

How large is the mean-field framework? LLN and CLT results for diffusions on (random) graphs

Eric Luçon
MAP5, Université Paris Cité

Joint works with S. Delattre & GB. Giacomin (Paris Cité) and F. Coppini (Firenze)
& C. Poquet (Lyon 1).

Summer school Mean-field Model, Rennes



Outline

- 1 LLN for empirical measures for perturbations of mean-field diffusions
- 2 Fluctuation results

Diffusions interacting on a (random) graph

Let \mathcal{G}_n a graph with vertices $V_n := \{1, \dots, n\}$ and for any $i, j \in V_n$, denote by $\varepsilon_{i,j}^{(n)} = 1$ (resp. $\varepsilon_{i,j}^{(n)} = 0$) if the edge $j \rightarrow i$ is present in \mathcal{G}_n (resp. absent). Consider n interacting diffusions $X_t^i \in \mathcal{X}$, $i = 1, \dots, n$, $t \geq 0$ solving

$$dX_t^i = \frac{1}{np_n} \sum_{j=1}^n \varepsilon_{i,j}^{(n)} \Gamma(X_t^i, X_t^j) dt + dB_t^i, \quad i = 1, \dots, n.$$

- 1 Also possible to add some **local dynamics**: $F(X_t^i)dt$,
- 2 **Additive noise**: B^1, \dots, B^n : standard i.i.d. Brownian motions.
- 3 Assume $\mathcal{X} = \mathbb{T} := \mathbb{R}/2\pi$: each X^i is a phase on the torus (extensions to \mathbb{R}^d possible).

We place ourselves in a situation where the $\varepsilon_{i,j}^n$ encode for a graph \mathcal{G}_n that is well-approximated by a bounded graphon W (see the first example of P-E. Jabin's lecture).

$$dX_t^i = \frac{1}{np_n} \sum_{j=1}^n \varepsilon_{i,j}^{(n)} \Gamma(X_t^i, X_t^j) dt + dB_t^i, \quad i = 1, \dots, n.$$

Homogeneity

Further simplification here: assume that $W \equiv 1$: **we are looking at homogeneous graphs.**

The renormalisation by np_n is here to ensure that the interaction remains of order 1 as $n \rightarrow \infty$. If $d_n^i := \sum_{j=1}^n \varepsilon_{i,j}^{(n)}$ is the degree of vertex i , we will assume that $d_n \sim np_n$ as $n \rightarrow \infty$.

Remark: Extensions to inhomogeneous graphs/nontrivial **bounded** graphons possible and easy.

Dense vs Diluted

We are interested in two regimes

- The **dense case** $p_n \equiv p \in (0, 1]$: the degree of each vertex remains of order n .
- The **diluted case** $p_n \rightarrow 0$ as $n \rightarrow \infty$: the degree of each vertex is $o(n)$.

A detour to the mean-field framework

In case \mathcal{G}_n is the complete graph,

$$dX_t^i = \frac{1}{n} \sum_{j=1}^n \Gamma(X_t^i, X_t^j) dt + dB_t^i, \quad i = 1, \dots, n.$$

Rewriting the interaction in terms of the empirical measure of the system

$$\mu_{n,t} := \frac{1}{n} \sum_{j=1}^n \delta_{X_t^j}$$

gives

$$dX_t^i = \int_{\mathcal{X}} \Gamma(X_t^i, y) \mu_{n,t}(dy) dt + dB_t^i, \quad i = 1, \dots, n.$$

Crucial assumptions/properties are

- **All-to-all interactions:** the graph of interaction between particles in the complete graph K_n on $\{1, \dots, n\}$,
- **Homogeneous interactions:** the strength of interaction is of the same order $\frac{1}{n}$, uniformly on all edges ($i \rightarrow j$),
- **Exchangeability at any time:** assuming the initial condition (X_0^1, \dots, X_0^n) to be i.i.d., the law of the vector (X_t^1, \dots, X_t^n) at any $t > 0$ is invariant by permutation.

Theorem [McKean, Sznitman, etc.]

- The X^i , $i = 1, \dots, n$ have symmetric laws P_n on $\mathcal{C}([0, T], \mathcal{X})^n$ which are μ -chaotic, where μ is the law of the nonlinear process solution to

$$\begin{cases} d\bar{X}_t &= \int \Gamma(\bar{X}_t, y) \mu_t(dy) dt + dB_t, \\ \mu_t &= \text{Law}(\bar{X}_t). \end{cases}$$

- Equivalently, the empirical measure μ_n converges weakly as $n \rightarrow \infty$ towards μ , weak solution to the nonlinear Fokker Planck equation

$$\partial_t \mu_t = \frac{1}{2} \partial_x^2 \mu_t - \partial_x \left(\left\{ \int \Gamma(\cdot, y) \mu_t(dy) \right\} \mu_t \right).$$

- The previous convergence may be formalized as

$$\mathbb{E} \left(\sup_{t \in [0, T]} d_{BL}(\mu_{n,t}, \mu_t) \right) \leq \frac{C(T)}{\sqrt{n}}$$

for the bounded-Lipschitz distance defined as

$$d_{BL}(\mu, \nu) = \sup \left\{ \left| \int f d\mu - \int f d\nu \right|, \|f\|_\infty \leq 1, |f|_{Lip} \leq 1 \right\}.$$

From a modelling point of view, the homogeneity and exchangeability of the initial mean-field system

$$dX_t^i = \frac{1}{n} \sum_{j=1}^n \Gamma(X_t^i, X_t^j) dt + dB_t^i, \quad i = 1, \dots, n \quad (\text{MF})$$

suffers from several limitations:

- in many applications, the graph of interaction is not complete (e.g. neuroscience) and interactions are not homogeneous along the graph,
- one may not want the initial condition to be i.i.d., only that (see [Gärtner, Oelschläger] for (MF))

$$\mu_{n,0} \xrightarrow[n \rightarrow \infty]{\text{weakly}} \mu_0$$

Just one motivation for this: in order to look at the behavior of (Markovian) (MF) on a time-scale that goes beyond bounded $[0, T]$, one may want to re-iterate the typical estimate

$$\mathbb{E} \left(\sup_{t \in [0, T]} d_{BL}(\mu_{n,t}, \mu_t) \right) \leq \frac{C(T)}{\sqrt{n}}$$

on $[T, 2T]$, $[2T, 3T]$, etc. [Bertini, Giacomin, Poquet, Coppini, L.]

But at any T , the initial condition $\mu_{n,T}$ for $(\mu_{n,s}, s \in [T, 2T])$ is not i.i.d.!

Universality of the mean-field class

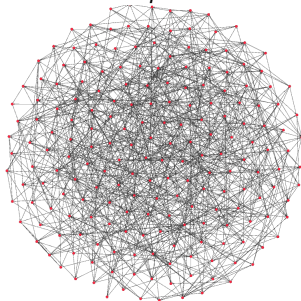
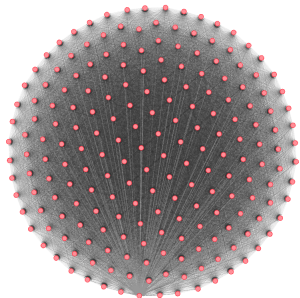
- How universal the mean-field framework is? How much can we perturb the complete graph of interaction K_n into some graph \mathcal{G}_n and nonetheless conserve similar asymptotics (in particular the same mean-field limit) for the empirical measure as $n \rightarrow \infty$?
- At which level is this universality true? law of large numbers, fluctuations, large deviations?
- what is the possible range of dilution/sparsity of the graph \mathcal{G}_n ?
- Is it possible to quantify the proximity of μ_n to its mean-field limit μ in terms of the proximity between \mathcal{G}_n and K_n ? for which graph topology?
- what does it imply on the local or global structure of the graph \mathcal{G}_n ?

Example 1: Erdős-Rényi graph

\mathcal{G}_n : Erdős-Rényi graph with parameter $p_n \in [0, 1]$: the $\varepsilon_{i,j}^{(n)}$ are independent variables with Bernoulli law with parameter p_n . Then d_n^i is Binomial($n - 1, p_n$) so that $\mathbb{E}(d_n^i) \approx np_n$ so that we look at

$$dX_t^i = \frac{1}{np_n} \sum_{j=1}^n \varepsilon_{i,j}^{(n)} \Gamma(X_t^i, X_t^j) dt + dB_t^i, \quad i = 1, \dots, n$$

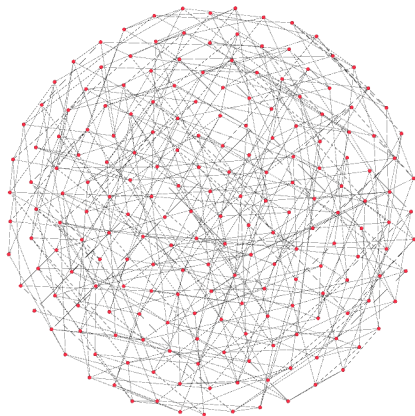
Complete graph VS Erdős-Rényi graph, with $n = 200$ and $p = 0.05$:



Example 2: Random regular graphs

One can construct a graph \mathcal{G}_n in which each vertex has degree $d = d_n$ provided $3 \leq d < n$ and dn is even and defining $p_n = \frac{d_n}{n}$, so that one can also define

$$dX_t^i = \frac{1}{np_n} \sum_{j=1}^n \varepsilon_{i,j}^{(n)} \Gamma(X_t^i, X_t^j) dt + dB_t^i, \quad i = 1, \dots, n$$



The LLN

$$dX_t^i = \frac{1}{np_n} \sum_{j=1}^n \varepsilon_{i,j}^{(n)} \Gamma(X_t^i, X_t^j) dt + dB_t^i, \quad i = 1, \dots, n$$

Local empirical measures

The interaction is no longer a functional of the empirical measure μ_n but rather of a collection of local empirical measures

$$\mu_{n,t}^{(i)} := \frac{1}{np_n} \sum_{j=1}^n \varepsilon_{i,j}^{(n)} \delta_{X_t^j}.$$

Here $\mu_n^{(i)}$ accounts for the direct neighbors of the vertex i . But the dynamics of a neighbor j of i itself depends on the local empirical measure $\mu_n^{(j)}$, etc. : **a whole hierarchy of empirical measures** appears, indexed by local patterns in the graph.

LLN: naive approach, synchronous coupling

Compare

- 1 the particle system

$$dX_t^i = \frac{1}{n\rho_n} \sum_{j=1}^n \varepsilon_{i,j}^{(n)} \Gamma(X_t^i, X_t^j) dt + dB_t^i, \quad i = 1, \dots, n$$

- 2 with i.i.d. copies \bar{X}_i of the nonlinear process, with same initial condition and Brownian motion

$$d\bar{X}_t^i = \int \Gamma(\bar{X}_t^i, y) \mu_t(dy) dt + dB_t^i, \quad i = 1, \dots, n$$

As in the mean-field case, we want to prove that

$$\sup_{i=1, \dots, n} \mathbf{E} \left[\sup_{s \in [0, t]} |X_s^i - \bar{X}_s^i|^2 \right] \xrightarrow{n \rightarrow \infty} 0.$$

Suppose that

$$b_n = b_n(\mathcal{G}_n) := \sup_{i=1, \dots, n} \left| \frac{d_n^i}{np_n} - 1 \right| \xrightarrow{n \rightarrow \infty} 0. \quad (1)$$

Theorem [Delattre, Giacomini, L., 2016]

Suppose that X_0^i , $i = 1, \dots, n$ i.i.d. with law μ_0 . Suppose that $np_n \rightarrow \infty$. Under Lipschitz regularity of Γ , assuming condition (1), there exists some constant $C_\Gamma > 0$ and n_0 such that for all $n \geq n_0$ and any $t \geq 0$,

$$\sup_{i=1, \dots, n} \mathbf{E} \left[\sup_{s \in [0, t]} |X_s^i - \bar{X}_s^i|^2 \right] \leq C_\Gamma \left(\frac{1}{np_n} + b_n^2 \right) \exp(C_\Gamma t) \xrightarrow{n \rightarrow \infty} 0. \quad (2)$$

In particular,

$$\mathbf{E} \left[\sup_{s \in [0, t]} d_{BL}(\mu_{n,s}, \mu_s) \right] \xrightarrow{n \rightarrow \infty} 0, \quad (3)$$

where $(\mu_t)_{t \in [0, T]}$ solves the NFP with initial condition μ_0 .

The proof is elementary

Apply Ito's formula to $|X_t^i - \bar{X}_t^i|^2$:

$$\mathbf{E} \left[\sup_{0 \leq s \leq t} |X_s^i - \bar{X}_s^i|^2 \right] \leq C \int_0^t \mathbf{E} \left[\sup_{0 \leq v \leq u} |X_v^i - \bar{X}_v^i|^2 \right] du \\ + \int_0^t \mathbf{E} \left[\left| \frac{1}{np_n} \sum_{j=1}^n \varepsilon_{i,j}^{(n)} \Gamma(X_u^i, X_u^j) - \int \Gamma(\bar{X}_u^i, y) \mu_u(dy) \right|^2 \right] du$$

and split the last term within the integral into the sum of

- $\mathbf{E} \left[\left| \frac{1}{np_n} \sum_{j=1}^n \varepsilon_{i,j}^{(n)} \left\{ \Gamma(X_u^i, X_u^j) - \Gamma(\bar{X}_u^i, \bar{X}_u^j) \right\} \right|^2 \right]$, \rightarrow Grönwall term
- $\mathbf{E} \left[\left| \frac{1}{np_n} \sum_{j=1}^n \varepsilon_{i,j}^{(n)} \Gamma \left\{ (\bar{X}_u^i, \bar{X}_u^j) - \int \Gamma(\bar{X}_u^i, y) \mu_u(dy) \right\} \right|^2 \right]$, \rightarrow covariance term, of order $\frac{1}{np_n}$
- $\left| \frac{1}{np_n} \sum_{j=1}^n \varepsilon_{i,j}^{(n)} - 1 \right|^2 \mathbf{E} \left[\left| \int \Gamma(\bar{X}_u^i, y) \mu_u(dy) \right|^2 \right]$, \rightarrow bounded by b_n^2 .

About $b_n \rightarrow 0$ and the initial condition

Propagation of chaos

$$\sup_{i=1, \dots, n} \mathbf{E} \left[\sup_{s \in [0, t]} |X_s^i - \bar{X}_s^i|^2 \right] \rightarrow 0 \quad (4)$$

is valid under the condition

$$b_n = b_n(\mathcal{G}_n) := \sup_{i=1, \dots, n} \left| \frac{d_n^i}{np_n} - 1 \right| \xrightarrow{n \rightarrow \infty} 0.$$

- Example 1, $\text{ER}(\rho_n)$: the last condition is satisfied for almost every realisation of $\text{ER}(\rho_n)$ as long as

$$np_n \gg \ln n$$

This condition is optimal for (4), as $\rho_n \sim \frac{\ln n}{n}$ is the threshold for connectivity in $\text{ER}(\rho_n)$ (but not necessarily optimal for the convergence of the empirical measure!)

- Example 2, regular graphs with degree d_n : last condition true when $d_n \rightarrow \infty$.

Why we are not very satisfied with this result

- 1 The condition $b_n \rightarrow 0$ does not even require the graph \mathcal{G}_n to be connected (hence the result does not distinguish at all between (i) some ER(1/2) and (ii) two disjoint mean-field $K_{n/2}^{(1)} \cup K_{n/2}^{(2)}$. Solution to this “paradox”: the convergence $\sup_{i=1, \dots, n} \mathbf{E} \left[\sup_{s \in [0, t]} |X_s^i - \bar{X}_s^i|^2 \right] \rightarrow 0$ is only valid on small (logarithmic) times, but does not say anything on the long time behavior of the system.

Conclusion: in one needs to look at the longtime behavior of the system,
 $b_n \rightarrow 0$ is not the correct condition.

- 2 For the convergence of the empirical measure, for ER graphs, we need $np_n \gg \ln n$, but one expects the result to be valid under $np_n \rightarrow \infty$ only.
- 3 We want to discard the hypothesis that X_0^i are i.i.d. One may even want that the initial condition depends on the graph !

Theorem, Convergence of μ_n , [Coppini, 2022, Coppini, L., Poquet, 2022]

Let $(\mathcal{G}_n)_n$ a (deterministic) sequence of graph on $\{1, \dots, n\}$. Suppose that $d_{BL}(\mu_{n,0}, \mu_0) \rightarrow 0$ (not necessarily i.i.d. and may depend on the graph). Then, if \mathcal{G}_n satisfies

$$\|W_{\mathcal{G}_n} - \mathbf{1}\|_{\infty \rightarrow 1} = \sup_{s_i, t_j \in \pm 1} \frac{1}{n^2} \sum_{i,j=1}^n \left(\frac{\varepsilon_{i,j}^{(n)}}{\rho_n} - 1 \right) s_i t_j \xrightarrow{n \rightarrow \infty} 0 \quad (\text{C})$$

then

$$\mathbb{E} \left(\sup_{t \in [0, T]} d_{BL}(\mu_{n,t}, \mu_t) \right) \xrightarrow{n \rightarrow \infty} 0.$$

Examples

- Ex 1, ER(ρ_n) case: condition (C) is true as long as $n\rho_n \rightarrow \infty$, and this condition is optimal: when $n\rho_n \rightarrow \lambda$, \mathcal{G}_n converges locally to a Galton-Watson tree [Oliveira, Reis, Stolerman 2020], [Lacker, Ramanan, Wu, 2020].
- Ex 2, regular graphs with degree d_n : condition (C) is true for Ramanujan graphs (i.e. regular graphs for which the second highest eigenvalue verifies $\lambda(d_n) \leq 2\sqrt{d_n - 1}$).

The effect on non-exchangeability

Consider Example 1: ER(p_n) graphs. What we have is: almost surely w.r.t. the graph,

- 1 Convergence of marginals: $\sup_{i=1, \dots, n} \mathbf{E} \left[\sup_{s \in [0, t]} |X_s^i - \bar{X}_s^i|^2 \right] \xrightarrow{n \rightarrow \infty} 0$,
when $p_n \gg \frac{\ln n}{n}$ (and this is optimal!)
- 2 Convergence of empirical measure: $\mathbb{E} \left(\sup_{t \in [0, T]} d_{BL}(\mu_{n,t}, \mu_t) \right) \xrightarrow{n \rightarrow \infty} 0$,
when $p_n \gg \frac{1}{n}$ (and this is optimal!)

Non-exchangeability breaks propagation of chaos

When $\frac{1}{n} \ll p_n \ll \frac{\ln n}{n}$, item (1) is false, but (2) is true: the convergence of marginals is no longer equivalent to the convergence of the empirical measure.

Recall that

$$\mu_{n,t}^{(i)} := \frac{1}{np_n} \sum_{j=1}^n \varepsilon_{i,j}^{(n)} \delta_{X_t^j}.$$

Theorem (Convergence of local measures, [Coppini, L., Poquet, 2022])

Let \mathcal{G}_n be a sequence of $ER(p_n)$ graphs. Suppose that $d_{BL}(\mu_{n,0}, \mu_0) \rightarrow 0$ (not necessarily i.i.d. but independent on the graph). Suppose that

$$p_n \gg \frac{1}{n^{1/3}},$$

then for almost every realisation of the graph \mathcal{G}_n , we have that, for all $l \geq 1$

$$\mathbb{E} \left(\sup_{t \in [0, T]} d_{BL}(\mu_{n,t}^{(l)}, \mu_t) \right) \xrightarrow{n \rightarrow \infty} 0$$

Sketch of proof

Define for all test function f and $s \leq T$, $P_{s,T}f(x) = \mathbb{E}_B (f(\Phi_s^T(x)))$ where $t \mapsto \Phi_s^t(x)$ solves $dX_t = \int \Gamma(X_t, y) \mu_t(dy) + dB_t$ with $\Phi_s^s(x) = x$. Then, for any T , one has that $\partial_t \langle \mu_t, P_{t,T} \rangle = 0$. Hence, one expects that $\partial_t \langle \mu_{n,t}, P_{t,T} \rangle \approx 0$, up to order terms that one can control in n . More precisely, one has

$$\begin{aligned} \mathbf{E} |\langle \mu_T^n - \mu_T, f \rangle| &\leq \mathbf{E} |\langle \mu_0^n - \mu_0, P_{0,T}f \rangle| + \mathbf{E} \left| \frac{1}{n} \sum_{k=1}^n \int_0^T \partial_x P_{t,T}f(X_t^k) dB_t^k \right| \\ &\quad + \int_0^T \mathbf{E} \left| \frac{1}{n^2} \sum_{i,j=1}^n \left(\frac{\varepsilon_{i,j}^n}{\rho_n} - 1 \right) \partial_x P_{t,T}f(X_t^i) \Gamma(X_t^i, X_t^j) \right| dt \\ &+ \int_0^T \mathbf{E} \left| \frac{1}{n} \sum_{i=1}^n \partial_x P_{t,T}f(X_t^i) \langle \Gamma(X_t^i, \cdot), \mu_t^n - \mu_t \rangle \right| dt := (A) + (B) + (C) + (D) \end{aligned}$$

- (A): initial condition
- (B): noise term
- (C): graph term, controlled by $\|W_{\mathcal{G}_n} - \mathbf{1}\|_{\infty \rightarrow 1}$, via Grothendieck inequality
- (D): controlled by $d_{BL}(\mu_{n,t}, \mu_t)$.

Extensions

1 Inhomogenous graphs:

- [Medvedev, 2014]: no noise, Neunzert approach.
- [L. 2020]: quenched results for diffusions on W -random graphs (bounded or in L^p)
- [Bayraktar, Wu, 2020]: annealed results for bounded W
- [Bet, Coppini, Nardi, 2020]: random graphons

2 Sparse connections:

- [Lacker, Ramanan, Wu, 19-20], [Oliveira, Reis, Stolerman, 19-20]: interaction on locally tree-like graphs
- [Jabin, Poyato, Soler, 2021]: sparse connection and measured-valued graphons

3 Beyond bounded times

- [Coppini, 2022]: long-term stability for Kuramoto-type interaction
- [Poquet, Le Bris, 2023]: uniform in time convergence for F confining

4 Other types of (jump) dynamics

- [Agathe-Nerine, 2022]: Hawkes processes

Outline

- 1 LLN for empirical measures for perturbations of mean-field diffusions
- 2 Fluctuation results

Review of the pure mean-field case

Beyond the previous LLN result, one is interested in CLT results: the fluctuation process is

$$\eta_{n,t} := \sqrt{n}(\mu_{n,t} - \mu_t)$$

The process η_n is a signed measure, element of $\mathcal{C}([0, +\infty), \mathcal{S}')$, where \mathcal{S}' is the classical Schwartz space of distributions.

Classical approaches in the pure mean-field case:

- Girsanov transform and asymptotics for U-statistics: finite-dimensional convergence of the field $\{\langle \eta_n, f \rangle, f \in L^2(\mu), \mathbb{E}_\mu(f) = 0\}$ towards some Gaussian process [Sznitman, Shiga, Tanaka, Hitsuda, Budhiraja, Wu, etc.]
- Semi-martingale approach [Fernandez, Méléard, Jourdain etc.]:
 - 1 Write a semimartingale decomposition for η_n ,
 - 2 Prove tightness of η_n (typically in $\mathcal{C}([0, T], W^{-j, \alpha})$, where $W^{-j, \alpha}$ is the dual of the set of test functions g s.t. $\sum_{k \leq j} \int \mathcal{X} \frac{|\partial_x^k g(x)|^2}{1+|x|^{2\alpha}} dx < +\infty$, [Rebolledo, Mitoma, Joffe, Métivier]
 - 3 Identify the limit as the unique solution of a linear SPDE

The result of Fernandez and Méléard (1997) in the MF case

Ito's formula gives, for all test function f

$$\langle \eta_{n,t}, f \rangle = \langle \eta_{n,0}, f \rangle + \int_0^t \langle \eta_{n,s}, \mathcal{L}_{\mu_{n,s}}(f) \rangle ds + W_{n,t}(f),$$

where

$$\mathcal{L}_v f := \frac{1}{2} \partial_x^2 f + \langle v(dx'), \Gamma(\cdot, x') \partial_x f(\cdot) \rangle + \langle v(dx'), \Gamma(x', \cdot) \partial_x f(x') \rangle$$

and W_n is an explicit martingale converging to some Gaussian process W .

Theorem [Fernandez, Méléard, 1997]

There exist $j \geq 1$, $\alpha > 0$, such that for iid initial condition with sufficient moments, the process η_n converges in $\mathcal{C}([0, +\infty), W^{-j, \alpha})$ as $n \rightarrow \infty$ to η , unique solution to the linear SPDE

$$\eta_t = \eta_0 + \int_0^t \mathcal{L}_{\mu_s}^* \eta_s ds + W_t,$$

Remark

- The proof relies heavily on the exchangeability of the initial condition
- The miracle of mean-field set-up again: we have a closed formulation of the fluctuation process.

Fluctuations on $\mathcal{G}_n = ER(p_n)$

There is no longer a closed equation for the fluctuation process: Ito's formula gives again

$$\eta_{n,t} = \eta_{n,0} + \int_0^t \mathcal{L}_{\mu_{n,s}}^* \eta_{n,s} ds + \int_0^t \Theta^* \hat{\eta}_{n,s} ds + W_{n,t},$$

for the auxiliary process:

$$\hat{\eta}_{n,t} = \frac{1}{n^{3/2}} \sum_{i,j=1}^n \left(\frac{\varepsilon_{i,j}^{(n)}}{p_n} - 1 \right) \delta_{(X_t^i, X_t^j)}$$

Question

If one believes in the universality of the mean-field fluctuations, one is left with proving that

$$\hat{\eta}_n \rightarrow 0, \text{ in some } H^{-j}(\mathbb{T}) \text{ as } n \rightarrow \infty$$

Dealing with the auxiliary process: first wrong approach

$$\hat{\eta}_{n,t} = \frac{1}{n^{3/2}} \sum_{i,j=1}^n \left(\frac{\varepsilon_{i,j}^{(n)}}{\rho_n} - 1 \right) \delta_{(X_t^i, X_t^j)}$$

First guess: apply $\hat{\eta}_n$ to the test function $f \equiv 1$:

$$\langle \hat{\eta}_n, 1 \rangle = \frac{1}{n^{3/2}} \sum_{i,j=1}^n \left(\frac{\varepsilon_{i,j}^{(n)}}{\rho_n} - 1 \right)$$

By Bernstein inequality, one has immediately that for all $\varepsilon > 0$

$$\mathbb{P} \left(|\langle \hat{\eta}_n, 1 \rangle| > \frac{1}{n^{\frac{1}{2}-\varepsilon} \rho_n^{1-\varepsilon}} \right) \leq 2 \exp \left(-\frac{n^\varepsilon}{4} \right)$$

and hence $\langle \hat{\eta}_n, 1 \rangle \rightarrow 0$ a.s. when $\rho_n \gg \frac{1}{n^{1/2-\varepsilon}}$.

Problem

The presence of $\delta_{(X_t^i, X_t^j)}$ makes the previous argument no longer applicable. X_t^i, X_t^j depend in a nontrivial way on the sequence $(\varepsilon_{i,j}^n)$: independence is broken.

$$\hat{\eta}_{n,t} = \frac{1}{n^{3/2}} \sum_{i,j=1}^n \left(\frac{\varepsilon_{i,j}^{(n)}}{p_n} - 1 \right) \delta_{(X_t^i, X_t^j)}$$

Idea: apply again Ito's formula and pursue this decomposition on $\hat{\eta}_n$:

$$\hat{\eta}_{n,t} = \hat{\eta}_{n,0} + \int_0^t \hat{\mathcal{L}}_{\mu_{n,s}}^* \hat{\eta}_n \, \mathbf{s} ds + \mathbf{C}_{n,t} + \hat{W}_{n,t},$$

Again, the remaining term \mathbf{C}_n depends itself on higher statistics within the graph, i.e. e.g. quantities such that

$$\frac{1}{n^3} \sum_{i,j,k=1}^n \left(\frac{\varepsilon_{i,j}^{(n)}}{p_n} - 1 \right) \left(\frac{\varepsilon_{i,k}^{(n)}}{p_n} - 1 \right) \delta_{(X_t^i, X_t^j, X_t^k)}$$

etc.

Question

How to close this hierarchy of empirical measure?

Main result

Good news: the remainder term C_n vanishes as $n \rightarrow \infty$: the fluctuations are only captured by the 2-order expansion $(\eta_n, \hat{\eta}_n)$.

Theorem [Coppini, L., Poquet, 2022]

There exists $3 < r < r'$ such that if the initial fluctuations $(\eta_{n,0}, \hat{\eta}_{n,0})$ satisfies $\sup_n \mathbf{E} \left(\|\eta_{n,0}\|_{-r}^{1+\alpha} \right) < \infty$, $\sup_n \mathbf{E} \left(\|\hat{\eta}_{n,0}\|_{-r}^{1+\alpha} \right) < \infty$ and converge in $H^{-r'}(\mathbb{T}) \otimes H^{-r'}(\mathbb{T}^2)$ and if the dilution condition holds

$$\rho_n \gg \frac{1}{n^{1/4}}.$$

Then, for almost every realisation of the graph \mathcal{G}_n , $(\eta_n, \hat{\eta}_n)$ converges in $\mathcal{C} \left([0, T], H^{-r'}(\mathbb{T}) \otimes H^{-r'}(\mathbb{T}^2) \right)$ towards the unique solution to the system of coupled SPDEs

$$\begin{cases} \eta_t = \eta_0 + \int_0^t \mathcal{L}_{\mu_s}^* \eta_s ds + \int_0^t \Theta^* \hat{\eta}_s ds + W_t, \\ \hat{\eta}_t = \hat{\eta}_0 + \int_0^t \hat{\mathcal{L}}_{\mu_s}^* \hat{\eta}_s ds, \end{cases}$$

where $(W_t)_{t \in [0, T]}$ is an explicit Gaussian process, independent of $(\eta_0, \hat{\eta}_0)$.

Universality of fluctuations

Corollary

Suppose in addition that the initial condition is chosen **independently of the graph**. Then, under the previous assumption, the fluctuations are the same as in the mean-field case: $\hat{\eta} \equiv 0$ and η_n converges to

$$\eta_t = \eta_0 + \int_0^t \mathcal{L}_{\mu_s}^* \eta_s ds + W_t$$

Hence, the mean-field CLT is universal, provided we choose the initial condition independently on the graph.

Remark

It is possible to choose well-prepared initial conditions (that depend on the graph) such that the fluctuations are captured by $(\eta, \hat{\eta})$, not only η . Hence, fluctuations are non universal if one chooses initial conditions that depend on the graph.

CLT for local fluctuations

We are also interested in the joint convergence of

$$(\zeta_n^1, \zeta_n^2, \eta_n)$$

where ζ_n^l is the fluctuation field associated to the local empirical measure

$$\zeta_n^l := \sqrt{n\rho_n} (\mu_n^l - \mu).$$

Theorem [Coppini, L., Poquet, 2022]

Suppose that (X_0^1, \dots, X_0^n) are i.i.d. with law μ_0 , independent from the graph. Suppose that $\liminf_n n\rho_n^5 = \infty$ and denote by $\rho := \lim_{n \rightarrow \infty} \rho_n \in [0, 1]$. Then, for a.e. realizations of the graph, $(\zeta^{n,1}, \zeta^{n,2}, \eta^n)$ converges as $n \rightarrow \infty$ in $\mathcal{C}([0, T], (\mathcal{S}^l)^3)$ to (ζ^1, ζ^2, η) solution to

$$\begin{cases} \zeta_t^l = \zeta_0^l + \int_0^t \mathcal{U}_s^* \zeta_s^l ds + \sqrt{\rho} \int_0^t \mathcal{V}_s^* \eta_s ds + W_t^l, & l = 1, 2, \\ \eta_t = \eta_0 + \int_0^t \mathcal{L}_{\mu_s}^* \eta_s ds + W_t. \end{cases} \quad (5)$$

for explicit linear operators $\mathcal{U}_s, \mathcal{V}_s$ and for $(\zeta_0^1, \zeta_0^2, \eta_0) \perp\!\!\!\perp (W_t^1, W_t^2, W_t)$ Gaussian processes with explicit covariance.

Consequence: phase transitions for local measures

Corollary

Under the previous assumptions,

- if $p_n \rightarrow p > 0$ (dense case), $(\zeta^1, \zeta^2) = \lim_{n \rightarrow \infty} (\zeta_n^1, \zeta_n^2)$ are correlated (they are equal in the MF case!)
- if $p_n \rightarrow 0$ (diluted case), $(\zeta^1, \zeta^2) = \lim_{n \rightarrow \infty} (\zeta_n^1, \zeta_n^2)$ are independent.

Idea of proof

The proof follows the usual steps of (i) tightness of the processes $(\eta_n, \hat{\eta}_n)$ and (ii) uniqueness of the limit. The key argument is to control the terms in the expansion of the fluctuation process, the first one being the auxiliary process

$$\hat{\eta}_{n,t} = \frac{1}{n^{3/2}} \sum_{i,j=1}^n \left(\frac{\varepsilon_{i,j}^{(n)}}{\rho_n} - 1 \right) \delta_{(X_t^i, X_t^j)}$$

but really higher-order functionals, indexed by local trees within the graph:

$$C_{n,t}^{\leftarrow} := \frac{1}{n^3} \sum_{i,j,k=1}^n \left(\frac{\varepsilon_{i,j}^{(n)}}{\rho_n} - 1 \right) \left(\frac{\varepsilon_{i,k}^{(n)}}{\rho_n} - 1 \right) \delta_{(X_t^i, X_t^j, X_t^k)},$$

$$C_{n,t}^{\rightarrow} := \frac{1}{n^3} \sum_{i,j,k=1}^n \left(\frac{\varepsilon_{i,j}^{(n)}}{\rho_n} - 1 \right) \left(\frac{\varepsilon_{j,k}^{(n)}}{\rho_n} - 1 \right) \delta_{(X_t^i, X_t^j, X_t^k)}$$

Key idea: Grothendieck inequalities

The proof relies on (extensions of) the Grothendieck inequality, whose most simple instance is

Theorem, Grothendieck

There is a universal constant \mathcal{K} such that for any array $a_{i,j}$, for any Hilbert space H ,

$$\sup \left\{ \left| \sum_{j,k} a_{jk} \langle x_j, y_k \rangle_H \right| : \|x_j\|_H, \|y_k\|_H \leq 1 \right\} \\ \leq \mathcal{K} \sup \left\{ \left| \sum_{j,k} a_{jk} s_j t_k \right| : s_j = \pm 1, t_k = \pm 1 \right\}$$

This identity gives an estimate on Sobolev norms of the process $\hat{\eta}_n$ in terms of similar quantities where the Dirac has been replaced by signs in ± 1 : we have removed the dependence!

The price we have to pay is that we need to control such weighted sums in the worst-case scenario, which requires stronger concentration estimates: a union bound on the sup gives a factor 4^n so that the previous

$$\mathbb{P} \left(\sup_{s,t} \left| \frac{1}{n^{3/2}} \sum_{i,j=1}^n \left(\frac{\varepsilon_{i,j}^{(n)}}{\rho_n} - 1 \right) s_i t_j \right| > \frac{1}{n^{\frac{1}{2}-\varepsilon} \rho_n^{1-\varepsilon}} \right) \leq 2 \times 4^n \exp \left(-\frac{n^\varepsilon}{4} \right)$$

is no longer summable ! **And this does not work for $\hat{\eta}_n$!**

In order to deal with $C_{n,t}^{\leftarrow}$, $C_{n,t}^{\rightarrow}$, we need higher order inequalities. Bad news: Grothendieck inequalities for multilinear functionals are false in general. Good news: there is a class of functionals for which they remain true [Blei, 2014].

Let $m \geq 1$, $\mathcal{U} = (S_1, \dots, S_N)$ of non empty sets with $\cup_{i=1}^N S_i = \{1, 2, \dots, m\}$, for $\alpha = (\alpha_j)_{1 \leq j \leq m} \in \mathbb{Z}^m$, define the projections $\pi_{S_i}(\alpha) = (\alpha_j)_{j \in S_i}$. Consider the functional $v_{\mathcal{U}} : \ell^2(\mathbb{Z}^{|S_1|}) \times \dots \times \ell^2(\mathbb{Z}^{|S_N|}) \rightarrow \mathbb{C}$ defined as $v_{\mathcal{U}}(x_1, \dots, x_N) = \sum_{\alpha \in \mathbb{Z}^m} x_1(\pi_{S_1}(\alpha)) \cdots x_N(\pi_{S_N}(\alpha))$. Denote, for $1 \leq j \leq m$, by $k_j(\mathcal{U}) = |\{i : j \in S_i\}|$ and by $\mathcal{I}_{\mathcal{U}}$ the minimal incidence $\mathcal{I}_{\mathcal{U}} = \min \{k_j(\mathcal{U}) : j \in \{1, \dots, m\}\}$.

Theorem

Suppose that $\mathcal{I}_{\mathcal{U}} \geq 2$. Then there exists a positive constant $\mathcal{K}_{\mathcal{U}}$, depending only on the covering \mathcal{U} , such that for any finitely supported scalar n -array $a_{j_1 \dots j_N}$,

$$\sup \left\{ \left| \sum_{j_1, \dots, j_N} a_{j_1 \dots j_N} v_{\mathcal{U}}(x_1, \dots, x_N) : \|x_1\|_{\ell^2(\mathbb{Z}^{|S_1|})} \leq 1, \dots, \|x_N\|_{\ell^2(\mathbb{Z}^{|S_N|})} \leq 1 \right| \right\} \\ \leq \mathcal{K}_{\mathcal{U}} \sup \left\{ \left| \sum_{j_1, \dots, j_N} a_{j_1 \dots j_N} s_{1,j_1} \cdots s_{N,j_N} : s_{1,j_1} = \pm 1, \dots, s_{N,j_N} = \pm 1 \right| \right\}. \quad (6)$$

Conclusion

- At the level of the LLN, the mean-field limit remains universal for diffusions on random graphs for both the empirical measure and local empirical measures as long as $np_n \rightarrow \infty$.
- These results remains largely true for inhomogeneous connections (W -random graphs)
- At level of the CLT, mean-field fluctuations remain universal as long as the initial condition is independent of the graph, but not be universal in general.
- The optimality of the dilution regime (for now $np_n^4 \rightarrow \infty$) remains unclear.

F. Coppini, E. Luçon, and C. Poquet. *Central limit theorems for global and local empirical measures of diffusions on Erdős–Rényi graphs*, June 2022, <https://arxiv.org/abs/2206.06655>.

Thank you for your attention!