

1. Questions and Motivation

Let us consider a linear torus directed graph (or directed network) of vertices $\{1, \ldots, n\}$ in the sense that each node *i* in the network connects only with its neighboring vertex i + 1 for i = 1, ..., n - 1, and the boundary vertex n connects with vertex 1.

On some probability space, based on this torus graph let us consider the simple Ornstein-Uhlenbeck type system (or a Gaussian cascade)

$$dX_{t,i} = (X_{t,i+1} - X_{t,i})dt + dW_{t,i}; \quad t \ge 0, \quad i = 1, ...$$

$$dX_{t,n} = (X_{t,1} - X_{t,n})dt + dW_{t,n}$$

with initial independent and identically distributed random variables $X_{0,i}$, independent of standard Brownian motions $(W_{\cdot,i})$, $1 \le i \le n$.

For comparison, on the same probability space, we consider a typical mean-field interacting system where each particle is attracted towards the mean, defined by

$$dX_{t,i} = \left(\frac{1}{n} \sum_{j=1}^{n} X_{t,j} - X_{t,i}\right) dt + dW_{t,i}; \quad t \ge 0, \quad i =$$

The particle $X_{i,i}$ at node *i* is *directly* attracted towards the mean $(X_{\cdot,1} + \cdots + X_{\cdot,n})/n$ of the system.

Questions.

Q1. What is the essential difference between the system (1) and (2) for large $n \to \infty$?

Q2. Can we detect the type of interaction from the particle behavior at one node?

Motivation.

• Effects of graph (network) structure: mean-field type and local directed chain dependence.

2. An extension of McKean-Vlasov stochastic equation with constraints

Let us introduce a mixed system of linear equations:

$$dX_{t,i} = \left(u \cdot X_{t,i+1} + (1-u) \cdot \frac{1}{n} \sum_{j=1}^{n} X_{t,j} - X_{t,i}\right) dt + dX_{t,n} = \left(u \cdot X_{t,1} + (1-u) \cdot \frac{1}{n} \sum_{j=1}^{n} X_{t,j} - X_{t,n}\right) dt + dX_{t,n}$$

Detecting Mean-field Tomoyuki Ichiba (University of California, Santa Barbara, ichiba@pstat.ucsb.edu) at Brown University, May 2018, Seminar on Stochastic Processes. based on joint work [DFI] with Nils Detering and Jean-Pierre Fouque

.., n-1, (1)

 $1, \ldots, n$. (2)

 $-\mathrm{d}W_{t,i}$, (3)

 $\mathrm{d}W_{t,n}$

for $t \ge 0$, i = 1, ..., n-1 with the initial $X_{0,i}$, $1 \le i \le n$, and for fixed $u \in [0, 1]$. (3) contains both (1) u = 1 and (2) u = 0.

• A bit more generally, on a filtered probability space $(\Omega, \mathcal{F}, (\mathcal{F}_t), \mathbb{P})$, given a constant $u \in [0,1]$ and a functional $b: [0,\infty) \times \mathbb{R} \times \mathcal{M}(\mathbb{R}) \to \mathbb{R}$ \mathbb{R} , let us consider a non-linear diffusion pair $(X_t^{(u)}, \tilde{X}_t^{(u)}), t \geq 0$, described by the stochastic differential equation of McKean-Vlasov type:

 $dX_t^{(u)} = b(t, X_t^{(u)}, F_t^{(u)}) dt + dB_t; \quad t \ge 0,$

driven by a BM $(B_t, t \ge 0)$, where $F_{\cdot}^{(u)}$ is the weighted p.m.

 $F_t^{(u)}(\cdot) := u \cdot \delta_{\widetilde{X}^{(u)}}(\cdot) + (1 - 1)$

of the Dirac mass $\delta_{\widetilde{X}_{t}^{(u)}}(\cdot)$ of $\widetilde{X}_{t}^{(u)}$ and law $\mathcal{L}_{X_{t}^{(u)}}$ of $X_{t}^{(u)}$. We shall assume that the law of $X_{\cdot}^{(u)}$ is identical to that of $\widetilde{X}_{\cdot}^{(u)}$, and $\widetilde{X}_{\cdot}^{(u)}$ is independent of the Brownian motion, i.e.,

> $Law((X_t^{(u)}, t \ge 0)) \equiv Law((\widetilde{X}_t^{(u)}, t \ge 0)) \text{ and }$ (6)

> > $\boldsymbol{\sigma}(\widetilde{X}_t^{(u)}, t \geq 0) \perp \boldsymbol{\sigma}(B_t, t \geq 0).$

Let us also assume that the Brownian motion B_{\cdot} is independent of the initial value $(X_0^{(u)}, \widetilde{X}_0^{(u)})$.

Proposition. Suppose that $b(\cdot)$ is Lipschitz and is at most linear growth. Then, for each $u \in [0,1]$ there exists a weak solution $(\Omega, \mathcal{F}, (\mathcal{F}_t), \mathbb{P})$, $(X^{(u)}_{\cdot}, \tilde{X}^{(u)}_{\cdot}, B_{\cdot})$ to the infinite-dimensional McKean-Vlasov equation (4) with (5)-(6). This solution is unique in law.

Let us take a linear functional $b(t, x, \mu) := -\int_{\mathbb{R}} (x - y) \mu(dy)$ for $t \ge 0, x \in \mathbb{R}, \mu \in \mathcal{M}(\mathbb{R})$ of mean-reverting type. (4) is reduced to

 $dX_t^{(u)} = -\left(u\left(X_t^{(u)} - \widetilde{X}_t^{(u)}\right) + (1 - u)\left(X_t^u - \mathbb{E}[X_t^{(u)}]\right)\right)dt + dB_t.$ (7)

• As $n \to \infty$, the first two components $(X_{.,1}, X_{.,2})$ of (3) converges weakly to $(X^{(u)}, \widetilde{X}^{(u)})$ in (7). Following the martingale method [O], one can show that the joint distribution and marginal distribution of $(X^{(u)}, \widetilde{X}^{(u)})$ satisfies an integral equation. The details, variants and fluctuation results are found in [DFI]. This answers the question Q1.

(4)

$$-u)\cdot\mathcal{L}_{X_{t}^{(u)}}(\cdot) \tag{5}$$



Simulated sample paths of pair: $X_{\cdot}^{(1)}$ (green) $0 \le t \le 1$, $\widetilde{X}_{\cdot}^{(1)}$ (blue) $0 \le t \le 10$ with u = 1.

3. Detecting presence of mean-field

Assume $X_0^{(u)} \equiv 0 \equiv \widetilde{X}_0^{(u)}$. Let us consider the following problem of a single observer: The observer only observes $X_t := X_t^{(u)}, t \ge 0$ but does neither know the value $u \in [0, 1]$ nor $\widetilde{X}_t^{(u)}$, $t \ge 0$ in (7). The value u in (7) indicates how much $X_{\cdot}^{(u)}$ is attracted towards the

neighborhood $\widetilde{X}_{\cdot}^{(u)}$ and (1-u) indicates how much it is attracted towards the average $\mathbb{E}[X_t^{(u)}]$ (= 0). In this context, Q2 is rephrased as

the observer detect the value $u \in [0, 1]$?

Yes, after observing for a sufficiently long time! (7) with (6) is solvable explicitly, and a method-of moments estimator is consistent :

$$li$$

 T -

where

$$\widehat{u}_M := \begin{bmatrix} 1 \end{bmatrix}$$

A modified version

$$\widehat{u}_m := \left(\int_0^T X_t^2 dt \right)^{-1} \cdot \left(\int_0^T X_t^2 dt + \int_0^T X_t dX_t \right) \\= 1 - \left(2 \int^T X_t^2 dt \right)^{-1} \left(T - X_T^2 \right).$$

$$\left(\int_{0}^{T} X_{t}^{2} \mathrm{d}t\right)^{-1} \cdot \left(\int_{0}^{T} X_{t}^{2} \mathrm{d}t + \int_{0}^{T} X_{t} \mathrm{d}X_{t}\right)$$
$$= 1 - \left(2\int_{0}^{T} X_{t}^{2} \mathrm{d}t\right)^{-1} \left(T - X_{T}^{2}\right).$$

of the conditional maximum likelihood estimator

$$\widehat{u} := \left(\int_0^T \mathbb{E} \left[\widetilde{X}_t^2 | \mathcal{F}_T^X \right] dt \right)^{-1} \cdot \mathbb{E} \left[\int_0^T X_t \widetilde{X}_t dt + \int_0^T \widetilde{X}_t dX_t \, \Big| \, \mathcal{F}_T^X \right]$$

Part of research is supported by the National Science Foundation under grants NSF-DMS-13-13373 and NSF-DMS-16-15229.

References

- Springer Berlin.
- [DFI] DETERING, C., FOUQUE, J.-P., ICHIBA, T. (2018) An infinite-dimensional McKean-Vlasov stochastic equations. Preprint.
- [O] Oelschläger, K. (1984) Martingale approach to the law of large numbers for weakly interacting stochastic processes. Ann. Probab. 2 458–479.

Q2'. Only given the filtration $\mathcal{F}_t^X := \sigma(X_s^{(u)}, 0 \le s \le t), t \ge 0$, can

$$\lim_{n \to \infty} \widehat{u}_M = u \quad a.s. \,,$$

$$-\left(\frac{2}{T}\int_{0}^{T}X_{t}^{2}\mathrm{d}t\right)^{-1/2}\right]^{1/2}.$$
 (8)

underestimates the value, i.e., $\lim_{T\to\infty} \widehat{u}_m = 1 - \sqrt{1 - u^2} \le u \in [0, 1]$. The detailed study of \hat{u} and filtering problem is an ongoing research.

[[]SZ] SZNITMAN, A.S. (1991) Topics in propagation of chaos. École d'Été de Probabilités de Saint-Flour XIX – 1989 In Lecture Notes in Math. 1464 165–251,