0(\mu) := \frac{1}{2} \int \left( \int a\varphi(x, w) d\mu(a, w) - y \right)^2 d\nu(x, y) + \frac{\lambda}{2} \int a^2 d\mu(a, w).$$

The functional  $\mathcal{R}_0$  is related to the initial minimization problem through the identity:

$$R(\mathbf{a}, \mathbf{w}) = \mathcal{R}_0 \left( \frac{1}{n} \sum_{i=1}^n \delta_{(a^i, w^i)} \right),$$

for every  $\mathbf{a} = (a^1, \dots, a^n)$  and  $\mathbf{w} = (w^1, \dots, w^n)$ . For any  $\mu \in \mathcal{P}(\mathbb{R} \times \mathbb{R}^{d-1})$ , we write the disintegration of the measure  $\mu$  as:

$$\mu(da, dw) = \mu(da|w) \tilde{\pi}_\# \mu(dw).$$

For every  $\sigma > 0$ , we define the functional  $\mathcal{R}_\sigma$  as follows, for every  $\mu \in \mathcal{P}_2(\mathbb{R} \times \mathbb{R}^{d-1})$ :

$$\mathcal{R}_\sigma(\mu) := \mathcal{R}_0(\mu) + \sigma^2 \int \log \left( \frac{d\mu(\cdot|w)}{d\mathcal{L}^1}(a) \right) d\mu(a, w), \quad (23)$$

whenever  $\mu(\cdot|w)$  is absolutely continuous w.r.t. the Lebesgue measure  $\mathcal{L}^1$ , and  $\mathcal{R}_\sigma(\mu) = +\infty$  otherwise. For every  $\mu \in \mathcal{P}_2(\mathbb{R}^d)$ , we define:

$$\tilde{v}_\mu(a, w) := \tilde{b}((a, w), \mu) + \sigma^2 \partial_a \log \left( \frac{d\mu(\cdot|w)}{d\mathcal{L}^1}(a) \right),$$

whenever  $\mu(\cdot|w) \ll \mathcal{L}^1$ , or  $\sigma = 0$ .

If  $\mu, \mu^* \in \mathcal{P}_2(\mathbb{R}^d)$ , by [AGS08, Lem. 12.4.7], there exists a Borel map on  $\mathbb{R}^{d-1} \rightarrow \mathcal{P}_2(\mathbb{R} \times \mathbb{R})$  which, to every  $w \in \mathbb{R}^{d-1}$ , associated a probability measure  $\gamma(\cdot|w) \in \Pi_2^0(\mu_*(\cdot|w), \mu(\cdot|w))$ , where we recall that  $\Pi_2^0(\mu^*(\cdot|w), \mu(\cdot|w))$  is the set of 2-Wasserstein optimal transport maps between  $\mu^*(\cdot|w)$  and  $\mu(\cdot|w)$ , as introduced after Eq. (8).

**Lemma 4.** *Let Assumptions 2 and 8 hold true. Consider  $\varpi \in \mathcal{P}_2(\mathbb{R}^{d-1})$  and  $\mu, \mu^* \in \mathcal{P}_2(\mathbb{R}^d)$  such that  $\tilde{\pi}_{\#}\mu = \tilde{\pi}_{\#}\mu^* = \varpi$ . Assume that either  $\sigma = 0$ , or that the following holds for  $\varpi$ -almost all  $w$ :  $\mu^*(\cdot|w) \ll \mathcal{L}^1$  and*

$$\int \left( \partial_a \log \frac{d\mu(\cdot|w)}{d\mathcal{L}^1}(a) \right)^2 d\mu(a|w) < \infty.$$

*Let  $w \mapsto \gamma(\cdot|w)$  be a measurable selection of the correspondence  $w \mapsto \Pi_2^0(\mu_*(\cdot|w), \mu(\cdot|w))$ . Then,*

$$\mathcal{R}_\sigma(\mu) - \mathcal{R}_\sigma(\mu^*) \geq - \int \int \tilde{v}_{\mu^*}(a_*, w)(a - a_*) d\gamma(a_*, a|w) d\varpi(w) + \frac{\lambda}{2} \int \mathbb{W}_2^2(\mu(\cdot|w), \mu^*(\cdot|w)) d\varpi(w).$$

*Proof.* The proof is provided in Section 7.2.  $\square$

**Lemma 5.** *Let Assumptions 2 and 8 hold true. Consider  $\varpi \in \mathcal{P}_2(\mathbb{R}^d)$ , and  $\rho \in \mathbb{V}_2^{(\sigma^2, 0)}$  such that  $\tilde{\pi}_{\#}\rho_0 = \varpi$ . In that case,  $\tilde{\pi}_{\#}\rho_t = \varpi$  for all  $t$ . If  $\sigma > 0$ , then, for every  $t > 0$ ,  $\rho_t(\cdot|w) \ll \mathcal{L}^1$  for  $\varpi$ -almost every  $w$ . Moreover, for every  $t > 0$  and  $\varpi$ -almost every  $w$ ,*

$$\int \left( \partial_a \log \frac{d\rho_t(\cdot|w)}{d\mathcal{L}^1}(a) \right)^2 d\rho_t(a|w) < \infty. \quad (24)$$

*Finally,  $\mathcal{R}_\sigma(\rho_t)$  is finite for all  $t > 0$ , and for all  $t_2 > t_1 > 0$ ,*

$$\mathcal{R}_\sigma(\rho_{t_2}) - \mathcal{R}_\sigma(\rho_{t_1}) \leq - \int_{t_1}^{t_2} \int \tilde{v}_{\rho_t}(a, w)^2 d\rho_t(a, w) dt. \quad (25)$$

*Proof.* The proof is provided in Section 7.3.  $\square$

For every  $\varpi \in \mathcal{P}_2(\mathbb{R}^{d-1})$ , define the set

$$S(\varpi) := \{ \mu \in \mathcal{P}_2(\mathbb{R}^d) : \tilde{\pi}_{\#}\mu = \varpi \text{ and } \tilde{v}_\mu = 0, \mu\text{-a.e.} \}.$$

**Corollary 2.** *Let Assumptions 2 and 8 hold true. For every  $\epsilon > 0$ , the map  $\rho \mapsto \mathcal{R}_\sigma(\rho_\epsilon)$  is well defined on  $\mathbb{V}_2^{(\sigma^2, 0)} \rightarrow \mathbb{R}$ , lower semicontinuous, and is a Lyapunov function for the set:*

$$\Lambda_\epsilon := \{ \rho \in \mathbb{V}_2^{(\sigma^2, 0)} : \exists \varpi \in \mathcal{P}_2(\mathbb{R}^{d-1}), \exists \mu \in S(\varpi), \forall t \geq \epsilon, \rho_t = \mu \}.$$

*Moreover,  $\text{BC}_2^{(\sigma^2, 0)} \subset \overline{\Lambda_0}$ .*

*Proof.* It is an immediate consequence of Lem. 5.  $\square$

**Proposition 10.** *Let Assumption 8 hold true. Then, for every  $\varpi \in \mathcal{P}_2(\mathbb{R}^{d-1})$ , there exists a unique minimizer, denoted by  $\mu^*(\varpi)$ , of  $\mathcal{R}_\sigma$  among all  $\mu \in \mathcal{P}_2(\mathbb{R}^d)$  such that  $\tilde{\pi}_{\#}\mu = \varpi$ . Moreover,  $\mu^*(\varpi)$  is the unique measure  $\mu$  satisfying  $v_\mu = 0$   $\mu$ -a.e., and  $\tilde{\pi}_{\#}\mu = \varpi$ .*

*Proof.* As discussed after the statement of Prop. 9, there exists a recurrent point  $\rho$  such that  $\tilde{\pi}_{\#}\rho_0 = \varpi$ . By Cor. 2,  $\rho \in \Lambda_0$ , which implies that  $\rho_0 \in S(\varpi)$ . This shows that, for every  $\varpi \in \mathcal{P}_2(\mathbb{R}^{d-1})$ ,  $S(\varpi)$  is non empty.

Consider an arbitrary  $\mu^* \in S(\varpi)$ . By Lem. 4,  $\mu^*$  is a minimizer of  $\mathcal{R}_\sigma$ , among the set of measures with marginal  $\varpi$ . This shows existence. Let  $\mu$  be another such minimizer. By Lem. 4,  $W_2(\mu^*(\cdot|w), \mu(\cdot|w)) = 0$  for  $\varpi$ -almost every  $w$ . Thus,  $\mu = \mu^*$ .  $\square$

We are now able to state the main result of this paragraph. Define:

$$\mu_k^n := \frac{1}{n} \sum_{i=1}^n \delta_{(a_k^{i,n}, w_0^{i,n})}.$$

**Theorem 3.** *Let Assumptions 2, 7 and 8 hold true. Assume that  $w_0^{1,1}$  has the distribution  $\varpi \in \mathcal{P}_2(\mathbb{R}^{d-1})$ . Then,*

$$\frac{\sum_{l=1}^k \gamma_l W_2(\mu_l^n, \mu^*(\varpi))}{\sum_{l=1}^k \gamma_l} \xrightarrow[(k,n) \rightarrow (\infty, \infty)]{\mathbb{P}} 0.$$

*Proof.* Put together Prop. 9, Cor.1, Cor. 2 and Prop. 10.  $\square$

## 5 Proofs of Section 3

### 5.1 Proof of Proposition 4

In this paragraph, consider  $1 \leq p \leq 2$ . Note that  $(\Phi_t(m^n))$  belongs to  $\mathcal{P}_p(\mathcal{C})$ . In the light of Lemma 2 and Prop 1, we should establish two points: first, the weak $\star$ -relatively compactness of the family of intensities  $\{\mathbb{I}(\Phi_t(m^n))\}_{t,n}$ ; second, a uniform integrability condition of the  $p$ th order moments of the measures  $\mathbb{I}(\Phi_t(m^n)(x))$ . These results are respectively stated in Lemmas 6 and 7 below.

**Lemma 6.** *We posit the assumptions of Prop. 4. The family of intensities  $\{\mathbb{I}(\Phi_t(m^n))\}_{t,n}$  is weak $\star$ -relatively compact in  $\mathcal{P}(\mathcal{C})$ .*

*Proof.* Let us establish the first point. For every bounded continuous function  $\phi : \mathcal{C} \rightarrow \mathbb{R}$ , we have

$$\mathbb{I}(\Phi_t(m^n))(\phi) := \mathbb{E} \left[ \int \phi(x) d(\Phi_t(m^n)(x)) \right] = \frac{1}{n} \sum_{i \in [n]} \mathbb{E} \phi(\bar{X}_{t+}^{i,n}) = \mathbb{E} \left[ \phi(\bar{X}_{t+}^{1,n}) \right],$$

where we used the exchangeability stated in Assumption 3-(i). Let us define the measure  $\hat{\mathbb{I}}_t^n \in \mathcal{P}(\mathbb{R}^d)$  as

$$\hat{\mathbb{I}}_t^n(\phi) := \mathbb{E} \left[ \psi(\bar{X}_t^{1,n}) \right],$$

for each measurable function  $\psi : \mathbb{R}^d \rightarrow \mathbb{R}_+$ . According to Theorem 7.3 in [Bil99], the weak $\star$ -relative compactness of the sequence  $(\hat{\mathbb{I}}_t^n)_{t,n}$  in  $\mathcal{P}(\mathcal{C})$  is guaranteed if and only if the weak $\star$ -relative compactness of  $(\hat{\mathbb{I}}_t^n)_{t,n}$  in  $\mathcal{P}(\mathbb{R}^d)$  is ensured, and if the following equicontinuity condition

$$\lim_{\delta \rightarrow 0} \limsup_{t,n} \mathbb{P} \left( w_{\bar{X}_{t+}^{1,n}}^T(\delta) \geq \varepsilon \right) = 0 \quad (26)$$

is met for every  $\varepsilon, T > 0$ , where  $w_x^T(\delta)$  is the modulus of continuity of a function  $x$  on the interval  $[0, T]$ . The weak $\star$ -relative compactness of  $(\hat{\mathbb{I}}_t^n)_{t,n}$  in  $\mathcal{P}(\mathbb{R}^d)$ , follows directly from Assumption 4. Using the notation  $k_t := \inf\{k : \sum_{i=1}^k \gamma_i \geq t\}$ , and using the definition in Eq. (1), we obtain the decomposition:

$$\begin{aligned} \bar{X}_t^{1,n} - \bar{X}_s^{1,n} &= P_{s,t}^n + N_{s,t}^n + U_{s,t}^n, \quad (27) \\ P_{s,t}^n &:= \frac{1}{n} \sum_{j=1}^n \left( \sum_{k=k_s}^{k_t-2} \gamma_{k+1} b(X_k^{1,n}, X_k^{j,n}) + (\tau_{k_s} - s) b(X_{k_s-1}^{1,n}, X_{k_s-1}^{j,n}) + (\tau_{k_t} - t) b(X_{k_t-1}^{1,n}, X_{k_t-1}^{j,n}) \right) \\ N_{s,t}^n &:= \sum_{k=k_s}^{k_t-2} \sqrt{\gamma_{k+1}} \zeta_{k+1}^{1,n} + \frac{\tau_{k_s} - s}{\gamma_{k_s}} \sqrt{\gamma_{k_s}} \zeta_{k_s}^{1,n} + \frac{\tau_{k_t} - t}{\gamma_{k_t}} \sqrt{\gamma_{k_t}} \zeta_{k_t}^{1,n} \\ U_{s,t}^n &:= \frac{1}{n} \sum_{i=1}^n \left( \sum_{k=k_s}^{k_t-2} \gamma_{k+1} \zeta_{k+1}^{i,n} + (\tau_{k_s} - s) \zeta_{k_s}^{i,n} + (\tau_{k_t} - t) \zeta_{k_t}^{i,n} \right). \end{aligned}$$

Let the sequence  $(\tilde{\gamma}_k)$  be defined by:  $\tilde{\gamma}_{k_s} := \tau_{k_s} - s$ ,  $\tilde{\gamma}_{k_t} := \tau_{k_t} - t$  and  $\tilde{\gamma}_k := \gamma_k$  for all  $k \neq k_{t_s}, k_{t_t}$ . Note that:

$$\sum_{k=k_s-1}^{k_t-1} \tilde{\gamma}_{k+1} = t - s. \quad (28)$$

Moreover, we have:

$$\frac{\tau_{k_s} - s}{\gamma_{k_s}} \sqrt{\gamma_{k_s}} \leq \sqrt{\tilde{\gamma}_{k_s}}, \quad \text{and} \quad \frac{\tau_{k_t} - t}{\gamma_{k_t}} \sqrt{\gamma_{k_t}} \leq \sqrt{\tilde{\gamma}_{k_t}}. \quad (29)$$

The term  $N_{s,t}^n$  is expressed as a sum of martingale increments, with respect to the filtration  $\mathcal{F}_k^n$ . Let  $\|\cdot\|_\alpha$  denote the  $\alpha$ -norm in  $\mathbb{R}^d$ . We apply Burkholder's inequality stated in Theorem 1.1 of [BDG72] to the components of the vector  $N_{s,t}^n$  in  $\mathbb{R}^d$ . As Eq. (28) and (29) hold:

$$\mathbb{E} \left( \|N_{s,t}^n\|_4^4 \right) \leq C(t-s) \mathbb{E} \left[ \sum_{k=k_s-1}^{k_t-1} \tilde{\gamma}_{k+1} \left\| \xi_{k+1}^{1,n} \right\|_4^4 \right],$$



where  $C$  is a constant independent of  $s, t$  and  $n$ . As Assumption 3-(ii) holds, there exists a constant  $C > 0$  independent of  $s, t$ , and  $n$ , such that

$$\sup_{n \in \mathbb{N}} \mathbb{E} \left( \|N_{s,t}^n\|^4 \right) \leq C(t-s)^2. \quad (30)$$

Furthermore, using Jensen's inequality along with Eq. (28), we obtain

$$\|P_{s,t}^n\|^2 \leq \frac{(t-s)}{n} \sum_{j \in [n]} \sum_{k=k_s-1}^{k_t-1} \tilde{\gamma}_{k+1} \left\| b(X_k^{1,n}, X_k^{j,n}) \right\|^2.$$

Using Assumptions 1 and 3, there exists a constant  $C$ , independent of  $s, t, n$ , such that

$$\sup_{n \in \mathbb{N}} \mathbb{E} \left( \|P_{s,t}^n\|^2 \right) \leq C(t-s)^2. \quad (31)$$

Also, by Jensen's inequality, we have

$$\|U_{s,t}^n\|^2 \leq \frac{(t-s)}{n} \sum_{i \in [n]} \sum_{k=k_s-1}^{k_t-1} \tilde{\gamma}_{k+1} \left\| \zeta_{k+1}^{i,n} \right\|^2.$$

Since, by Assumption 3, we have  $\sup_{k,n} \mathbb{E}[\|\zeta_k^{1,n}\|^2] < \infty$ , there exists a constant  $C$  independent of  $n, s$ , and  $t$ , such that:

$$\sup_{n \in \mathbb{N}} \mathbb{E} \left( \|U_{s,t}^n\|^2 \right) \leq C(t-s)^2. \quad (32)$$

Combining Equations (31), (30) and (32), we have shown:

$$\sup_{n \in \mathbb{N}} \mathbb{E} \left[ \|P_{s,t}^n\|^2 + \|N_{s,t}^n\|^4 + \|U_{s,t}^n\|^2 \right] \leq C(t-s)^2, \quad (33)$$

where  $0 \leq s < t < \infty$ , and  $C$  is a positive constant, independent of  $s, t, n$ . Using [Leo23, Th. 2.8] and Markov's inequality, Eq. (26) hold.  $\square$

**Lemma 7.** *We posit the assumptions of Prop. 4. For every  $T > 0$ ,*

$$\lim_{a \rightarrow \infty} \sup_{t \in \mathbb{R}_+, n \in \mathbb{N}^*} \mathbb{E} \left[ \int \sup_{s \in [0, T]} \|x_s\|^p \mathbf{1}_{\sup_{s \in [0, T]} \|x_s\| \geq a} d\Phi_t(m^n)(x) \right] = 0.$$

*Proof.* By the exchangeability stated in Assumption 3-(i), we obtain:

$$\mathbb{E} \left[ \int \sup_{u \in [0, T]} \|x_u\|^p \mathbf{1}_{\sup_{u \in [0, T]} \|x_u\| > a} d\Phi_t(m^n)(x) \right] = \mathbb{E} \left[ \sup_{u \in [0, T]} \left\| \bar{X}_{t+u}^{1,n} \right\|^p \mathbf{1}_{\sup_{u \in [0, T]} \left\| \bar{X}_{t+u}^{1,n} \right\| > a} \right],$$

for every  $k, t, n$ . Recalling the decomposition introduced in Eq. (27), for every  $u \in [0, T]$ :

$$\left\| \bar{X}_{t+u}^{1,n} \right\|^p \leq 4^{p-1} \left( \left\| \bar{X}_t^{1,n} \right\|^p + \|N_{t,t+u}^n\|^p + \|P_{t,t+u}^n\|^p + \|U_{t,t+u}^n\|^p \right).$$

Hence,

$$\begin{aligned} \left\| \bar{X}_{t+u}^{1,n} \right\|^p \mathbf{1}_{\sup_{u \in [0, T]} \left\| \bar{X}_{t+u}^{1,n} \right\| > a} &\leq 4^p \left( \left\| \bar{X}_t^{1,n} \right\|^p \mathbf{1}_{\left\| \bar{X}_t^{1,n} \right\| > a/4} + \|N_{t,t+u}^n\|^p \mathbf{1}_{\sup_{u \in [0, T]} \|N_{t,t+u}^n\| > a/4} \right. \\ &\quad \left. + \|P_{t,t+u}^n\|^p \mathbf{1}_{\sup_{u \in [0, T]} \|P_{t,t+u}^n\| > a/4} + \|U_{t,t+u}^n\|^p \mathbf{1}_{\sup_{u \in [0, T]} \|U_{t,t+u}^n\| > a/4} \right). \end{aligned}$$

Therefore, for each  $T > 0$ , it suffices to obtain the uniform integrability of the four collections of random variables:  $(\|\bar{X}_t^{1,n}\|^p : t \in \mathbb{R}_+, n \in \mathbb{N}^*)$ ,  $(\sup_{u \in [0, T]} \|N_{t,t+u}^n\|^p : t \in \mathbb{R}_+, n \in \mathbb{N}^*)$ ,  $(\sup_{u \in [0, T]} \|P_{t,t+u}^n\|^p : t \in \mathbb{R}_+, n \in \mathbb{N}^*)$ , and  $(\sup_{u \in [0, T]} \|U_{t,t+u}^n\|^p : t \in \mathbb{R}_+, n \in \mathbb{N}^*)$ .

$(\|\bar{X}_t^{1,n}\|^p : t \in \mathbb{R}_+, n \in \mathbb{N}^*)$  is uniformly integrable by Assumption 4–(i) when  $p < 2$ , and by Assumption 4–(ii) when  $p = 2$ . As obtained in Eq. (30), Burkholder inequality stated in Theorem 1.1 of [BDG72] yields:

$$\mathbb{E} \left[ \sup_{u \in [0, T]} \|N_{t, t+u}^n\|^4 \right] \leq CT^2,$$

where  $C$  is a constant independent of  $n, t$ , and  $T$ . Hence, since  $p < 4$ , we obtain the uniform integrability of  $\{\sup_{u \in [0, T]} \|N_{t, t+u}^n\|^p : t \in \mathbb{R}_+, n \in \mathbb{N}^*\}$ . As obtained in Eq. (31) and Eq. (32), we derive:

$$\sup_{u \in [0, T]} \|P_{t, t+u}^n\|^p \leq \frac{CT^{p-1}}{n} \sum_{j \in [n]} \sum_{k=k_t-1}^{k_t+T-1} \tilde{\gamma}_{k+1} \left( 1 + \|X_k^{j,n}\|^p + \|X_k^{1,n}\|^p \right),$$

and

$$\sup_{u \in [0, T]} \|U_{t, t+u}^n\|^2 \leq \frac{CT}{n} \sum_{j \in [n]} \sum_{k=k_t-1}^{k_t+T-1} \tilde{\gamma}_{k+1} \|\zeta_k^{j,n}\|^2,$$

where  $C$  remains a constant independent of  $n$  and  $t$ . Using Assumption 4–(i) when  $p < 2$ , and Assumption 4–(ii) when  $p = 2$ , by de la Vallée Poussin theorem, there exists a non-decreasing, convex, and non-negative function  $F : \mathbb{R}_+^* \rightarrow \mathbb{R}$  such that

$$\lim_{h \rightarrow \infty} \frac{F(h)}{h} = \infty, \text{ and } \sup_{k \in \mathbb{N}, n \in \mathbb{N}^*} \mathbb{E} \left[ F \left( \|X_k^{1,n}\|^p \right) \right] < \infty.$$

Hence, by Jensen's inequality, and the exchangeability stated in Assumption 3,

$$\mathbb{E} \left[ F \left( \sup_{u \in [0, T]} \|P_{t, t+u}^n\|^p \right) \right] \leq \frac{1}{T} \sum_{k=k_t-1}^{k_t+T-1} \tilde{\gamma}_{k+1} \mathbb{E} \left[ F \left( CT^p \left( 1 + \|X_k^{1,n}\|^p \right) \right) \right].$$

Consequently,

$$\sup_{t \in \mathbb{R}_+, n \in \mathbb{N}^*} \mathbb{E} \left[ F \left( \sup_{u \in [0, T]} \|P_{t, t+u}^n\|^p \right) \right] \leq \sup_{k \in \mathbb{N}, n \in \mathbb{N}^*} \mathbb{E} \left[ F \left( CT^p \left( 1 + \|X_k^{1,n}\|^p \right) \right) \right] < \infty.$$

Therefore, de la Vallée Poussin theorem yields the uniform integrability of the collection

$$\left( \sup_{u \in [0, T]} \|P_{t, t+u}^n\|^p : t \in \mathbb{R}_+, n \in \mathbb{N}^* \right).$$

The uniform integrability of the collection  $(\sup_{u \in [0, T]} \|U_{t, t+u}^n\|^p : t \in \mathbb{R}_+, n \in \mathbb{N}^*)$  is obtained, by the same arguments. This completes the proof.  $\square$

To conclude the proof of Prop. 4, it is sufficient to remark that the tightness conditions provided in Lemma 2 are satisfied, thanks to Lemmas 6 and 7, with Prop. 1.

## 5.2 Proof of Proposition 5

The core of the proof is provided by the following proposition.

**Proposition 11.** *Let Assumptions 1, 2, 3 and 4–(i) hold,*

$$\lim_{(t,n) \rightarrow (\infty, \infty)} \mathbb{E} |G(\Phi_t(m^n))| = 0,$$

for each function  $G \in \mathcal{G}_p$ .

*Proof.* We need to show that for each  $\mathbb{R}_+ \times \mathbb{N}$ -valued sequence  $(t_n, \varphi_n) \rightarrow (\infty, \infty)$  as  $n \rightarrow \infty$ , the convergence  $\mathbb{E} |G(\Phi_{t_n}(m^{\varphi_n}))| \rightarrow 0$  holds true, where  $G = G_{r, \phi, h_1, \dots, h_r, t, s, v_1, \dots, v_r}$  has the form of Eq. (10), with  $0 \leq v_1 \leq \dots \leq v_r \leq s \leq t$ . We take  $\varphi_n = n$  for notational simplicity, and we write  $m_n := \Phi_{t_n}(m^n) \in \mathcal{P}_p(\mathcal{C})$ . We have

$$G(m_n) = \frac{1}{n} \sum_{i \in [n]} \left( \phi(\bar{X}_{t_n+t}^{i,n}) - \phi(\bar{X}_{t_n+s}^{i,n}) - \int_{t_n+s}^{t_n+t} \frac{1}{n} \sum_{j \in [n]} \psi(\bar{X}_u^{i,n}, \bar{X}_u^{j,n}) du \right) Q^{i,n}, \quad (34)$$

where we set  $\psi(x, y) := \langle \nabla \phi(x), b(x, y) \rangle + \sigma^2 \Delta \phi(x)$ , and

$$Q^{i,n} := \prod_{j=1}^r h_j(X_{t_n+v_j}^{i,n}).$$

We note right away that  $|Q^{i,n}| \leq C$  where  $C$  depends on the functions  $h_j$  only, and furthermore, the random variables  $\{Q^{i,n}\}_{i \in [n]}$  are  $\mathcal{F}_{k_{t_n+s}}^n$ -measurable, where we recall that the integer  $k_t$  is defined by  $k_t := \inf\{k : \sum_{i=1}^k \gamma_i \geq t\}$ .

In the remainder, we suppress the superscript  $(n)$  from most of our notations for clarity. To deal with the right hand side of (34), we begin by expressing  $\phi(\bar{X}_{t_n+t}^i) - \phi(\bar{X}_{t_n+s}^i)$  as a telescoping sum in the discrete random variables  $X_k^i$ :

$$\begin{aligned} \phi(\bar{X}_{t_n+t}^i) - \phi(\bar{X}_{t_n+s}^i) &= \sum_{k=k_{t_n+s}}^{k_{t_n+t}-2} (\phi(X_{k+1}^i) - \phi(X_k^i)) \\ &\quad + \phi(\bar{X}_{t_n+t}^i) - \phi(X_{k_{t_n+t}-1}^i) + \phi(X_{k_{t_n+s}}^i) - \phi(\bar{X}_{t_n+s}^i). \end{aligned}$$

The summands at the right hand side of this expression can be decomposed as follows. Remember the form (1) of our algorithm. Denoting as  $H_\phi(x)$  the Hessian matrix of  $\phi$  at  $x$ , we know by the Taylor-Lagrange formula that there exists  $\theta_{k+1} \in [\tau_k, \tau_{k+1}]$  such that

$$\begin{aligned} \phi(X_{k+1}^i) - \phi(X_k^i) &= \langle \nabla \phi(X_k^i), X_{k+1}^i - X_k^i \rangle + \frac{1}{2} (X_{k+1}^i - X_k^i)^T H_\phi(\bar{X}_{\theta_{k+1}}^i) (X_{k+1}^i - X_k^i) \\ &= \gamma_{k+1} \frac{1}{n} \sum_{j \in [n]} \langle \nabla \phi(X_k^i), b(X_k^i, X_k^j) \rangle + \gamma_{k+1} \sigma^2 \Delta \phi(X_k^i) \\ &\quad + \sqrt{2\gamma_{k+1}} \langle \nabla \phi(X_k^i), \xi_{k+1}^i \rangle + \gamma_{k+1} \langle \nabla \phi(X_k^i), \zeta_{k+1}^i \rangle \\ &\quad + \frac{1}{2} (X_{k+1}^i - X_k^i)^T H_\phi(\bar{X}_{\theta_{k+1}}^i) (X_{k+1}^i - X_k^i) - \gamma_{k+1} \sigma^2 \Delta \phi(X_k^i) \\ &= \frac{1}{n} \sum_{j \in [n]} \psi(X_k^i, X_k^j) + \sqrt{2\gamma_{k+1}} \langle \nabla \phi(X_k^i), \xi_{k+1}^i \rangle + \gamma_{k+1} \langle \nabla \phi(X_k^i), \zeta_{k+1}^i \rangle \\ &\quad + \frac{1}{2} (X_{k+1}^i - X_k^i)^T H_\phi(\bar{X}_{\theta_{k+1}}^i) (X_{k+1}^i - X_k^i) - \gamma_{k+1} \sigma^2 \Delta \phi(X_k^i) \\ &= \frac{1}{n} \sum_{j \in [n]} \psi(X_k^i, X_k^j) + \gamma_{k+1} \langle \nabla \phi(X_k^i), \zeta_{k+1}^i \rangle \\ &\quad + \frac{1}{2} (X_{k+1}^i - X_k^i)^T H_\phi(\bar{X}_{\theta_{k+1}}^i) (X_{k+1}^i - X_k^i) - \gamma_{k+1} (\xi_{k+1}^i)^T H_\phi(X_k^i) \xi_{k+1}^i \\ &\quad + \sqrt{2\gamma_{k+1}} \langle \nabla \phi(X_k^i), \xi_{k+1}^i \rangle + \gamma_{k+1} (\xi_{k+1}^i)^T H_\phi(X_k^i) \xi_{k+1}^i - \gamma_{k+1} \sigma^2 \Delta \phi(X_k^i). \end{aligned}$$

In this last expression, the terms  $n^{-1} \sum_{j \in [n]} \psi(X_k^i, X_k^j)$  will be played against the integral term at the right hand side of (34), and the other terms will be proven to have negligible effects. Notice that since  $\text{tr}(H_\phi(\bar{X}_k^i)) = \Delta \phi(X_k^i)$ , the term

$$\eta_{k+1}^i := \sqrt{2\gamma_{k+1}} \langle \nabla \phi(X_k^i), \xi_{k+1}^i \rangle + \gamma_{k+1} (\xi_{k+1}^i)^T H_\phi(X_k^i) \xi_{k+1}^i - \gamma_{k+1} \sigma^2 \Delta \phi(X_k^i)$$

in the expression above is a martingale increment term with respect to the filtration  $(\mathcal{F}_k^n)_k$ , thanks to Assumption 3-(ii).

To proceed, considering the integral at the right hand side of (34), we can write

$$\begin{aligned} \int_{t_n+s}^{t_n+t} \psi(\bar{X}_u^i, \bar{X}_u^j) du &= \\ &= \int_{\tau_{k_{t_n+s}}}^{\tau_{k_{t_n+t}-1}} \psi(\bar{X}_u^i, \bar{X}_u^j) du + \int_{t_n+s}^{\tau_{k_{t_n+s}}} \psi(\bar{X}_u^i, \bar{X}_u^j) du + \int_{\tau_{k_{t_n+t}-1}}^{t_n+t} \psi(\bar{X}_u^i, \bar{X}_u^j) du, \end{aligned}$$

and with these decompositions, we obtain  $G(\mathbf{m}_n) = \sum_{l=1}^8 \chi_l^n$ , where:

$$\begin{aligned}
\chi_1^n &:= \frac{1}{n} \sum_{i \in [n]} \left\{ \sum_{k=k_{t_n+s}}^{k_{t_n+t}-2} \frac{1}{n} \sum_{j \in [n]} \gamma_{k+1} \psi(X_k^i, X_k^j) - \int_{\tau_{k_{t_n+s}}}^{\tau_{k_{t_n+t}-1}} \frac{1}{n} \sum_{j \in [n]} \psi(\bar{X}_u^i, \bar{X}_u^j) du \right\} Q^i, \\
\chi_2^n &:= \frac{1}{n} \sum_{i \in [n]} \left\{ \phi(\bar{X}_{t_n+t}^i) - \phi(X_{k_{t_n+t}-1}^i) + \phi(X_{k_{t_n+s}}^i) - \phi(\bar{X}_{t_n+s}^i) \right\} Q^i, \\
\chi_3^n &:= -\frac{1}{n} \sum_{i \in [n]} \left\{ \int_{t_n+s}^{\tau_{k_{t_n+s}}} \frac{1}{n} \sum_{j \in [n]} \psi(\bar{X}_u^i, \bar{X}_u^j) du + \int_{\tau_{k_{t_n+t}-1}}^{t_n+t} \frac{1}{n} \sum_{j \in [n]} \psi(\bar{X}_u^i, \bar{X}_u^j) du \right\} Q^i, \\
\chi_4^n &:= \frac{1}{n} \sum_{i \in [n]} Q^i \sum_{k=k_{t_n+s}}^{k_{t_n+t}-2} \gamma_{k+1} \langle \nabla \phi(X_k^i), \zeta_{k+1}^i \rangle, \\
\chi_5^n &:= \frac{1}{n} \sum_{i \in [n]} \sum_{k=k_{t_n+s}}^{k_{t_n+t}-2} \gamma_{k+1} (\zeta_{k+1}^i)^T \left( H_\phi(\bar{X}_{\theta_{k+1}}^i) - H_\phi(X_k^i) \right) (\zeta_{k+1}^i) Q^i, \\
\chi_6^n &:= \frac{1}{n^2} \sum_{i,j \in [n]} \sum_{k=k_{t_n+s}}^{k_{t_n+t}-2} \left( \sqrt{2} \gamma_{k+1}^{3/2} b(X_k^i, X_k^j)^T H_\phi(\bar{X}_{\theta_{k+1}}^i) \zeta_{k+1}^i \right) Q^i \\
&\quad + \frac{1}{n^3} \sum_{i,p,q \in [n]} \sum_{k=k_{t_n+s}}^{k_{t_n+t}-2} \left( \frac{1}{2} \gamma_{k+1}^2 b(X_k^i, X_k^p)^T H_\phi(\bar{X}_{\theta_{k+1}}^i) b(X_k^i, X_k^q) \right) Q^i, \\
\chi_7^n &:= \frac{1}{n^2} \sum_{i,j \in [n]} \sum_{k=k_{t_n+s}}^{k_{t_n+t}-2} \gamma_{k+1}^{3/2} \left( \left( \sqrt{\gamma_{k+1}} \left( b(X_k^i, X_k^j) + \frac{\zeta_{k+1}^i}{2} \right) + \sqrt{2} \zeta_{k+1}^i \right)^T \right. \\
&\quad \left. H_\phi(\bar{X}_{\theta_{k+1}}^i) \zeta_{k+1}^i \right) Q^i, \quad \text{and} \\
\chi_8^n &:= \frac{1}{n} \sum_{i \in [n]} \sum_{k=k_{t_n+s}}^{k_{t_n+t}-2} \eta_{k+1}^i Q^i.
\end{aligned}$$

To prove our proposition, we show that  $\mathbb{E}|\chi_l^n| \rightarrow 0$  for all  $l \in [8]$ . The notation  $E_\times^n$  will be generically used to refer to error terms.

Let us start with  $\mathbb{E}|\chi_1^n|$ . For  $i, j \in [n]$ , writing

$$E_{i,j}^n := \sum_{k=k_{t_n+s}}^{k_{t_n+t}-2} \gamma_{k+1} \psi(X_k^i, X_k^j) - \int_{\tau_{k_{t_n+s}}}^{\tau_{k_{t_n+t}-1}} \psi(\bar{X}_u^i, \bar{X}_u^j) du$$

and using the boundedness of  $Q^i$  and the exchangeability as stated by Assumption 3-(i), we obtain that

$$\mathbb{E}|\chi_1^n| \leq C (\mathbb{E}|E_{1,2}^n| + \mathbb{E}|E_{1,1}^n|/n).$$

We begin by providing a bound on the second moments of  $E_{1,1}^n$  and  $E_{1,2}^n$ . Recalling the definition of  $\psi$ , and using the compactness of the support of  $\phi$  along with Assumption 1, we obtain that

$$\begin{aligned}
\mathbb{E}(E_{i,j}^n)^2 &\leq 2(t-s)^2 \max_{u \in [t_n+s, t_n+t]} \mathbb{E} \|\psi(\bar{X}_u^i, \bar{X}_u^j)\|^2 \\
&\leq C(t-s)^2 \left( 1 + \sup_{u \geq 0} \mathbb{E}(\bar{X}_u^1)^2 \right) \\
&\leq C(t-s)^2
\end{aligned}$$

thanks to Assumption 4-(i). To obtain that  $\mathbb{E}|\chi_1^n| \rightarrow 0$ , we thus need to show that  $\mathbb{E}|E_{1,2}^n| \rightarrow 0$ .

By Prop. 4 above, the sequence  $(\mathbf{m}_n)$  of  $\mathcal{P}(\mathcal{C})$ -valued random variables is tight. By Lemma 1, this is equivalent to the weak $\star$ -relative compactness of the sequence of intensities  $(\mathbb{I}(\mathbf{m}_n))$ . For each Borel set  $A \in \mathcal{B}(\mathcal{C})$ , we furthermore have that

$$\mathbb{I}(\mathbf{m}_n)(A) = \frac{1}{n} \sum_{i \in [n]} \mathbb{P} \left[ \bar{X}_{t_n+}^{i,n} \in A \right] = \mathbb{P} \left[ \bar{X}_{t_n+}^{1,n} \in A \right]$$

by the exchangeability, thus, the sequence of random variables  $(\bar{X}_{t_n^+}^{1,n})_n$  is tight. Let us work on the random variables  $U_n^1 := \pi_{[0,t-s]} \# \bar{X}_{t_n^+}^1$  and  $U_n^2 := \pi_{[0,t-s]} \# \bar{X}_{t_n^+}^2$  defined on the set  $\mathcal{C}([0, t-s])$  of continuous functions on the interval  $[0, t-s]$ . Since  $(\bar{X}_{t_n^+}^{1,n})_n$  is tight, given an arbitrary  $\varepsilon > 0$ , there is a compact set  $\mathcal{K}_\varepsilon \subset \mathcal{C}([0, t-s])$  such that

$$\forall n \in \mathbb{N}^*, \quad \mathbb{P}[U_n^1 \notin \mathcal{K}_\varepsilon] \leq \varepsilon.$$

Writing  $\bar{\gamma}_l = \sup_{k \geq l} \gamma_k$ , we now have

$$\begin{aligned} |E_{1,2}^n| &\leq \sum_{k=k_{t_n^+}+s}^{k_{t_n^+}+t-2} \gamma_{k+1} \max_{\delta \in [0, \gamma_{k+1}]} |\psi(\bar{X}_{\tau_k+\delta}^1, \bar{X}_{\tau_k+\delta}^2) - \psi(\bar{X}_{\tau_k}^1, \bar{X}_{\tau_k}^2)| \\ &\leq (t-s) \max_{\substack{u,v \in [0,t-s] \\ |u-v| \leq \bar{\gamma}_{k_{t_n^+}+s}}} |\psi(U_n^1(u), U_n^2(u)) - \psi(U_n^1(v), U_n^2(v))|. \end{aligned}$$

We thus can write

$$\begin{aligned} \mathbb{E}|E_{1,2}^n| &= \mathbb{E}|E_{1,2}^n| \mathbf{1}_{(U_n^1, U_n^2) \in \mathcal{K}_\varepsilon} + \mathbb{E}|E_{1,2}^n| \mathbf{1}_{(U_n^1, U_n^2) \notin \mathcal{K}_\varepsilon} \\ &\leq (t-s) \sup_{f,g \in \mathcal{K}_\varepsilon} \max_{\substack{u,v \in [0,t-s] \\ |u-v| \leq \bar{\gamma}_{k_{t_n^+}+s}}} |\psi(f(u), g(u)) - \psi(f(v), g(v))| + \sqrt{\mathbb{E}(E_{1,2}^n)^2} \sqrt{2\mathbb{P}[U_n^1 \notin \mathcal{K}_\varepsilon]}. \end{aligned} \tag{35}$$

By the Arzelà-Ascoli theorem, the functions in  $\mathcal{K}_\varepsilon$  are uniformly equicontinuous and bounded. Since  $\psi$  is a continuous function, one can easily check that the set of functions  $\mathcal{S}$  on  $[0, t-s]$  defined as

$$\mathcal{S} := \{u \mapsto \psi(f(u), g(u)) : f, g \in \mathcal{K}_\varepsilon\}$$

is a set of uniformly equicontinuous functions. As a consequence, the first term at the right hand side of the inequality in (35) converges to zero as  $n \rightarrow \infty$ , since  $\bar{\gamma}_{k_{t_n^+}+s} \rightarrow 0$ . The second term is bounded by  $C\sqrt{\varepsilon}$  thanks to the bound we obtained on  $\mathbb{E}(E_{1,2}^n)^2$ . Since  $\varepsilon$  is arbitrary, we obtain that  $\mathbb{E}|E_{1,2}^n| \rightarrow 0$ , thus,  $\mathbb{E}|\chi_1^n| \rightarrow 0$ .

The terms  $\chi_n^2$ ,  $\chi_n^3$ , and  $\chi_n^5$  are dealt with similarly to  $\chi_n^1$ . Considering  $\chi_n^2$ , we have by the exchangeability that  $\mathbb{E}|\chi_n^2| \leq C\mathbb{E}|E_1^n|$ , with

$$\begin{aligned} E_1^n &= \phi(\bar{X}_{t_n^+}^1) - \phi(X_{k_{t_n^+}+t-1}^1) + \phi(X_{k_{t_n^+}+s}^1) - \phi(\bar{X}_{t_n^+}^1) \\ &= \phi(\bar{X}_{t_n^+}^1) - \phi(\bar{X}_{\tau_{k_{t_n^+}+t-1}}^1) + \phi(\bar{X}_{\tau_{k_{t_n^+}+s}}^1) - \phi(\bar{X}_{t_n^+}^1). \end{aligned}$$

Keeping the notations  $U_n^1 := \pi_{[0,t-s]} \# \bar{X}_{t_n^+}^1$  and  $\bar{\gamma}_l$  introduced above, we have

$$|E_1^n| \leq 2 \max_{\substack{u,v \in [0,t-s] \\ |u-v| \leq \bar{\gamma}_{k_{t_n^+}+s}}} |\phi(U_n^1(u)) - \phi(U_n^1(v))|.$$

Taking  $\varepsilon > 0$ , selecting the compact  $\mathcal{K}_\varepsilon \subset \mathcal{C}([0, t-s])$  as we did for  $\chi_1^n$ , and recalling that the function  $\phi$  is bounded, we have

$$\mathbb{E}|E_1^n| \leq 2 \sup_{f \in \mathcal{K}_\varepsilon} \max_{\substack{u,v \in [0,t-s] \\ |u-v| \leq \bar{\gamma}_{k_{t_n^+}+s}}} \|\phi(f(u)) - \phi(f(v))\| + C\mathbb{P}[U_n^1 \notin \mathcal{K}_\varepsilon],$$

and we obtain the  $\mathbb{E}|\chi_n^2| \rightarrow 0$  by the same argument as for  $\chi_n^1$ .

The treatment of  $\chi_n^3$  is very similar to  $\chi_n^2$  and is omitted. Let us provide some details for  $\chi_n^5$ . Here we have by exchangeability that

$$\mathbb{E}|\chi_5^n| \leq \sum_{k=k_{t_n^+}+s}^{k_{t_n^+}+t-2} \gamma_{k+1} \mathbb{E}|E_k^{1,n}|,$$

where

$$E_k^{1,n} := (\xi_{k+1}^1)^T \left( H_\phi(\bar{X}_{\theta_{k+1}}^1) - H_\phi(X_k^1) \right) (\xi_{k+1}^1) Q^1.$$

satisfies

$$|E_k^{1,n}| \leq C \|\xi_{k+1}^1\|^2 \max_{\substack{u,v \in [0,t-s] \\ |u-v| \leq \bar{\gamma}_{k_{t_n+s}}} \|H_\phi(U_n^1(u)) - H_\phi(U_n^1(v))\|.$$

Therefore,

$$\begin{aligned} \mathbb{E} |E_k^{1,n}| &= \mathbb{E} |E_k^{1,n}| \mathbf{1}_{U_n^1 \in \mathcal{K}_\varepsilon} + \mathbb{E} |E_k^{1,n}| \mathbf{1}_{U_n^1 \notin \mathcal{K}_\varepsilon} \\ &\leq C \mathbb{E} \|\xi_{k+1}\|^2 \sup_{f \in \mathcal{K}_\varepsilon} \max_{\substack{u,v \in [0,t-s] \\ |u-v| \leq \bar{\gamma}_{k_{t_n+s}}} \|H_\phi(f(u)) - H_\phi(f(v))\| + \sqrt{\mathbb{E}(E_k^{1,n})^2} \sqrt{\mathbb{P}[U_n^1 \notin \mathcal{K}_\varepsilon]}. \end{aligned}$$

Since  $\mathbb{E} \|\xi_{k+1}\|^2$  and  $\mathbb{E}(E_k^{1,n})^2$  are bounded, we obtain that  $\mathbb{E} |\chi_5^n| \rightarrow 0$ .

Considering the term  $\chi_n^4$ , we have by exchangeability

$$\begin{aligned} \mathbb{E} |\chi_4^n| &\leq C \mathbb{E} \left| \sum_{k=k_{t_n+s}}^{k_{t_n+t-2}} \gamma_{k+1} \langle \nabla \phi(X_k^1), \zeta_{k+1}^1 \rangle \right| \\ &\leq C \mathbb{E} \left| \sum_{k=k_{t_n+s}}^{k_{t_n+t-2}} \gamma_{k+1} \langle \nabla \phi(X_k^1), \mathbb{E}[\zeta_{k+1}^1 | \mathcal{F}_k^n] \rangle \right| + C \mathbb{E} \left| \sum_{k=k_{t_n+s}}^{k_{t_n+t-2}} \gamma_{k+1} \langle \nabla \phi(X_k^1), \zeta_{k+1}^{\circ 1} \rangle \right| \\ &:= \mathbb{E} |\chi_{4,1}^n| + \mathbb{E} |\chi_{4,2}^n|, \end{aligned}$$

where  $\zeta_k^{\circ 1} = \zeta_k^1 - \mathbb{E}[\zeta_k^1 | \mathcal{F}_{k-1}^n]$  is a martingale increment with respect to the filtration  $(\mathcal{F}_k^n)_k$ . We have

$$\mathbb{E} |\chi_{4,1}^n| \leq C(t-s) \sup_{l \geq k_{t_n+s}} \mathbb{E} \|\mathbb{E}[\zeta_{l+1}^1 | \mathcal{F}_l^n]\|,$$

which converges to zero by Assumption 3-(iii). By the martingale property, we furthermore have

$$\mathbb{E} (\chi_{4,2}^n)^2 \leq C \sum_{k=k_{t_n+s}}^{k_{t_n+t-2}} \gamma_{k+1}^2 \leq C \bar{\gamma}_{k_{t_n+s}} (t-s),$$

which also converges to zero. Thus,  $\mathbb{E} |\chi_4^n| \rightarrow 0$ .

We now turn to  $\chi_6^n$ . Here we write

$$\chi_6^n = \frac{1}{n} \sum_{i \in [n]} \sum_{k=k_{t_n+s}}^{k_{t_n+t-2}} \gamma_{k+1}^{3/2} E_k^i,$$

where

$$\begin{aligned} E_k^i &:= \frac{1}{n} \sum_{j \in [n]} \sqrt{2} b(X_k^i, X_k^j)^T H_\phi(\bar{X}_{\theta_{k+1}}^i) \xi_{k+1}^i Q^i \\ &\quad + \frac{1}{n^2} \sum_{p,q \in [n]} \frac{1}{2} \sqrt{\gamma_{k+1}} b(X_k^i, X_k^p)^T H_\phi(\bar{X}_{\theta_{k+1}}^i) b(X_k^i, X_k^q) Q^i \end{aligned}$$

satisfies

$$|E_k^i| \leq \frac{C}{n} \sum_{j \in [n]} (1 + \|X_k^j\|) \|\xi_{k+1}^i\| + \frac{C}{n^2} \sqrt{\gamma_{k+1}} \sum_{p,q \in [n]} (1 + \|X_k^p\|)(1 + \|X_k^q\|).$$

We readily obtain from Assumptions 3, and 4-(i) that  $\mathbb{E} |E_k^i| \leq C$ , which leads to  $\mathbb{E} |\chi_6^n| \rightarrow 0$ .

The treatment of the term  $\chi_7^n$  is similar and is omitted.

We finally deal with  $\chi_8^n$  that involves the martingale increments  $\eta_k^i$ . We decompose this term by writing

$$\begin{aligned} \chi_8^n &= \sum_{k=k_{t_n+s}}^{k_{t_n+t-2}} \frac{1}{n} \sum_{i \in [n]} \sqrt{2\gamma_{k+1}} \langle \nabla \phi(X_k^i), \xi_{k+1}^i \rangle Q^i \\ &\quad + \sum_{k=k_{t_n+s}}^{k_{t_n+t-2}} \frac{1}{n} \sum_{i \in [n]} \gamma_{k+1} ((\xi_{k+1}^i)^T H_\phi(X_k^i) \xi_{k+1}^i - \sigma^2 \Delta \phi(X_k^i)) Q^i \\ &:= \chi_{8,1}^n + \chi_{8,2}^n. \end{aligned}$$

Since the random vectors  $\xi_1^{k+1}, \dots, \xi_n^{k+1}$  are decorrelated conditionally to  $\mathcal{F}_k^n$  by Assumption 3-(ii), we obtain that

$$\mathbb{E} \left[ \left( \frac{1}{n} \sum_{i \in [n]} \sqrt{2\gamma_{k+1}} \langle \nabla \phi(X_k^i), \xi_{k+1}^i \rangle Q^i \right)^2 \middle| \mathcal{F}_k^n \right] \leq C \frac{\gamma_{k+1}}{n},$$

and by the martingale property,

$$\mathbb{E}(\chi_{8,1}^n)^2 \leq \sum_{k=k_{t_n+s}}^{k_{t_n+t}-2} C \frac{\gamma_{k+1}}{n} \leq \frac{C(t-s)}{n}.$$

Using the martingale property again along with the inequality  $(\sum_1^n a_i)^2 \leq n \sum_1^n a_i^2$ , we also have

$$\begin{aligned} \mathbb{E}(\chi_{8,2}^n)^2 &\leq \sum_{k=k_{t_n+s}}^{k_{t_n+t}-2} \gamma_{k+1}^2 \mathbb{E} \left( \frac{1}{n} \sum_{i \in [n]} ((\xi_{k+1}^i)^T H_\phi(X_k^i) \xi_{k+1}^i - \sigma^2 \Delta \phi(X_k^i)) Q^i \right)^2 \\ &\leq C \sum_{k=k_{t_n+s}}^{k_{t_n+t}-2} \gamma_{k+1}^2 \\ &\leq \bar{\gamma}_{k_{t_n+s}} C(t-s). \end{aligned}$$

It results that  $\mathbb{E}(\chi_8^n)^2 \rightarrow 0$ . The proof of Prop. 11 is completed.  $\square$

*Proof of Proposition 5.* Let  $(t_n, \varphi_n)_n$  be a  $\mathbb{R}_+ \times \mathbb{N}^*$ -valued sequence such that the distribution of  $(\Phi_{t_n}(m^{\varphi_n}))_n$  converges to a measure  $M \in \mathcal{M}$ , which exists thanks to the tightness of  $(\Phi_{t_n}(m^{\varphi_n}))_n$  as established by Prop. 4. Let  $G \in \mathcal{G}_p$ . By the continuity of  $G$  as established by Lemma 3,  $G(\Phi_{t_n}(m^{\varphi_n}))$  converges in distribution to  $G_\# M \in \mathcal{P}(\mathbb{R})$ . On the other hand, we know by the previous proposition that  $G(\Phi_{t_n}(m^{\varphi_n}))$  converges in probability to zero. Therefore,  $G_\# M = \delta_0$ .

Let  $\text{supp}(M) \subset \mathcal{P}_p(\mathcal{C})$  be the support of  $M$ , and let  $\rho \in \text{supp}(M)$ . By definition of the support,  $M(\mathcal{N}) > 0$  for each neighborhood  $\mathcal{N}$  of  $\rho$ . Therefore, since  $G_\# M = \delta_0$ , there exists a sequence  $(\rho_l)_{l \in \mathbb{N}}$  such that  $\rho_l \in \text{supp}(M)$ ,  $G(\rho_l) = 0$ , and  $\rho_l \rightarrow_l \rho$  in  $\mathcal{P}_p(\mathcal{C})$ . By the continuity of  $G$ , we obtain that  $G(\rho) = 0$ , which shows that  $\text{supp}(M) \subset G^{-1}(\{0\})$ . Since  $G$  is arbitrary, we obtain that  $\text{supp}(M) \subset \mathcal{V}_p = \bigcap_{G \in \mathcal{G}_p} G^{-1}(\{0\})$ , and the theorem is proven.  $\square$

### 5.3 Proof of Theorem 1

Throughout this paragraph, we assume that  $1 \leq p \leq 2$ .

We define the following collection  $(M_t^n : t \geq 0, n \in \mathbb{N}^*)$  of r.v. on  $\mathcal{P}(\mathcal{P}_p(\mathcal{C}))$ :

$$M_t^n := \frac{1}{t} \int_0^t \delta_{\Phi_s(m^n)} ds. \quad (36)$$

**Lemma 8.** *The collection of r.v.  $(M_t^n, t \geq 0, n \in \mathbb{N}^*)$  is tight in  $\mathcal{P}(\mathcal{P}_p(\mathcal{C}))$ .*

*Proof.* Based on Lemma 1, we just need to establish that the family of measures  $(\mathbb{I}(M_t^n))$  is relatively compact in the space  $\mathcal{P}(\mathcal{P}_p(\mathcal{C}))$ . Recall that  $\mathbb{I}(M_t^n)$  is the probability measure which, to every Borel subset  $A \subset \mathcal{P}_p(\mathcal{C})$ , associates:

$$\mathbb{I}(M_t^n)(A) = \frac{1}{t} \int_0^t \mathbb{P}(\Phi_s(m^n) \in A) ds$$

Consider  $\varepsilon > 0$ . By Prop. 4, there exists a compact set  $\mathcal{K} \in \mathcal{P}_p(\mathcal{C})$  such that  $\mathbb{P}(\Phi_s(m^n) \in \mathcal{K}) > 1 - \varepsilon$ , for all  $s, n$ . As a consequence,  $\mathbb{I}(M_t^n)(\mathcal{K}) > 1 - \varepsilon$ . The proof is completed.  $\square$

Let us denote by  $\mathcal{M}$  the set of weak $\star$  accumulation points of the net  $((M_t^n)_\# \mathbb{P} : t \geq 0, n \in \mathbb{N}^*)$ , as  $(t, n) \rightarrow (\infty, \infty)$ . By Lemma 8,  $\mathcal{M}$  is a non empty subset of  $\mathcal{P}(\mathcal{P}_p(\mathcal{C}))$ . Define:

$$\mathcal{V}_p = \{M \in \mathcal{P}(\mathcal{P}_p(\mathcal{C})) : M(\mathcal{V}_p) = 1\}.$$

**Lemma 9.** *For every  $\Upsilon \in \mathcal{M}$ ,  $\Upsilon(\mathcal{V}_p) = 1$ .*

*Proof.* Consider  $\Upsilon \in \mathcal{M}$ . Without restriction, we write  $\Upsilon$  as the weak $\star$  limit of some sequence of the form  $(M_{t_n}^n)_{\#}\mathbb{P}$ . The distance  $W_p(\cdot, V_p)$  to the set  $V_p$  (which is non empty by Prop. 5) is a continuous function on  $\mathcal{P}_p(\mathcal{C})$ . Denoting by  $\langle \cdot, \cdot \rangle$  the natural dual pairing on  $C_b(\mathcal{P}_p(\mathcal{C})) \times \mathcal{P}(\mathcal{P}_p(\mathcal{C}))$ , the function  $\langle W_p(\cdot, V_p), \cdot \rangle$  is a continuous on  $\mathcal{P}(\mathcal{P}_p(\mathcal{C}))$ . Thus, the sequence of real r.v.  $\langle W_p(\cdot, V_p), M_{t_n}^n \rangle$  converges in distribution to  $\langle W_p(\cdot, V_p), \cdot \rangle_{\#}\Upsilon$ . These variables being bounded, we obtain by taking the limits in expectation:

$$\begin{aligned} \int \int W_p(m, V_p) dM(m) d\Upsilon(M) &= \lim_{n \rightarrow \infty} \mathbb{E}(\langle W_p(\cdot, V_p), M_{t_n}^n \rangle) \\ &= \lim_{n \rightarrow \infty} \frac{1}{t_n} \int_0^{t_n} \mathbb{E}(W_p(\Phi_s(m^n), V_p)) ds \\ &\leq \limsup_{(n,t) \rightarrow (\infty, \infty)} \mathbb{E}(W_p(\Phi_t(m^n), V_p)) = 0, \end{aligned}$$

where the last equality is due to Prop. 5. As  $V_p$  is closed by Prop. 2, this concludes the proof.  $\square$

For every  $t \geq 0$ , define  $(\Theta_t)_{\#\#} = ((\Theta_t)_{\#})_{\#}$ . Define:

$$\mathcal{I} := \{M \in \mathcal{P}(\mathcal{P}_p(\mathcal{C})) : \forall t > 0, M = (\Theta_t)_{\#\#}M\}.$$

In other words, for every  $M \in \mathcal{I}$  and for every  $t > 0$ ,  $(\Theta_t)_{\#}$  preserves  $M$ .

**Lemma 10.** *For every  $\Upsilon \in \mathcal{M}$ ,  $\Upsilon(\mathcal{I}) = 1$ .*

*Proof.* Similarly to the proof of Lemma 9, assume without restriction that  $\Upsilon = \lim_{n \rightarrow \infty} (M_{t_n}^n)_{\#}\mathbb{P}$  in the weak $\star$  sense. Set  $t > 0$ . The map  $M \mapsto d_L(M, (\Theta_t)_{\#\#}M)$  is continuous on  $\mathcal{P}(\mathcal{P}_p(\mathcal{C}))$ , where we recall that  $d_L$  stands for the Lévy-Prokhorov distance. Thus, by Fatou's lemma,

$$\int d_L(M, (\Theta_t)_{\#\#}M) d\Upsilon(M) \leq \limsup_{n \rightarrow \infty} \mathbb{E}(d_L(M_{t_n}^n, (\Theta_t)_{\#\#}M_{t_n}^n)). \quad (37)$$

Note that:

$$(\Theta_t)_{\#\#}M_{t_n}^n = \frac{1}{t_n} \int_t^{t+t_n} \delta_{(\Theta_s)_{\#}m^n} ds.$$

In particular, for every Borel set  $A \subset \mathcal{P}_p(\mathcal{C})$ ,  $|(\Theta_t)_{\#\#}M_{t_n}^n(A) - M_{t_n}^n(A)| \leq 2t/t_n$ . The Lévy-Prokhorov distance being bounded by the total variation distance,  $d_L(M_{t_n}^n, (\Theta_t)_{\#\#}M_{t_n}^n) \leq 2t/t_n$  which tends to zero. The l.h.s. of Eq. (37) is zero, which proves the statement for a fixed value of  $t$ . The proof of the statement for all  $t$ , is easily concluded by a using dense denumerable subset argument.  $\square$

Define:  $\mathcal{B}_p = \{M \in \mathcal{P}(\mathcal{P}_p(\mathcal{C})) : M(\text{BC}_p) = 1\}$ .

**Proposition 12.** *For every  $\Upsilon \in \mathcal{M}$ ,  $\Upsilon(\mathcal{B}_p) = 1$ .*

*Proof.* Consider an arbitrary sequence of the form  $((M_{t_n}^n)_{\#}\mathbb{P})$  where  $t_n \rightarrow \infty$ , converging in distribution to some measure  $\Upsilon \in \mathcal{M}$  as  $n \rightarrow \infty$ . By Lemma 10, the map  $(\Theta_t)_{\#} : \mathcal{P}_p(\mathcal{C}) \rightarrow \mathcal{P}_p(\mathcal{C})$  preserves the measure  $M$ , for all  $M$   $\Upsilon$ -a.e., and for all  $t$ . By Lemma 9,  $M(V_p) = 1$ . Thus, the restriction of the map  $(\Theta_t)_{\#}$  to  $V_p$ , still denoted by  $(\Theta_t)_{\#} : V_p \rightarrow V_p$  preserves the measure  $M$  as well, for all  $M$   $\Upsilon$ -a.e.. By the Poincaré recurrence theorem, stated in Theorem 2.3 of [Mañ87], it follows that  $M(\text{BC}_p) = 1$  for all  $M$   $\Upsilon$ -a.e.  $\square$

*Proof of Theorem 1.* To conclude, assume by contradiction that the conclusion of Theorem 1 does not hold. Then, there exists  $\varepsilon > 0$  and a sequence, which, without restriction, we may assume to have the form  $((M_{t_n}^n)_{\#}\mathbb{P})$ , such that for all  $n$  large enough,

$$\mathbb{E}(\langle W_p(\cdot, \text{BC}_p), M_{t_n}^n \rangle) > \varepsilon, \quad (38)$$

where  $\langle \cdot, \cdot \rangle$  is the natural dual pairing on  $C_b(\mathcal{P}_p(\mathcal{C})) \times \mathcal{P}(\mathcal{P}_p(\mathcal{C}))$ . By Lemma 8, one can extract an other subsequence, which we still denote by  $((M_{t_n}^n)_{\#}\mathbb{P})$ , converging to  $\Upsilon \in \mathcal{M}$ . As a consequence,

$$\lim_{n \rightarrow \infty} \mathbb{E}(\langle W_p(\cdot, \text{BC}_p), M_{t_n}^n \rangle) = \int \int W_p(m, \text{BC}_p) dM(m) d\Upsilon(M) = 0,$$

where we used the fact that, due to Prop. 12,  $\int W_p(m, \text{BC}_p) dM(m) = 0$  for  $\Upsilon$ -almost all  $M$ . This contradicts Eq. (38).  $\square$



## 5.4 Proof of Corollary 1

Throughout this paragraph, we assume that  $1 \leq p \leq 2$ . Consider the r.v.

$$Y_n(s) := W_p \left( \frac{1}{n} \sum_{i=1}^n \delta_{\bar{X}_s^{i,n}}, (\pi_0)_\# \text{BC}_p \right).$$

**Lemma 11.** *The r.v.  $(Y_n(s))^p : s > 0, n \in \mathbb{N}$  are uniformly integrable.*

*Proof.* Note that  $Y_n(s)^p \leq C(1 + \frac{1}{n} \sum_i \|\bar{X}_s^{i,n}\|^p)$ . Hence, for each  $a > 0$ ,  $Y_n(s)^p \mathbf{1}_{Y_n(s) > a} \leq \frac{1}{n} \sum_{i \in \mathbb{N}} C(1 + \|\bar{X}_s^{i,n}\|^p) \mathbf{1}_{C(1 + \|\bar{X}_s^{i,n}\|^p) > a}$ . By the exchangeability stated in Assumption 3, the random variables  $(Y_n(s) : s > 0, n \in \mathbb{N})$  are uniformly integrable if the random variables  $(\|\bar{X}_s^{1,n}\|^p : s > 0, n \in \mathbb{N})$  are uniformly integrable. We conclude using Assumption 4-(i) if  $p < 2$ , or Assumption 4-(ii) if  $p = 2$ .  $\square$

Recall the definition of  $M_t^n$  in Eq. (36), and recall that  $\mathcal{M}$  is the set of cluster points of  $((M_t^n)_\# \mathbb{P} : t \geq 0, n \in \mathbb{N}^*)$  as  $(n, t) \rightarrow (\infty, \infty)$ . Consider an arbitrary sequence  $t_n \rightarrow \infty$ , such that  $(M_{t_n}^n)_\# \mathbb{P}$  converges to some measure  $\Upsilon \in \mathcal{M}$ . Consider  $\varepsilon > 0$ . By Lemma 11; there exists  $a > 0$  such that  $\sup_{n,s} \mathbb{E}(Y_n(s) \mathbf{1}_{Y_n(s) > a}) < \varepsilon$ . Using the inequality  $y \leq a \wedge y + y \mathbf{1}_{y > a}$ , we obtain:

$$\begin{aligned} \mathbb{E} \left( \frac{1}{t_n} \int_0^{t_n} Y_n(s) ds \right) &\leq \mathbb{E} \left( \frac{1}{t_n} \int_0^{t_n} a \wedge Y_n(s) ds \right) + \varepsilon \\ &= \mathbb{E} \left( \int a \wedge W_p((\pi_0)_\# m, (\pi_0)_\# \text{BC}_p) dM_{t_n}^n(m) \right) + \varepsilon \end{aligned} \quad (39)$$

The restriction of  $\pi_0$  to  $\mathcal{P}_p(\mathcal{C})$ , which we still denote by  $\pi_0$ , is continuous on  $(\mathcal{P}_p(\mathcal{C}), W_p) \rightarrow (\mathcal{P}_p(\mathbb{R}^d), W_p)$ , where  $W_p$  represents the  $p$ -th order Wasserstein distance on  $\mathcal{P}(\mathbb{R}^d)$ . As a consequence, the pushforward map  $(\pi_0)_\# : \mathcal{P}(\mathcal{P}_p(\mathcal{C})) \rightarrow \mathcal{P}(\mathcal{P}_p(\mathbb{R}^d))$  is continuous. Therefore, as  $(\pi_0)_\# \text{BC}_p$  is non empty by Prop. 3, the function  $M \mapsto \int a \wedge W_p((\pi_0)_\# m, (\pi_0)_\# \text{BC}_p) dM(m)$  is bounded and continuous on  $\mathcal{P}(\mathcal{P}_p(\mathcal{C}))$ . Recall that  $M_{t_n}^n$  converges in distribution to  $\Upsilon$ , and noting that, by Prop. 3,

$$\int \int W_p((\pi_0)_\# m, (\pi_0)_\# \text{BC}_p) dM(m) d\Upsilon(M) = 0.$$

Therefore, by letting  $n \rightarrow \infty$  in Eq. (39), we obtain  $\limsup_n \mathbb{E}(\frac{1}{t_n} \int_0^{t_n} Y_n(s) ds) \leq \varepsilon$ . As  $\varepsilon$  is arbitrary,

$$\lim_{n \rightarrow \infty} \mathbb{E} \left( \frac{1}{t_n} \int_0^{t_n} Y_n(s) ds \right) = 0. \quad (40)$$

In order to establish the statement of Corollary 1, we now should consider replacing the integral in Eq. (40) by a sum. This last part is only technical. Recall the definition of  $k_t := \inf\{k : \sum_{i=1}^k \gamma_i \geq t\}$ , and  $\tau_k$  in Eq. (4). Let  $(\alpha_n)$  be a sequence of integers tending to infinity. By the triangular inequality,

$$\begin{aligned} \mathbb{E} \left( \frac{\sum_{l=1}^{\alpha_n} \gamma_l W_p(\mu_l^n, (\pi_0)_\# \text{BC}_p)}{\sum_{l=1}^{\alpha_n} \gamma_l} \right) &= \mathbb{E} \left( \frac{1}{\tau_{\alpha_n}} \int_0^{\tau_{\alpha_n}} W_p(\mu_{k_s}^n, (\pi_0)_\# \text{BC}_p) ds \right) \\ &\leq \mathbb{E} \left( \frac{1}{\tau_{\alpha_n}} \int_0^{\tau_{\alpha_n}} W_p(\mu_{k_s}^n, \frac{1}{n} \sum_{i \in [n]} \delta_{\bar{X}_s^{i,n}}) ds \right) \\ &\quad + \mathbb{E} \left( \frac{1}{\tau_{\alpha_n}} \int_0^{\tau_{\alpha_n}} Y_n(s) ds \right). \end{aligned}$$

The second term in the righthand side of the above inequality tends to zero by Eq. (40) with  $t_n = \tau_{\alpha_n}$ . We should therefore establish that the first term vanishes. For an arbitrary integer  $l$  and  $s \in [\tau_l, \tau_{l+1}]$ ,

$$\mathbb{E} \left[ W_p \left( \mu_l^n, \frac{1}{n} \sum_{i \in [n]} \delta_{\bar{X}_s^{i,n}} \right) \right] \leq \mathbb{E} \left( \left( \frac{1}{n} \sum_{i \in [n]} \|X_l^{i,n} - \bar{X}_s^{i,n}\|^p \right)^{1/p} \right) \leq (\mathbb{E}(\|X_l^{1,n} - \bar{X}_s^{1,n}\|^p))^{1/p}.$$

where the last inequality uses Jensen's inequality and the exchangeability assumption. Continuing the estimation,

$$\begin{aligned}
\mathbb{E}(\|X_l^{1,n} - \bar{X}_s^{1,n}\|^p) &\leq \mathbb{E}(\|X_{l+1}^{1,n} - X_l^{1,n}\|^p) \\
&\leq \mathbb{E} \left[ 3^{p-1} \gamma_{l+1}^p \frac{1}{n} \sum_{j \in [n]} \|b(X_l^{1,n}, X_l^{j,n})\|^p \right] + \mathbb{E} \left[ 3^{p-1} \gamma_{l+1}^{p/2} \|\xi_{l+1}^{1,n}\|^p \right] \\
&\quad + \mathbb{E} \left[ 3^{p-1} \gamma_{l+1}^p \|\zeta_{l+1}^{1,n}\|^p \right]. \\
&\leq C(\gamma_{l+1}^{p/2} + \gamma_{l+1}^p),
\end{aligned}$$

where we used Assumptions 1, and 3. Consequently,

$$\mathbb{E} \left( \frac{1}{\tau_{\alpha_n}} \int_0^{\tau_{\alpha_n}} W_p(\mu_{k_s}^n, \frac{1}{n} \sum_{i \in [n]} \delta_{\bar{X}_s^{i,n}}) ds \right) \leq \frac{\sum_{i=1}^{\alpha_n} \gamma_l (C(\gamma_{l+1}^{p/2} + \gamma_{l+1}^p))^{1/p}}{\sum_{i=1}^{\alpha_n} \gamma_l}.$$

As Assumption 2 holds,  $C(\gamma_{l+1}^{p/2} + \gamma_{l+1}^p) \rightarrow_{l \rightarrow \infty} 0$ , and  $\sum_{l \geq 1} \gamma_l = \infty$ . Therefore, by Stolz-Cesàro theorem, the r.h.s. of the above inequality converges to 0 when  $n \rightarrow \infty$ . Hence,

$$\lim_{n \rightarrow 0} \mathbb{E} \left( \frac{\sum_{l=1}^{\alpha_n} \gamma_l W_p(\mu_l^n, (\pi_0)_{\#} \text{BC}_p)}{\sum_{l=1}^{\alpha_n} \gamma_l} \right) = 0,$$

for an arbitrary sequence  $(\alpha_n)$  diverging to  $\infty$ . By Markov's inequality, Corollary 1 is proven.

## 6 Proofs of Section 4.1

The Assumptions 5 and  $\sigma > 0$  are standing in this section.

### 6.1 Proof of Prop. 6

**Lemma 12.** *Let  $\rho \in \mathcal{V}_2$ . For every  $t > 0$ ,  $\rho_t$  admits a density  $x \mapsto \varrho(t, x) \in C^1(\mathbb{R}^d, \mathbb{R})$ . For every  $R > 0, t_2 > t_1 > 0$ , there exists a constant  $C_{R, t_1, t_2} > 0$  such that:*

$$\inf_{t \in [t_1, t_2], \|x\| \leq R} \varrho(t, x) \geq C_{R, t_1, t_2}, \tag{41}$$

and there exist a constant  $C_{t_1, t_2} > 0$ , such that

$$\sup_{x \in \mathbb{R}^d, t \in [t_1, t_2]} \|\nabla \varrho(t, x)\| + \varrho(t, x) \leq C_{t_1, t_2}. \tag{42}$$

Finally,

$$\sup_{t \in [t_1, t_2]} \int (1 + \|x\|^2) \|\nabla \varrho(t, x)\| dx < \infty. \tag{43}$$

*Proof.* The result is an application of Th.1.2 in [MPZ21] with the non homogeneous vector field  $\tilde{b}(t, x) := \int b(x, y) d\rho_t(y)$ . The proof consists in verifying the conditions of the latter theorem. By Assumption 5, for every  $(x, y, T) \in (\mathbb{R}^d)^2 \times \mathbb{R}_+$ ,

$$\begin{aligned}
\sup_{t \in [0, T]} \|\tilde{b}(t, x) - \tilde{b}(t, y)\| &\leq \|\nabla V(x) - \nabla V(y)\| + \sup_{t \in [0, T]} \int \|\nabla U(x - z) - \nabla U(y - z)\| d\rho_t(x) \\
&\leq C(\|x - y\|^\beta \vee \|x - y\|),
\end{aligned}$$

Moreover,

$$\sup_{t \in [0, T]} \tilde{b}(t, x) \leq C(1 + \|x\|) + \int \sup_{t \in [0, T]} \|y_t\| d\rho(y) \leq C(1 + \|x\|). \tag{44}$$

As  $\sigma > 0$ , [MPZ21, Th. 1.2] applies:  $\rho$  admits a density  $x \mapsto \varrho(t, x) \in C^1(\mathbb{R}^d)$ , for  $0 < t \leq T$ , and there exists four constants  $(C_{i,T}, \lambda_{i,T})_{i \in [2]}$ , such that:

$$\begin{aligned} \frac{1}{C_{1,T} t^{d/2}} \int \exp\left(-\frac{\|x - \theta_t(y)\|^2}{\lambda_{1,T} t}\right) d\rho_0(y) &\leq \varrho(t, x) \leq \frac{C_{1,T}}{t^{d/2}} \int \exp\left(-\frac{\lambda_{1,T}}{t} \|x - \theta_t(y)\|^2\right) d\rho_0(y) \\ \|\nabla \varrho(t, x)\| &\leq \frac{C_{2,T}}{t^{(d+1)/2}} \int \exp\left(-\frac{\lambda_{2,T}}{t} \|x - \theta_t(y)\|^2\right) d\rho_0(y), \end{aligned}$$

where the map  $t \mapsto \theta_t(y)$  is a solution to the ordinary differential equation:  $\frac{d\theta_t(y)}{dt} = \tilde{b}(t, \theta_t(y))$  with initial condition  $\theta_0(y) = y$ . By Grönwall's lemma and Eq. (44), there exists a constant  $C_T$  such that  $\|\theta_t(y)\| \leq C_T \|y\|$ , for every  $n, y$ , and  $t \leq T$ . For every  $t_1 \leq t \leq t_2$ , and every  $x$ , we obtain using a change of variables:

$$\begin{aligned} (C_{1,t_2} t_1^{d/2})^{-1} \geq \varrho(t, x) &\geq C_{1,t_2} t_2^{-d/2} \exp\left(-\frac{2}{\lambda_{1,t_2} t_1} \|x\|^2\right) \int \exp\left(-\frac{2C_{t_2}}{\lambda_{1,t_2} t_1} \|y\|^2\right) d\rho_0(y) \\ \int (1 + \|x\|^2) \|\nabla \varrho(t, x)\| dx &\leq C_{2,t_2} t_1^{-(d+1)/2} \int (1 + 2\|x\|^2 + 2C_{t_2}^2 \int \|y\|^2 d\rho_0(y)) e^{-\lambda_{2,t_2} t_2^{-1} \|x\|^2} dx, \end{aligned}$$

and  $\|\nabla \varrho(t, x)\| \leq C_{2,t_2} t_1^{-(d+1)/2}$ . Consequently,  $\rho$  satisfies Eq. (41), Eq. (42) and Eq. (43).  $\square$

For every  $\rho \in \mathcal{V}_2$  and every  $t > 0$ , recall the definition of the velocity field  $v_t$  in Eq. (16):  $v_t(x) := -\nabla V(x) - \int \nabla U(x, y) d\rho_t(y) - \sigma^2 \nabla \log \varrho(t, x)$ , where  $\varrho(t, x)$  is the density of  $\rho_t$  defined in Lem. 12.

**Lemma 13.** *For every  $\rho \in \mathcal{V}_2$ , and every  $t_2 > t_1 > 0$ ,*

$$\int_{t_1}^{t_2} \int \|v_t(x)\| d\rho_t(x) dt < \infty. \quad (45)$$

Moreover, for every  $\psi \in C_c^\infty(\mathbb{R}_+ \times \mathbb{R}^d, \mathbb{R})$ ,

$$\int \psi(t_2, x) d\rho_{t_2}(x) - \int \psi(t_1, x) d\rho_{t_1}(x) = \int_{t_1}^{t_2} \int (\partial_t \psi(t, x) + \langle \nabla_x \psi(t, x), v_t(x) \rangle) \rho_t(dx) dt. \quad (46)$$

*Proof.* The first point is a consequence of Lemma 12. Consider  $\phi \in C_c^\infty(\mathbb{R}^d, \mathbb{R})$  and  $\eta \in C_c^\infty(\mathbb{R}_+, \mathbb{R})$ . Using Eq. (10) and (11) with  $h_1 = \dots = h_r = 1$ , we obtain that for each  $\psi \in C_c^\infty(\mathbb{R}_+ \times \mathbb{R}^d, \mathbb{R})$  of the form  $\psi(t, x) = g(t)\phi(x)$ ,

$$\begin{aligned} \int \psi(t_2, x) d\rho_{t_2}(x) - \int \psi(t_1, x) d\rho_{t_1}(x) &= \\ &= \int_{t_1}^{t_2} \int (\partial_t \psi(t, x) + \langle \nabla \psi(s, x), b(x, \rho_t) \rangle + \sigma^2 \Delta \psi(t, x)) \rho_t(dx) dt. \end{aligned} \quad (47)$$

As the functions of the form  $(t, x) \mapsto g(t)\phi(x)$  are dense in  $C_c^\infty(\mathbb{R}_+ \times \mathbb{R}^d, \mathbb{R})$ , Eq (47) holds in fact for any smooth compactly supported  $\psi$ . Using Lemma 12 and an integration by parts of the Laplacian term, Eq. (46) follows.  $\square$

The goal now is to establish that the functional  $H$  given by Eq. (14) is a Lyapunov function. This claim will follow from the application of Eq. (46) to the functional  $(t, x) \mapsto \sigma^2 \log(\varrho(t, x)) + V(x) + \int U(x - y)\varrho(t, y)dy$ . However, this function is not necessarily smooth nor compactly supported. In order to be able to apply Lem. 13, mollification should be used. In the sequel, consider two fixed positive numbers  $t_2 > t_1$ .

Consider a smooth, compactly supported, even function  $\eta : \mathbb{R}^d \rightarrow \mathbb{R}_+$  such that  $\int \eta(x) dx = 1$ , and define  $\eta_\varepsilon(x) := \varepsilon^{-d} \eta(x/\varepsilon)$  for every  $\varepsilon > 0$ . For every  $t > 0$ , we introduce the density  $\varrho_\varepsilon(t, \cdot) := \eta_\varepsilon * \rho_\varepsilon(t, \cdot)$ , and we denote by  $\rho_t^\varepsilon(dx) = \varrho_\varepsilon(t, x) dx$  the corresponding probability measure. Finally, we define:

$$v_t^\varepsilon := \frac{\eta_\varepsilon * (v_t \varrho(t, \cdot))}{\varrho_\varepsilon(t, \cdot)}.$$

With these definitions at hand, it is straightforward to check that the statements of Lem. 13 hold when  $\rho_t, v_t$  are replaced by  $\rho_t^\varepsilon, v_t^\varepsilon$ . More specifically, we shall apply Eq. (46) using a specific smooth function  $\psi = \psi_{\varepsilon, \delta, R}$ , which we will define hereafter for fixed values of  $\delta, R > 0$ , yielding our main equation:

$$\int \psi_{\varepsilon, \delta, R}(t_2, x) \varrho_\varepsilon(t_2, x) dx - \int \psi_{\varepsilon, \delta, R}(t_1, x) \varrho_\varepsilon(t_1, x) dx = \int_{t_1}^{t_2} \int (\partial_t \psi_{\varepsilon, \delta, R}(t, x) + \langle \nabla \psi_{\varepsilon, \delta, R}(t, x), v_t^\varepsilon(x) \rangle) \varrho_\varepsilon(t, x) dx dt. \quad (48)$$

We now provide the definition of the function  $\psi_{\varepsilon, \delta, R} \in C_c^\infty(\mathbb{R}_+ \times \mathbb{R}^d, \mathbb{R})$  used in the above equality. Let  $\theta \in C_c^\infty(\mathbb{R}, \mathbb{R})$  be a nonnegative function supported by the interval  $[-t_1, t_1]$  and satisfying  $\int \theta(t) dt = 1$ . For every  $\delta \in (0, 1)$ , define  $\theta_\delta(t) = \theta(t/\delta)/\delta$ . We define  $\varrho^{\varepsilon, \delta}(\cdot, x) := \theta_\delta * \varrho^\varepsilon(\cdot, x)$ . The map  $t \mapsto \varrho^{\varepsilon, \delta}(t, \cdot)$  is well defined on  $[t_1, t_2]$ , non negative, and smooth in both variables  $t, x$ . In addition, we define  $V_\varepsilon := \eta_\varepsilon * V, U_\varepsilon := \eta_\varepsilon * U$ . Finally, we introduce a smooth function  $\chi$  on  $\mathbb{R}^d$  equal to one on the unit ball and to zero outside the ball of radius 2, and we define  $\chi_R(x) := \chi(x/R)$ . For every  $(t, x) \in [t_1, t_2] \times \mathbb{R}$ , we define:

$$\psi_{\varepsilon, \delta, R}(t, x) := (\sigma^2 \log \varrho^{\varepsilon, \delta}(t, x) + V_\varepsilon(x) + \int U_\varepsilon(x - y) \chi_R(y) \varrho^{\varepsilon, \delta}(t, y) dy) \chi_R(x). \quad (49)$$

We extend  $\psi_{\varepsilon, \delta, R}$  to a smooth compactly supported function on  $\mathbb{R}_+ \times \mathbb{R}^d$ , and we apply Eq. (48) to the latter. We now investigate the limit of both sides of the equality (48) as  $\delta, \varepsilon, R$  successively tend to 0, 0,  $\infty$ . First consider the lefthand side. Note that for all  $t \in [t_1, t_2]$ ,

$$\lim_{\varepsilon \rightarrow 0} \lim_{\delta \rightarrow 0} \psi_{\varepsilon, \delta, R}(t, x) \varrho_\varepsilon(t, x) := \left( \sigma^2 \log \varrho(t, x) + V(x) + \int U(x - y) \chi_R(y) \varrho(t, y) dy \right) \varrho(t, x) \chi_R(x).$$

The domination argument that allows to interchange limits and integrals is provided by Lem 12. Indeed, for a fixed  $R > 0$ , there exists a constant  $C_R$  such that  $\varrho^{\varepsilon, \delta}(t, x) \leq C_R$  and  $\psi_{\varepsilon, \delta, R}(t, x) \leq C_R$  for all  $\|x\| \leq R$  and all  $t \in [t_1, t_2]$ . As a consequence,

$$\lim_{\varepsilon \rightarrow 0} \lim_{\delta \rightarrow 0} \int \psi_{\varepsilon, \delta, R}(t, x) \varrho_\varepsilon(t, x) dx = \sigma^2 \int \chi_R(x) \varrho(t, x) \log \varrho(t, x) dx + \int V(x) \chi_R(x) d\rho_t(x) + \int U(x - y) \chi_R(y) \chi_R(x) \varrho(t, x) \varrho(t, y) dx dy.$$

By Eq. (42), the first term in the l.h.d. of the above equation converges to  $\sigma^2 \int \varrho(t, x) \log \varrho(t, x) dx$  as  $R \rightarrow \infty$ . Similarly,  $\int V(x) \chi_R(x) d\rho_t(x)$  tends to  $\int V d\rho_t$  as  $R \rightarrow \infty$ , by use of the linear growth condition on  $\nabla V$  in Assumption 5, along with the fact that  $\rho_t$  admits a second order moment. The same holds for the last term. Finally, we have shown that, for every  $t \in [t_1, t_2]$ ,

$$\lim_{R \rightarrow \infty} \lim_{\varepsilon \rightarrow 0} \lim_{\delta \rightarrow 0} \int \psi_{\varepsilon, \delta, R}(t, x) \varrho_\varepsilon(t, x) dx = H(\rho_t) + \frac{1}{2} \iint U(x - y) d\rho_t(y) d\rho_t(x),$$

where we recall the definition (14) as  $H(\rho_t) := \sigma^2 \int \log \varrho(t, \cdot) d\rho_t + \int V d\rho_t + \frac{1}{2} \iint U(x - y) d\rho_t(y) d\rho_t(x)$ . As  $\delta, \varepsilon, R$  successively tend to 0, 0,  $\infty$ , we have shown that the l.h.s. of Eq (48) converges to:

$$H(\rho_{t_2}) - H(\rho_{t_1}) + \frac{1}{2} \iint U(x - y) d\rho_{t_2}(y) d\rho_{t_2}(x) - \frac{1}{2} \iint U(x - y) d\rho_{t_1}(y) d\rho_{t_1}(x). \quad (50)$$

We should now identify the above term with the limit of the r.h.s. of Eq. (48) in the same regime. The latter is composed of two terms. First consider the second term:

$$\int_{t_1}^{t_2} \int \langle \nabla \psi_{\varepsilon, \delta, R}(t, x), v_t^\varepsilon(x) \rangle \rho_t^\varepsilon(dx) dt = \int_{t_1}^{t_2} \int \langle \nabla \psi_{\varepsilon, \delta, R}(t, x), \eta_\varepsilon * (v_t(x) \varrho(t, x)) \rangle dx dt.$$

We can let  $\delta \rightarrow 0$  in this equation and interchange the limit and the integral. This is justified by Lem. 12, which implies that for every  $R > 0$ , there exists a constant  $C_R$  such that for every  $\varepsilon > 0, \delta \in (0, 1), t \in [t_1, t_2], x \in \mathbb{R}^d$ ,

$$\|\nabla \psi_{\varepsilon, \delta, R}(t, x)\| \leq C_R. \quad (51)$$

Using Eq. (51) along with Eq. (45), the dominated convergence applies. Letting  $\varepsilon \rightarrow 0$  in a second step, the exact same argument applies, and we obtain:

$$\begin{aligned} & \lim_{\varepsilon \rightarrow 0} \lim_{\delta \rightarrow 0} \int_{t_1}^{t_2} \int \langle \nabla \psi_{\varepsilon, \delta, R}(t, x), v_t^\varepsilon(x) \rangle \varrho_\varepsilon(t, x) dx dt \\ &= \int_{t_1}^{t_2} \int \lim_{\varepsilon \rightarrow 0} \lim_{\delta \rightarrow 0} \langle \nabla \psi_{\varepsilon, \delta, R}(t, x), \eta_\varepsilon * (v_t(x) \varrho(t, x)) \rangle dx dt \\ &= \int_{t_1}^{t_2} \int \langle \nabla (\lim_{\varepsilon \rightarrow 0} \lim_{\delta \rightarrow 0} \psi_{\varepsilon, \delta, R}(t, x)), v_t(x) \rangle \varrho(t, x) dx dt, \end{aligned}$$

where the interchange between  $\nabla$  and the limits is again a consequence of Lem. 12. We now write the gradient in the above inner product. Note that:

$$\lim_{\varepsilon \rightarrow 0} \lim_{\delta \rightarrow 0} \psi_{\varepsilon, \delta, R}(t, x) = (\sigma^2 \log \varrho(t, x) + V(x) + \int U(x-y) \chi_R(y) \varrho(t, y) dy) \chi_R(x).$$

We obtain:

$$\begin{aligned} & \lim_{\varepsilon \rightarrow 0} \lim_{\delta \rightarrow 0} \int_{t_1}^{t_2} \int \langle \nabla \psi_{\varepsilon, \delta, R}(t, x), v_t^\varepsilon(x) \rangle \varrho_\varepsilon(t, x) dx dt = - \int_{t_1}^{t_2} \int \|v_t(x)\|^2 \chi_R(x) \varrho(t, x) dx dt \\ & \quad - \int_{t_1}^{t_2} \int \langle v_t(x), \int (1 - \chi_R(y)) \nabla U(x-y) d\rho_t(y) \rangle \chi_R(x) d\rho_t(x) \\ & \quad - \int_{t_1}^{t_2} \int \langle v_t(x), \nabla \chi_R(x) (V(x) + \int U(x-y) \chi_R(y) d\rho_t(y)) \rangle d\rho_t(x). \quad (52) \end{aligned}$$

By the dominated convergence theorem, Assumption 5 and Eq. (43), the last two terms in the r.h.s. of Eq.(52) tend to zero as  $R \rightarrow \infty$ , while the first term is handled by the monotone convergence theorem. We thus obtain:

$$\lim_{R \rightarrow \infty} \lim_{\varepsilon \rightarrow 0} \lim_{\delta \rightarrow 0} \int_{t_1}^{t_2} \int \langle \nabla \psi_{\varepsilon, \delta, R}(t, x), v_t^\varepsilon(x) \rangle \varrho_\varepsilon(t, x) dx dt = - \int_{t_1}^{t_2} \int \|v_t(x)\|^2 \varrho(t, x) dx dt. \quad (53)$$

As a last step, we should evaluate the limit of the first term in the r.h.s. of Eq. (48), which writes:  $\int_{t_1}^{t_2} \int \partial_t \psi_{\varepsilon, \delta, R}(t, x) \varrho_\varepsilon(t, x) dx dt$ . Here the domination argument allowing to interchange limits and integrals requires more attention, and is justified by the following lemma, whose proof is provided at the end of the section.

**Lemma 14.** *Let  $t_2 > t_1 > 0$  be fixed. For every  $R, \varepsilon > 0$ , there exists a constant  $C_{R, \varepsilon}$  such that for every  $\delta \in (0, 1)$ ,  $t \in [t_1, t_2]$ ,  $x \in \mathbb{R}^d$ ,*

$$|\partial_t \psi_{\varepsilon, \delta, R}(t, x)| \leq C_{R, \varepsilon}, \quad (54)$$

for every  $t \leq T$ ,  $\delta > 0$ , and every  $x \in \mathbb{R}^d$ .

By Eq. (54) and by the continuity of the map  $t \mapsto \partial_t \varrho^\varepsilon$  (see the proof of Lemma 14), we can expand the first term in the r.h.s. of Eq. (48) as:

$$\int_{t_1}^{t_2} \int \partial_t \psi_{\varepsilon, \delta, R}(t, x) d\rho_t^\varepsilon(x) dt = \int_{t_1}^{t_2} \int \partial_t \psi_{\varepsilon, \delta, R}(t, x) \varrho^{\varepsilon, \delta}(t, x) dx dt + o_{\varepsilon, R}(\delta), \quad (55)$$

where  $o_{\varepsilon, R}(\delta)$  represents a term which tends to zero as  $\delta \rightarrow 0$ , for fixed values of  $\varepsilon, R$ . Note that:

$$\partial_t \psi_{\varepsilon, \delta, R}(t, x) = \sigma^2 \frac{\partial_t \varrho^{\varepsilon, \delta}(t, x)}{\varrho^{\varepsilon, \delta}(t, x)} \chi_R(x) + \int U_\varepsilon(x-y) \chi_R(y) \chi_R(x) \partial_t \varrho^{\varepsilon, \delta}(t, y) dy. \quad (56)$$

Plugging this equality into (55) and noting that  $U_\varepsilon$  is even (because  $U$  and  $\eta_\varepsilon$  are), we obtain:

$$\begin{aligned}
& \int_{t_1}^{t_2} \int \partial_t \psi_{\varepsilon, \delta, R}(t, x) \varrho^{\varepsilon, \delta}(t, x) dx dt \\
&= \sigma^2 \int_{t_1}^{t_2} \int \partial_t \varrho^\varepsilon(t, x) \chi_R(x) dx dt + \frac{1}{2} \int_{t_1}^{t_2} \int \int U_\varepsilon(x - y) \partial_t (\varrho^{\varepsilon, \delta}(t, y) \varrho^{\varepsilon, \delta}(t, x)) \chi_R(x) \chi_R(y) dx dy dt \\
&= \sigma^2 \int \varrho^{\varepsilon, \delta}(t_2, x) \chi_R(x) dx - \sigma^2 \int \varrho^{\varepsilon, \delta}(t_1, x) \chi_R(x) dx \\
&+ \frac{1}{2} \int \int U_\varepsilon(x - y) \chi_R(x) \chi_R(y) \varrho^{\varepsilon, \delta}(t_2, x) \varrho^{\varepsilon, \delta}(t_2, y) dx dy \\
&- \frac{1}{2} \int \int U_\varepsilon(x - y) \chi_R(x) \chi_R(y) \varrho^{\varepsilon, \delta}(t_1, x) \varrho^{\varepsilon, \delta}(t_1, y) dx dy.
\end{aligned}$$

By the dominated convergence theorem, we finally obtain:

$$\begin{aligned}
\lim_{R \rightarrow \infty} \lim_{\varepsilon \rightarrow 0} \lim_{\delta \rightarrow 0} \int_{t_1}^{t_2} \int \partial_t \psi_{\varepsilon, \delta, R}(t, x) d\rho_t^\varepsilon(x) dt = \\
\frac{1}{2} \int \int U(x - y) \varrho(t_2, x) \varrho(t_2, y) dx dy - \frac{1}{2} \int \int U(x - y) \varrho(t_1, x) \varrho(t_1, y) dx dy. \quad (57)
\end{aligned}$$

Putting together Eq. (50), (53) and (57), and passing to the limit in the continuity equation (48), the statement of Prop. 6 follows.

**Proof of Lem. 14.** Using Eq. (48) and integration by parts,

$$\varrho^\varepsilon(t_2, x) - \varrho^\varepsilon(t_1, x) = \int_{t_1}^{t_2} \int \langle \nabla \eta_\varepsilon(x - y), b(y, \rho_s) \rangle d\rho_s(y) ds + \sigma^2 \int_{t_1}^{t_2} \int \Delta \eta_\varepsilon(x - y) d\rho_s(y) ds.$$

Since  $\rho \in \mathcal{P}_2(\mathcal{C})$ ,  $\sup_{t \in [1, T]} \|b(y, \rho_t)\| \leq C(1 + \|y\|) + C \int \sup_{t \in [1, T]} \|x_t\| d\rho(x)$ . As a consequence,  $\sup_{t \in [1, T]} \|b(y, \rho_t)\| \leq C(1 + \|y\|)$ . Along with the observation that, for any fixed  $\varepsilon$ ,  $\nabla \eta_\varepsilon$  and  $\Delta \eta_\varepsilon$  are bounded, it follows that  $t \mapsto \varrho^\varepsilon(t, x)$  is Lipschitz continuous on  $[t_1, t_2]$ , and that its derivative almost everywhere is given by:  $\partial_t \varrho^\varepsilon(t, x) = \int (\langle \nabla \eta_\varepsilon(x - y), b(y, \rho_t) \rangle + \Delta \eta_\varepsilon(x - y)) d\rho_t(y)$ . Thus, there exists a constant  $C_\varepsilon > 0$ , such that:

$$\sup_{t \in [t_1, t_2], x \in \mathbb{R}^d} \partial_t \varrho^\varepsilon(t, x) \leq C_\varepsilon.$$

Considering the second term in the r.h.s. of Eq. (56), the presence of the product of the compactly supported functions  $\chi_R(x) \chi_R(y)$  implies that the former is bounded in absolute value:

$$\left| \int U_\varepsilon(x - y) \chi_R(y) \chi_R(x) \partial_t \varrho^{\varepsilon, \delta}(t, y) dy \right| \leq C_{R, \varepsilon}.$$

On the otherhand, using the lower bound (41), the first term in the r.h.s. of Eq. (56), is also bounded, and finally, Eq. (54) follows.

## 6.2 Proof of Prop. 7

The map  $\bar{H} : \rho \mapsto H(\rho_\varepsilon)$  is real valued and lower semicontinuous by Prop. 6 and Fatou's lemma. Moreover, for every  $\rho \in \mathcal{V}_2$ ,  $\bar{H}(\Phi_t(\rho)) - \bar{H}(\rho) = H(\rho_{t+\varepsilon}) - H(\rho_\varepsilon) = - \int_\varepsilon^{t+\varepsilon} \int \|v_s\|^2 d\rho_s ds$ . Therefore,  $\bar{H}(\Phi_t(\rho))$  is decreasing w.r.t.  $t$ , and, as such,  $\bar{H}$  is a Lyapunov function. In addition, the identity  $\bar{H}(\Phi_t(\rho)) = \bar{H}(\rho)$  for all  $t$ , is equivalent to:  $v_t = 0$   $\rho_t$ -a.e., for every  $t \geq \varepsilon$ . By Lem. 13, this implies that  $\rho_t = \rho_\varepsilon$  for all  $t \geq \varepsilon$ . Thus,  $\bar{H}(\Phi_t(\rho)) = \bar{H}(\rho)$  for all  $t$ , if and only if  $v_\varepsilon = 0$  and  $\rho_t = \rho_\varepsilon$  for all  $t$ . This means that  $H$  is a Lyapunov function for the set  $\Lambda_\varepsilon$ . The first point is proven.

Consider a recurrent point  $\rho \in \mathcal{V}_2$ , say  $\rho = \lim \Phi_{t_n}(\rho)$ . By Prop. 3,  $\rho \in \Lambda_\varepsilon$ , for any  $\varepsilon > 0$ . This means that there exists  $\mu \in \mathcal{S}$  such that  $\rho_t = \mu$  for all  $t > 0$ . By continuity of the map  $(\pi_0)_\#$ ,  $\rho_0 = \lim \rho_{t_n}$ . Thus,  $\rho_0 = \mu$ . This means that  $\rho_t = \mu$  for all  $t \geq 0$ , which writes  $\rho \in \Lambda_0$ . The proof is complete.

### 6.3 Proof of Prop. 8

In this paragraph, Assumptions 2 and 5 hold. Therefore, Assumptions 1 and 3 also hold. Let  $k \in \mathbb{N}, n \in \mathbb{N}^*$ . We recall Eq.(1)

$$X_{k+1}^{i,n} = X_k^{i,n} - \gamma_{k+1} \nabla V(X_k^{i,n}) - \frac{\gamma_{k+1}}{n} \sum_{j \in [n]} \nabla U(X_k^{i,n} - X_k^{j,n}) + \sqrt{2\gamma_{k+1}} \xi_{k+1}^{i,n}.$$

Let us momentarily drop the upperscript  $n$  to simplify the notations, and we write  $\gamma$  as a shorthand notation for  $\gamma_{k+1}$ . Note that  $\nabla U(-x) = -\nabla U(x)$ . We expand:

$$\begin{aligned} \|X_{k+1}^i\|^2 &= \|X_k^i\|^2 - 2\gamma \langle \nabla V(X_k^i), X_k^i \rangle - 2\frac{\gamma}{n} \sum_j \langle \nabla U(X_k^i - X_k^j), X_k^i \rangle + 2\gamma \|\xi_{k+1}^i\|^2 \\ &\quad + \sqrt{2\gamma} T_{k+1}^i + \gamma^2 \|\nabla V(X_k^i)\|^2 + \frac{\gamma}{n} \sum_j \|\nabla U(X_k^i - X_k^j)\|^2. \end{aligned}$$

where we defined:

$$T_{k+1}^i := \langle \xi_{k+1}^i, X_k^i - \gamma \nabla V(X_k^i) - \frac{\gamma}{n} \sum_j \nabla U(X_k^i - X_k^j) \rangle.$$

Using Assumption 5 and Cauchy-Schwartz inequality, there exists constants  $C, \lambda > 0$  such that:

$$\begin{aligned} \|X_{k+1}^i\|^2 &\leq (1 - \lambda\gamma + C\gamma^2) \|X_k^i\|^2 - \frac{2\gamma}{n} \sum_j \langle \nabla U(X_k^i - X_k^j), X_k^i \rangle + 2\gamma \|\xi_{k+1}^i\|^2 \\ &\quad + \sqrt{2\gamma} T_{k+1}^i + C\gamma^2 (1 + n^{-1} \sum_j \|X_k^j\|^2). \end{aligned} \quad (58)$$

Note that  $\mathbb{E}(T_{k+1}^i | \mathcal{F}_k^n) = 0$ . As a preliminar, we first establish the bound:

$$\sup_{k,n} \left( \mathbb{E}(\|X_k^{1,n}\|^2 \|X_k^{2,n}\|^2) + \frac{1}{n} \mathbb{E}(\|X_k^{1,n}\|^4) \right) < \infty. \quad (59)$$

To that end, compute the average w.r.t.  $i \in [n]$  of both sides of Eq. (58). Setting  $S_k := \frac{1}{n} \sum_i \|X_k^i\|^2$ , and

$$\begin{aligned} \chi_k^U &:= \frac{1}{n^2} \sum_i \sum_j \langle \nabla U(X_k^i - X_k^j), X_k^i \rangle \\ \chi_{k+1}^\xi &:= \frac{1}{n} \sum_i \|\xi_{k+1}^i\|^2 \\ \chi_{k+1}^T &:= \frac{1}{n} \sum_i T_{k+1}^i. \end{aligned}$$

Eq. (58) leads to, for every  $k$  larger than some fixed constant,

$$S_{k+1} \leq (1 - \lambda\gamma) S_k - 2\gamma \chi_k^U + 2\gamma \chi_{k+1}^\xi + \sqrt{2\gamma} \chi_{k+1}^T + C\gamma^2.$$

Moreover, using that  $\nabla U(X_k^j - X_k^i) = -\nabla U(X_k^i - X_k^j)$ , we obtain:

$$\chi_k^U = \frac{1}{2n^2} \sum_i \sum_j \langle \nabla U(X_k^j - X_k^i), X_k^i - X_k^j \rangle \geq -C.$$

Therefore,  $S_{k+1} \leq (1 - \lambda\gamma) S_k + 2\gamma \chi_{k+1}^\xi + \sqrt{2\gamma} \chi_{k+1}^T + C\gamma$ , for large  $k$ . Raising to the square,

$$S_{k+1}^2 \leq (1 - \lambda\gamma)^2 S_k^2 + (2\gamma \chi_{k+1}^\xi + \sqrt{2\gamma} \chi_{k+1}^T + C\gamma)^2 + C S_k (2\gamma \chi_{k+1}^\xi + \sqrt{2\gamma} \chi_{k+1}^T + C\gamma).$$

Thus, for large  $k$ ,

$$\mathbb{E} S_{k+1}^2 \leq (1 - \lambda\gamma) \mathbb{E} S_k^2 + C\gamma^2 \mathbb{E}((\chi_{k+1}^\xi)^2) + C\gamma \mathbb{E}((\chi_{k+1}^T)^2) + C\gamma^2 + C\gamma \mathbb{E}(S_k \chi_{k+1}^\xi) + C\gamma \mathbb{E} S_k.$$

Note that  $\mathbb{E}((\chi_{k+1}^\xi)^2)$  is bounded uniformly in  $k, n$ . Moreover, by Jensen inequality,  $\mathbb{E}(S_k) \leq \sqrt{\mathbb{E}(S_k^2)}$ . Finally, using that  $\mathbb{E}(S_k \chi_{k+1}^\xi) = d\sigma^2 \mathbb{E}(S_k)$ , we obtain:

$$\mathbb{E}S_{k+1}^2 \leq (1 - \lambda\gamma)\mathbb{E}S_k^2 + C\gamma^2 + C\gamma\mathbb{E}((\chi_{k+1}^T)^2) + C\gamma^2 + C\gamma\sqrt{\mathbb{E}(S_k^2)}.$$

We inspect the term  $\mathbb{E}((\chi_{k+1}^T)^2)$ :

$$\begin{aligned} \mathbb{E}((\chi_{k+1}^T)^2) &= \frac{\sigma^2}{n^2} \sum_i \mathbb{E}\|X_k^i - \gamma \nabla V(X_k^i) - \frac{\gamma}{n} \sum_j \nabla U(X_k^i - X_k^j)\|^2 \\ &\leq \frac{C}{n^2} \sum_i \mathbb{E}\|X_k^i\|^2 + \gamma^2 \frac{C}{n^2} \sum_i \left(\frac{1}{n} \sum_j \|\nabla U(X_k^i - X_k^j)\|\right)^2 \\ &\leq \frac{C}{n^2} \sum_i \mathbb{E}\|X_k^i\|^2 + \gamma^2 \frac{C}{n^2} \sum_i \frac{1}{n} \sum_j (1 + \|X_k^i\|^2 + \|X_k^j\|^2) \\ &\leq \frac{C}{n} S_k + \gamma^2 \frac{C}{n^2}. \end{aligned}$$

We finally obtain:  $\mathbb{E}S_{k+1}^2 \leq (1 - \lambda\gamma)\mathbb{E}S_k^2 + C\gamma^2 + C\gamma\sqrt{\mathbb{E}(S_k^2)}$ . This proves that  $\mathbb{E}S_k^2$  is bounded uniformly in  $k, n$ . By exchangeability,  $\mathbb{E}S_k^2 = n^{-1}\mathbb{E}(\|X_k^1\|^4) + (1 - 1/n)\mathbb{E}(\|X_k^1\|^2\|X_k^2\|^2)$ . This proves Eq. (59).

We now expand  $\|X_{k+1}^i\|^2$  starting from (58). We use the notation  $\nabla U^i := n^{-1} \sum_j \nabla U(X_k^i - X_k^j)$ . For all  $k$  large enough,

$$\begin{aligned} \|X_{k+1}^i\|^4 &\leq (1 - \gamma\lambda)\|X_k^i\|^4 + (-\gamma\langle \nabla U^i, X_k^i \rangle + 2\gamma\|\xi_{k+1}^i\|^2 + \sqrt{2\gamma}T_{k+1}^i + C\gamma^2(1 + S_k))^2 \\ &\quad - 2\gamma\langle \nabla U^i, X_k^i \rangle\|X_k^i\|^2 + 2\gamma\|\xi_{k+1}^i\|^2\|X_k^i\|^2 + \sqrt{2\gamma}T_{k+1}^i\|X_k^i\|^2 + C\gamma^2\|X_k^i\|^2(1 + S_k) \end{aligned}$$

We take expectations. Note that  $\mathbb{E}\|\xi_{k+1}^i\|^4 \leq C$ ,  $\mathbb{E}S_k^2 \leq C$  and  $\mathbb{E}(\|\xi_{k+1}^i\|^2\|X_k^i\|^2) \leq C\mathbb{E}\|X_k^i\|^2 = C\mathbb{E}(S_k) \leq C$  (where as usual,  $C$  changes at each inequality). Thus

$$\begin{aligned} \mathbb{E}\|X_{k+1}^i\|^4 &\leq (1 - \gamma\lambda)\mathbb{E}\|X_k^i\|^4 + C\gamma^2\mathbb{E}\langle \nabla U^i, X_k^i \rangle^2 + C\gamma\mathbb{E}((T_{k+1}^i)^2) + C\gamma \\ &\quad - 2\gamma\mathbb{E}\langle \nabla U^i, X_k^i \rangle\|X_k^i\|^2 + C\gamma^2\mathbb{E}(\|X_k^i\|^2 S_k). \end{aligned}$$

It is straightforward to show that  $\mathbb{E}((T_{k+1}^i)^2) \leq C(1 + \gamma^2\mathbb{E}(\|\nabla U^i\|^2))$  and that, in turn,  $\mathbb{E}(\|\nabla U^i\|^2) \leq C(1 + \mathbb{E}S_k) \leq C$ . Thus,  $\mathbb{E}((T_{k+1}^i)^2) \leq C$ . Moreover, by Cauchy-Schwartz inequality followed by the triangular inequality,

$$\begin{aligned} \mathbb{E}\langle \nabla U^i, X_k^i \rangle^2 &\leq \mathbb{E}\left(\frac{1}{n} \sum_j \|\nabla U(X_k^i - X_k^j)\|^2\|X_k^i\|^2\right) \\ &\leq C\mathbb{E}\left(\frac{1}{n} \sum_j (1 + \|X_k^i\|^2 + \|X_k^j\|^2)\|X_k^i\|^2\right) \\ &\leq C + C\mathbb{E}\|X_k^1\|^4 + C\mathbb{E}\|X_k^1\|^2\|X_k^2\|^2. \end{aligned}$$

Note that the last term in the above inequality is bounded uniformly in  $k, n$ , by Eq. (59). Changing again the constants  $C, \lambda$ , we obtain that for large  $k$ ,

$$\mathbb{E}\|X_{k+1}^i\|^4 \leq (1 - \gamma\lambda)\mathbb{E}\|X_k^i\|^4 - 2\gamma\mathbb{E}\langle \nabla U^i, X_k^i \rangle\|X_k^i\|^2 + C\gamma.$$

The crux is to estimate the term  $-2\gamma\mathbb{E}\langle \nabla U^i, X_k^i \rangle\|X_k^i\|^2$ . By exchangeability, and using that  $\nabla U(0) = 0$ ,

$$\mathbb{E}\langle \nabla U^i, X_k^i \rangle\|X_k^i\|^2 = \frac{1}{n} \sum_{j \neq i} \mathbb{E}\langle \nabla U(X_k^i - X_k^j), X_k^i \rangle\|X_k^i\|^2 = \left(1 - \frac{1}{n}\right)\mathbb{E}\langle \nabla U(X_k^1 - X_k^2), X_k^1 \rangle\|X_k^1\|^2.$$

Moreover, using that  $\langle \nabla U(X_k^1 - X_k^2), X_k^1 - X_k^2 \rangle \geq -C$ ,

$$\begin{aligned} \mathbb{E}\langle \nabla U(X_k^1 - X_k^2), X_k^1 \rangle\|X_k^1\|^2 &\geq -C\mathbb{E}\|X_k^1\|^2 + \mathbb{E}[\langle \nabla U(X_k^1 - X_k^2), X_k^2 \rangle\|X_k^1\|^2] \\ &\geq -C\mathbb{E}\|X_k^1\|^2 - \mathbb{E}[\|\nabla U(X_k^1 - X_k^2)\|\|X_k^2\|\|X_k^1\|^2] \\ &\geq -C\mathbb{E}\|X_k^1\|^2 - C\mathbb{E}[(1 + \|X_k^1\| + \|X_k^2\|)\|X_k^2\|\|X_k^1\|^2] \\ &\geq -C\mathbb{E}\|X_k^1\|^2 - C\mathbb{E}[\|X_k^2\|\|X_k^1\|^3] - C\mathbb{E}[\|X_k^2\|^2\|X_k^1\|^2] - C \\ &\geq -C\mathbb{E}[\|X_k^2\|\|X_k^1\|^3] - C, \end{aligned}$$



where we used the fact, proven above, that  $\mathbb{E}\|X_k^1\|^2$  and  $\mathbb{E}[\|X_k^2\|^2\|X_k^1\|^2]$  are bounded, uniformly in  $n, k$ . The term  $\mathbb{E}[\|X_k^2\|\|X_k^1\|^3]$  can be handled by Cauchy-Schwartz inequality:

$$\mathbb{E}[\|X_k^2\|\|X_k^1\|^3] \leq \mathbb{E}(\|X_k^2\|^2\|X_k^1\|^2)^{\frac{1}{2}} \mathbb{E}(\|X_k^1\|^4)^{\frac{1}{2}} \leq C\mathbb{E}(\|X_k^1\|^4)^{\frac{1}{2}}.$$

We have shown that:

$$\mathbb{E}\langle \nabla U^i, X_k^i \rangle \|X_k^i\|^2 \geq -C\mathbb{E}(\|X_k^1\|^4)^{\frac{1}{2}} - C.$$

Putting all pieces together,

$$\mathbb{E}\|X_{k+1}^1\|^4 \leq (1 - \gamma\lambda)\mathbb{E}\|X_k^1\|^4 + C\gamma\sqrt{\mathbb{E}(\|X_k^1\|^4)} + C\gamma.$$

This proves that  $\mathbb{E}\|X_k^1\|^4$  is bounded, uniformly in  $k, n$ . The proof is complete.

## 7 Proofs of Section 4.2

### 7.1 Proof of Prop. 9

We recall the iterations:

$$a_{k+1}^{i,n} = a_k^{i,n}(1 - \lambda\gamma_{k+1}) + \frac{\gamma_{k+1}}{n} \sum_{j \in [n]} (K(w_0^{i,n}, w_0^{j,n})a_k^{j,n} - Q(w_0^{i,n}) + \gamma_{k+1}\tilde{\zeta}_{k+1}^{i,n} + \sqrt{2\gamma_{k+1}}\tilde{\xi}_{k+1}^{i,n}).$$

We denote  $I_{k,n} := \frac{1}{n} \sum_{i \in [n]} (a_k^{i,n})^2$ . The proof will be done in two steps. First, we will obtain a bound on  $\mathbb{E}(I_{k,n}^2)$ . Then, we can bound  $\mathbb{E}(a_{k,n}^{i,n})^4$  and the bound on  $\mathbb{E}(\tilde{\zeta}_k^{i,n})^4$  follows easily. Observe that:

$$\begin{aligned} (a_{k+1}^{i,n})^2 &= (a_k^{i,n})^2(1 - \lambda\gamma_{k+1})^2 - 2\frac{\gamma_{k+1}(1 - \lambda\gamma_{k+1})}{n} \sum_{j \in [n]} a_k^{i,n}(K(w_0^{i,n}, w_0^{j,n})a_k^{j,n} - Q(w_0^{i,n})) \\ &\quad + \sqrt{2\gamma_{k+1}}(1 - \gamma_{k+1}\lambda)\tilde{\xi}_{k+1}^{i,n}a_k^{i,n} + (1 - \lambda\gamma_{k+1})a_k^{i,n}\gamma_{k+1}\tilde{\zeta}_{k+1}^{i,n} \\ &\quad + \left( \frac{\gamma_{k+1}}{n} \sum_{j \in [n]} K(w_0^{i,n}, w_0^{j,n})a_k^{j,n} + \gamma_{k+1}\tilde{\zeta}_{k+1}^{i,n} + \sqrt{2\gamma_{k+1}}\tilde{\xi}_{k+1}^{i,n} \right)^2. \end{aligned} \quad (60)$$

Since  $K$  is a bounded positive semi-definite kernel,  $\sum_{i,j \in [n]} a_k^{i,n}K(w_0^{i,n}, w_0^{j,n})a_k^{j,n} \geq 0$ . Hence, we obtain:

$$\begin{aligned} \frac{1}{n} \sum_{i \in [n]} (a_{k+1}^{i,n})^2 &\leq \frac{1}{n} \sum_{i \in [n]} (a_k^{i,n})^2(1 - \lambda\gamma_{k+1} + C\gamma_{k+1}^2)^2 + \frac{2\gamma_{k+1}}{n} \sum_{i \in [n]} a_k^{i,n}Q(w_0^{i,n}) \\ &+ \frac{(1 - \lambda\gamma_{k+1})}{n} \sum_{i \in [n]} (\gamma_{k+1}\tilde{\zeta}_{k+1}^{i,n} + \sqrt{2\gamma_{k+1}}\tilde{\xi}_{k+1}^{i,n})a_k^{i,n} + C\gamma_{k+1}^2 \frac{1}{n} \sum_{i \in [n]} (\tilde{\zeta}_{k+1}^{i,n})^2 + C\gamma_{k+1} \frac{1}{n} \sum_{i \in [n]} (\tilde{\xi}_{k+1}^{i,n})^2. \end{aligned}$$

Since  $\varphi$  is bounded,  $(\tilde{\zeta}_{k+1}^{i,n})^2 \leq C(1 + y_{k+1}^2 + I_{k,n})$ , and

$$\begin{aligned} I_{k+1,n} &\leq I_{k,n}(1 - 2\lambda\gamma_{k+1} + C\gamma_{k+1}^2) + C\gamma_{k+1}\sqrt{I_{k,n}} \\ &\quad + \frac{(1 - \lambda\gamma_{k+1})}{n} \sum_{i \in [n]} (\gamma_{k+1}\tilde{\zeta}_{k+1}^{i,n} + \sqrt{2\gamma_{k+1}}\tilde{\xi}_{k+1}^{i,n})a_k^{i,n} + C\gamma_{k+1}^2(1 + y_{k+1}^2) + C\gamma_{k+1} \sum_{i \in [n]} (\tilde{\xi}_{k+1}^{i,n})^2. \end{aligned}$$

We have  $\mathbb{E}(\tilde{\xi}_{k+1}^{i,n} | \mathcal{F}_k^n) = \mathbb{E}(\tilde{\zeta}_{k+1}^{i,n} | \mathcal{F}_k^n) = 0$  and  $\mathbb{E}(y_{k+1}^2 + (\tilde{\xi}_{k+1}^{i,n})^2 | \mathcal{F}_k^n) < C$ . Raising to the square, taking the expectation of the above inequality, for  $k$  large enough, there exists  $\tilde{\lambda}$  such that:

$$\mathbb{E}[I_{k+1,n}^2] \leq \mathbb{E}[I_{k,n}^2] (1 - \tilde{\lambda}\gamma_{k+1}) + C\gamma_{k+1}\mathbb{E}[I_{k,n}^{3/2}] + C\gamma_{k+1}\mathbb{E}[I_{k,n}] + C\gamma_{k+1}^2.$$

The latter guarantees,  $\sup_{k,n} \mathbb{E} [I_{k,n}^2] \leq C$ . We will keep this in mind and now, going back to Eq. (60), we obtain for  $k$  large enough:

$$\begin{aligned} \mathbb{E} \left[ \frac{1}{n} \sum_{i \in [n]} (a_k^{i,n})^4 \right] &\leq \mathbb{E} \left[ \frac{1}{n} \sum_{i \in [n]} (a_{k+1}^{i,n})^4 \right] (1 - \tilde{\lambda} \gamma_{k+1}) + \frac{C \gamma_{k+1}}{n^2} \mathbb{E} \left[ \sum_{i,j \in [n]} |a_k^{i,n}|^3 (|a_k^{j,n}| + 1) \right] \\ &\quad + \frac{C \gamma_{k+1}}{n} \mathbb{E} \left[ \sum_{i \in [n]} (a_k^{i,n})^2 \right] + C \gamma_{k+1}^2 \mathbb{E} [I_{k,n}^2] + C \gamma_{k+1}^2. \end{aligned} \quad (61)$$

The larger term is controlled by Cauchy-Schwartz inequality

$$\sum_{i,j \in [n]} \mathbb{E} [ |a_k^{i,n}|^3 |a_k^{j,n}| ] \leq \sum_{i,j \in [n]} \sqrt{\mathbb{E} [(a_k^{i,n} a_k^{j,n})^2]} \sqrt{\mathbb{E} [(a_k^{i,n})^4]}.$$

Using the exchangeability,  $\mathbb{E}(I_{k,n}^2) = \frac{1}{n} \mathbb{E}(a_k^{1,n})^4 + \frac{n-1}{n} \mathbb{E}(a_k^{1,n} a_k^{2,n})^2$  and:

$$\begin{aligned} \frac{1}{n^2} \sum_{i,j \in [n]} \sqrt{\mathbb{E} [(a_k^{i,n} a_k^{j,n})^2]} \sqrt{\mathbb{E} [(a_k^{i,n})^4]} &= \frac{1}{n} \mathbb{E} [(a_k^{1,n})^4] + \frac{n-1}{n} \sqrt{\mathbb{E} [(a_k^{1,n} a_k^{2,n})^2]} \sqrt{\mathbb{E} [(a_k^{1,n})^4]} \\ &\leq \sqrt{\mathbb{E} [(a_k^{1,n})^4]} \sqrt{\frac{1}{n} \mathbb{E} [(a_k^{1,n})^4] + \frac{n-1}{n} \mathbb{E} [(a_k^{1,n} a_k^{2,n})^2]} \\ &\leq \sqrt{\mathbb{E} [(a_k^{1,n})^4]} \sqrt{\mathbb{E} [I_{k,n}^2]}. \end{aligned}$$

Finally, from Eq. (61), the bound on  $\mathbb{E}(I_{k,n}^2)$ , and for  $k$  large enough, we obtain

$$\mathbb{E} [(a_{k+1}^{1,n})^4] \leq \mathbb{E} [(a_{k+1}^{1,n})^4] (1 - \tilde{\lambda} \gamma_{k+1}) + C \gamma_{k+1} \mathbb{E} [(a_{k+1}^{1,n})^4]^{1/2} + C \gamma_{k+1} \mathbb{E} [(a_{k+1}^{1,n})^4]^{3/4} + C \gamma_{k+1}^2.$$

Consequently,  $\sup_{k,n} \mathbb{E}(a_{k+1}^{1,n})^4 < \infty$ . Remarking  $\mathbb{E}(\zeta_k^{i,n})^4 \leq C \mathbb{E}(a_k^{i,n})^4$ , Prop. 9 is proven.

## 7.2 Proof of Lem.4

Define  $A_\mu : w \mapsto \int a d\mu(a|w)$  and  $B_\mu : w \mapsto \int a^2 d\mu(a|w)$ . We use the notation  $K_\varpi f(w) := \int K(w, w') f(w') d\varpi(w)$ . We also denote by  $\langle f, g \rangle_\varpi := \int f(w) g(w) d\varpi(w)$  the inner product in  $L^2(\varpi)$ . Define the constant  $c := \int y^2 d\nu(x, y)$ . Expanding  $\mathcal{R}_0(\mu)$ , we obtain after some straightforward algebra:

$$\mathcal{R}_0(\mu) = \langle A_\mu, K_\varpi A_\mu - Q \rangle_\varpi + c + \frac{\lambda}{2} \int B_\mu d\varpi.$$

Therefore,

$$\begin{aligned} \mathcal{R}_0(\mu) - \mathcal{R}_0(\mu^*) &= \langle A_\mu, K_\varpi A_\mu \rangle - \langle A_{\mu^*}, K_\varpi A_{\mu^*} \rangle_\varpi - \langle Q, A_\mu - A_{\mu^*} \rangle_\varpi + \lambda \int \frac{B_\mu - B_{\mu^*}}{2} d\varpi \\ &\geq \langle K_\varpi A_{\mu^*} - Q, A_\mu - A_{\mu^*} \rangle_\varpi + \lambda \int \frac{B_\mu - B_{\mu^*}}{2} d\varpi, \end{aligned} \quad (62)$$

where we use the fact that  $\langle A_\mu - A_{\mu^*}, K_\varpi (A_\mu - A_{\mu^*}) \rangle_\varpi \geq 0$  to obtain the last inequality. By [AGS08, Lem. 12.4.7], there exists a Borel map on  $\mathbb{R}^{d-1} \rightarrow \mathcal{P}_2(\mathbb{R} \times \mathbb{R})$  which, to every  $w \in \mathbb{R}^{d-1}$ , associated a probability measure  $\gamma(\cdot|w) \in \Pi_2^0(\mu_*(\cdot|w), \mu(\cdot|w))$ , where we recall that  $\Pi_2^0(\mu^*(\cdot|w), \mu(\cdot|w))$  is the set of 2-Wasserstein optimal transport maps between  $\mu^*(\cdot|w)$  and  $\mu(\cdot|w)$ , as introduced after Eq. (8). We obtain:

$$\frac{B_\mu(w) - B_{\mu^*}(w)}{2} = \int \frac{a^2 - a_*^2}{2} d\gamma(a_*, a|w) = \int a_*(a - a_*) d\gamma(a_*, a|w) + \int \frac{(a - a_*)^2}{2} d\gamma(a_*, a|w).$$

Substituting this inequality in Eq. (62), and expanding the first term in the r.h.s. of Eq. (62) as a function of  $\gamma(\cdot|w)$ , we obtain:

$$\begin{aligned} \mathcal{R}_0(\mu) - \mathcal{R}_0(\mu^*) &\geq \int \int (K_\varpi A_{\mu^*}(w) - Q(w) + \lambda a_*)(a - a_*) d\gamma(a_*, a|w) d\varpi(w) \\ &\quad + \int \int \frac{(a - a_*)^2}{2} d\gamma(a_*, a|w) d\varpi(w). \end{aligned}$$

Note that  $K_\varpi A_{\mu^*}(w) - Q(w) + \lambda a_* = -\tilde{b}((a_*, w), \mu^*)$ . We obtain:

$$\mathcal{R}_0(\mu) - \mathcal{R}_0(\mu^*) \geq - \int \int \tilde{b}((a_*, w), \mu^*)(a - a_*) d\gamma(a_*, a|w) d\varpi(w) + \int \int \frac{(a - a_*)^2}{2} d\gamma(a_*, a|w) d\varpi(w). \quad (63)$$

We now study  $\mathcal{R}_\sigma(\mu) - \mathcal{R}_\sigma(\mu^*)$  for  $\sigma > 0$ . We make the assumption that  $\mu(\cdot|w)$  admit a density for  $\varpi$ -almost every  $w$ , which we denote by  $\mu(a|w)$  (in the opposite case,  $\mathcal{R}_\sigma(\mu) = +\infty$  and there is nothing to prove). Then,  $\mathcal{R}_\sigma(\mu) = \mathcal{R}_0(\mu) + \sigma^2 \int C_\mu(w) d\varpi(w)$ , where  $C_\mu(w) := \int \log \mu(a|w) \mu(da|w)$ . Since  $\int \partial_a (\log \mu^*(a|w))^2 d\mu^*(a|w) < \infty$  for  $\mu^*$ -a.e.  $w$ , one is able to apply [AGS08, 10.1.1.B, Prop. 9.3.9, Th. 10.4.6], which yields:

$$C_\mu(w) - C_{\mu^*}(w) \geq \int (a - a_*) \partial_a \log \mu^*(a|w) d\gamma(a_*, a|w).$$

Putting all pieces together, the result is complete.

### 7.3 Proof of Lem. 5

The proof is provided in the case where  $\sigma^2 > 0$  (the arguments are simpler when  $\sigma^2 = 0$ ). By Remark 2, the first point is immediate:  $\tilde{\pi}_{\#} \rho_t = \varpi$  for all  $t$ .

In order to establish the result, one has two options. The first alternative is to follow step by step the proof of Prop. 6. In the case  $\sigma^2 > 0$  (the case  $\sigma^2 = 0$  being easier), we establish using [MPZ21], that  $\rho_t(\cdot|w)$  admits a density w.r.t.  $\mathcal{L}^1$ , which satisfies regularity conditions. In particular, one can prove  $\int_{t_1}^{t_2} \int \|v_{\rho_t}\| d\rho_t dt < \infty$  for all  $t_2 > t_1 > 0$ . Then, by integration by part, it is easy to establish the following continuity equation:

$$\partial_t \rho_t + \nabla \cdot v_{\rho_t} \rho_t = 0,$$

in the sense of distributions on  $C_c^\infty([t_1, t_2] \times \mathbb{R}^d)$ . Using the continuity equation along with the mollification technique used in the proof of Prop. 7, Eq. (25) follows. Now, Eq. (25) proves, as a byproduct, that  $\int_{t_1}^{t_2} \int \|v_{\rho_t}\|^2 d\rho_t dt < \infty$ , which implies Eq. (24). The proof is concluded.

An alternative proof consists in using the concept of gradient flows on  $\mathcal{P}_2(\mathbb{R}^d)$ . Consider the functional  $\mathcal{F}_\varpi(\mu)$  which coincides with  $\mathcal{R}_\sigma(\mu)$  if  $\tilde{\pi}_{\#} \mu = \varpi$ , and  $\mathcal{F}_\varpi(\mu) = +\infty$  otherwise. By [AGS08, Th.11.2.1], there exists a locally Lipschitz curve, say  $(\mu_t)$ , defined on any interval of the form  $[0, T]$ , such that  $\mu_t \rightarrow \rho_0$  as  $t \rightarrow 0$ , and whose velocity field  $(v_t)$  satisfies  $-v_t \in \partial \mathcal{F}_\varpi(\mu_t)$ . It holds that  $\int_0^T \|v_t\|^2 d\rho_t dt < \infty$  by definition of the velocity. Also using the same result [AGS08, Th.11.2.1],  $\mathcal{R}_\sigma(\mu_{t_2}) - \mathcal{R}_\sigma(\mu_{t_1}) \leq - \int_{t_1}^{t_2} \int \|v_t\|^2 d\mu_t dt$  for all  $t_2 > t_1 \geq 0$ , since  $\mathcal{F}_\varpi = \mathcal{R}_\sigma$  along the curve  $(\mu_t)$ . Using [AGS08, Th. 10.4.6] and the same derivations as in the proof of Prop. 4, we establish that  $v_t = (\tilde{v}_{\mu_t}, 0)$ . Moreover, by [AGS08, Th. 8.2.1], there exists a measure on  $\mu \in \mathcal{P}(C([0, T]))$  such that  $\mu_t = \mu_t$  for all  $t$ , and such that  $\dot{x}_t = v_{\mu_t}(x_t)$  for  $\mu$ -almost every  $x$ , and almost every  $t$ . Thus, on  $[0, T]$ ,  $\mu$  satisfies the martingale problem given in Def. 1. As, by [CD22, Prop. 1], this problem has a unique solution, we obtain that  $\mu$  coincides with  $(\pi_{[0, T]})_{\#} \rho$ . In particular,  $\rho_t = \mu_t$ .

## A Technical proofs

### A.1 Proof of Proposition 1

Let  $I \subset \mathbb{R}$ , we denote by  $C(I, \mathbb{R}^d)$  the set of continuous function from  $I$  to  $\mathbb{R}^d$ . One can show, that  $(\rho_n)$  is a Cauchy sequence in the complete space  $(\mathcal{P}_p(C([0, k], \mathbb{R}^d)), W_p)$ . Thus, there exists a sequence of compact sets  $(K_k)$  in  $C([0, k], \mathbb{R}^d)$  such that:

$$(\pi_{[0, k]})_{\#} \rho_n(K_k) > 1 - \frac{\varepsilon}{2k},$$

for all  $k \in \mathbb{N}^*$ . Let  $\mathcal{K} := \bigcap_{k \geq 1} \pi_{[0, k]}^{-1}(K_k) \subset \mathcal{C}$ . The union bound yields  $\rho_n(\mathcal{K}) > 1 - \varepsilon$ . Referring to [Bou89, Theorem 2, Section X, Chapter 5],  $\mathcal{K}$  has a compact closure in  $\mathcal{C}$ . Hence, there exists a converging subsequence  $(\rho_{\varphi_n})$  converging to  $\rho \in \mathcal{P}(\mathcal{C})$ . Following the proof of [Vil09, Theorem

6.18], one can readily check that  $\lim_{n \rightarrow \infty} W_p((\pi_{[0,k]})_{\#} \rho_n, (\pi_{[0,k]})_{\#} \rho) = 0$ , for every  $k$ . Consequently,  $\lim_{n \rightarrow \infty} W_p(\rho_n, \rho) = 0$ , which means the completeness of  $\mathcal{P}_p(\mathcal{C})$ . It remains to obtain its separability.

As  $\mathcal{C}$  is Polish, there exists a dense sequence  $(x_n)$  in  $\mathcal{C}$ . Following the proof of [Vil09, Theorem 6.18], one can construct a sequence  $(\rho_n)$  in  $\mathcal{P}_p(\mathcal{C})$  from  $(x_n)$ , such that  $((\pi_{[0,k]})_{\#} \rho_n)$  is dense in  $\mathcal{C}([0, k], \mathbb{R}^d)$  for every  $k$ . With this result, it can be verified that  $(\rho_n)$  is dense in  $\mathcal{P}_p(\mathcal{C})$ .

## A.2 Proof of Lemma 2

Since Prop. 1 holds,  $(\mathbb{I}(\rho_n))$  is a weak $\star$ -relatively compact sequence in  $\mathcal{P}(\mathcal{C})$ , and there exists a sequence of compact sets  $(K_k)$  in  $\mathcal{C}$ , such that

$$\mathbb{I}(\rho_n)(K_k) > 1 - \frac{k}{2^k},$$

for every  $k \in \mathbb{N}^*$  and every  $n \in \mathbb{N}^*$ . Let  $\varepsilon > 0$ . We define the relatively compact set in  $\mathcal{P}(\mathcal{C})$ :

$$\mathcal{K}_\varepsilon := \left\{ \rho \in \mathcal{P}(\mathcal{C}) : \rho(K_k) > 1 - \frac{1}{k\varepsilon}, \text{ for every } k \in \mathbb{N}^*, \text{ such that } k\varepsilon > 1 \right\}.$$

The union bound and Markov's inequality yields:

$$\mathbb{P}(\rho_n \in \mathcal{K}_\varepsilon) > 1 - \varepsilon \tag{64}$$

for every  $n \in \mathbb{N}^*$ .

In order to be relatively compact in  $\mathcal{P}_p(\mathcal{C})$ , the set  $\mathcal{K}_\varepsilon$  must satisfy Eq. (p-UI). Since the sequence  $(\mathbb{I}(\rho_n))$  has uniformly integrable  $p$ -moments, there exists a sequence  $(a_{k,l})_{(k,l) \in (\mathbb{N}^*)^2}$ , such that for every  $l \in \mathbb{N}^*$ ,  $\lim_{k \rightarrow \infty} a_{k,l} = \infty$ , and

$$\forall (k, l) \in (\mathbb{N}^*)^2, \sup_{n \in \mathbb{N}^*} \mathbb{E} \left[ \int \sup_{t \in [0, l]} \|x_t\|^p \mathbf{1}_{\sup_{t \in [0, l]} \|x_t\| > a_{k,l}} d\rho_n(x) \right] \leq \frac{kl}{2^{k+l}}.$$

For  $\varepsilon > 0$ , we define a set that satisfies Eq. (p-UI):

$$\mathcal{U}_\varepsilon := \left\{ \rho \in \mathcal{P}_p(\mathcal{C}) : \int \sup_{t \in [0, l]} \|x_t\|^p \mathbf{1}_{\sup_{t \in [0, l]} \|x_t\| > a_{k,l}} d\rho(x) \leq \frac{1}{\varepsilon kl}, \text{ for every } k, l \in \mathbb{N}^* \right\}.$$

Using Markov's inequality and the union bound, we obtain

$$\mathbb{P}(\rho_n \in \mathcal{U}_\varepsilon) > 1 - \varepsilon. \tag{65}$$

Putting together Eq. (64) and Eq. (65),

$$\mathbb{P}(\rho_n \in \mathcal{K}_\varepsilon \cap \mathcal{U}_\varepsilon) > 1 - 2\varepsilon.$$

$\mathcal{K}_\varepsilon \cap \mathcal{U}_\varepsilon$  is a relatively compact set in  $\mathcal{P}_p(\mathcal{C})$ . Thus,  $(\rho_n)$  is tight in  $\mathcal{P}_p(\mathcal{C})$ .

## A.3 Proof of Lemma 3

Given  $G = G_{r, \phi, h_1, \dots, h_r, t, s, v_1, \dots, v_r} \in \mathcal{G}_p$ , we first want to show that  $G(\rho_n) \rightarrow G(\rho_\infty)$  as  $\rho_n \rightarrow \rho_\infty$  in  $\mathcal{P}_p(\mathcal{C})$ . This last convergence is characterized by the fact that  $\rho_n \rightarrow \rho_\infty$  in  $\mathcal{P}(\mathcal{C})$ , and that the sequence  $(\rho_n)$  has uniformly integrable  $p$ -moments as shown by (p-UI), which is written here as

$$\forall T > 0, \lim_{a \rightarrow \infty} \sup_{n \in \mathbb{N}} \int \mathbf{1}_{\sup_{u \in [0, T]} \|y_u\| > a} \left( \sup_{u \in [0, T]} \|y_u\|^p \right) d\rho_n(y) = 0.$$

We write  $G(\rho_n) = \int g(x, y) d(\rho_n \otimes \rho_n)(x, y)$ , where for  $x, y$  in  $\mathcal{C}$ :

$$g(x, y) := \left( \phi(x_t) - \phi(x_s) - \int_s^t (\langle \nabla \phi(x_u), b(x_u, y_u) \rangle + \sigma^2 \Delta \phi(x_u)) du \right) h(x),$$

and  $h(x) := \prod_{j=1}^r h_j(x_{t_j})$ . Using Cauchy-Schwartz inequality, we state a useful inequality:

$$|g(x, y)| \leq C \left( 1 + \int_s^t \|b(x_u, y_u)\| du \right), \quad (66)$$

where  $C = \|h\|_\infty \max(2\|\phi\|_\infty + \sigma^2(t-s)\|\Delta\phi\|_\infty, \|\nabla\phi\|_\infty)$ . Note that  $\rho_n \otimes \rho_n \rightarrow \rho_\infty \otimes \rho_\infty$  in  $\mathcal{P}(\mathcal{C} \times \mathcal{C})$ . Furthermore, using the bound (66) for our function  $g$ , and observing that  $t$  is the maximum of the time snapshots intervening in the definition of  $g$ , we have for each  $a > 0$

$$\begin{aligned} \sup_{n \in \mathbb{N}} \int \mathbf{1}_{|g(x,y)| > a} |g(x, y)| d(\rho_n \otimes \rho_n)(x, y) \\ \leq \sup_{n \in \mathbb{N}} \int \mathbf{1}_{C \left( 1 + t \sup_{u \in [0, t]} \|y_u\| \right) > a} C^p \left( 1 + t \sup_{u \in [0, t]} \|y_u\| \right)^p d\rho_n(y), \end{aligned}$$

therefore,

$$\lim_{a \rightarrow \infty} \sup_{n \in \mathbb{N}} \int \mathbf{1}_{|g(x,y)| > a} |g(x, y)| d(\rho_n \otimes \rho_n)(x, y) = 0,$$

which shows that  $G(\rho_n) \rightarrow G(\rho)$  by uniform integrability, and the first result of the lemma is established.

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