

Annealed and quenched limits for a diffusive disordered mean-field model with random jumps

Xavier Erny

École polytechnique (CMAP)

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1 Mathematical background

- Point processes
- Thinning

2 Model

- Neural networks model
- Definitions of the systems
- Heuristics

3 Convergence

- Result
- Finite-dimensional convergence
- Tightness

4 Prospect ?

Point process : definitions

Point process (or counting process) Z :

- a random countable set of \mathbb{R}_+ : $Z = \{T_i : i \in \mathbb{N}\}$
- a random point measure on \mathbb{R}_+ : $Z = \sum_{i \in \mathbb{N}} \delta_{T_i}$

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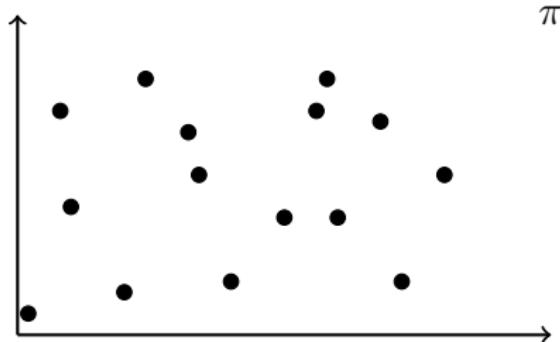
- a random countable set of \mathbb{R}_+ : $Z = \{T_i : i \in \mathbb{N}\}$
- a random point measure on \mathbb{R}_+ : $Z = \sum_{i \in \mathbb{N}} \delta_{T_i}$

A process λ is the **stochastic intensity** of Z if :

$$\forall 0 \leq a < b, \mathbb{E}[Z([a, b]) | \mathcal{F}_a] = \mathbb{E} \left[\int_a^b \lambda_t dt \middle| \mathcal{F}_a \right]$$

Thinning

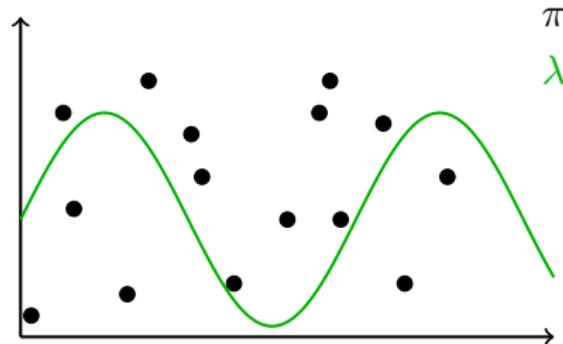
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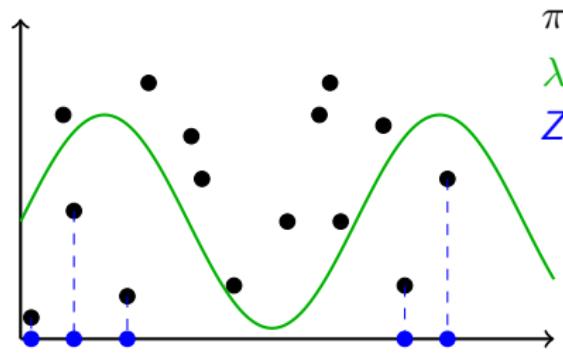


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$$Z(A) = \int_{A \times \mathbb{R}_+} \mathbf{1}_{\{z \leq \lambda(t)\}} d\pi(t, z)$$



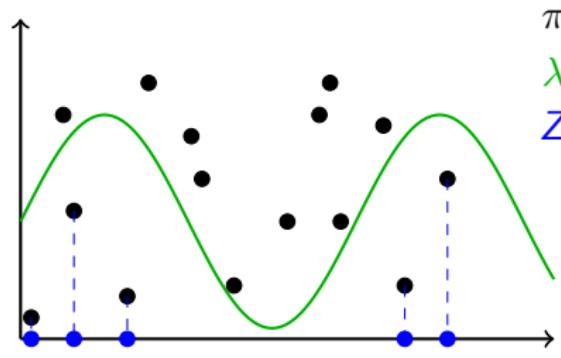
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Then : λ is the stochastic intensity of Z



Modeling in neuroscience

Neural activity = Set of spike times

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Here, $X^{N,i}$ solves an SDE directed by $(Z^{N,j})_{1 \leq j \leq N}$

N -neurons network model

$$dX_t^{N,i} = -\alpha X_t^{N,i} dt + \frac{1}{N^\beta} \sum_{j=1}^N \int u^{ji}(t) \mathbb{1}_{\{z \leq f(X_{t-}^{N,j})\}} d\pi^j(t, z)$$

with :

- π^j = PRM with intensity $dt \cdot dz$
- $\beta = 1$ or $1/2$
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- $X_t^{N,i} = X_{t-}^{N,i} + \frac{u^{ji}(t)}{N^\beta}$ if a neuron j emits a spike at t
 $\rightarrow u^{ji}(t)/N^\beta = \text{synaptic weight}$

Mean field limit

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- linear scaling $\beta = 1$ (LLN) :

[Delattre et al. (2016)] (Hawkes process, $u^{ji}(t) = 1$),

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centered synaptic weight : "balanced networks"
- - scaling $N^{-1} \Rightarrow$ limit ODE
 - scaling $N^{-1/2} \Rightarrow$ limit SDE (model with noise)

\Rightarrow various noises (the other neurons, the ion channels,...)

Diffusive scaling

- **Marked point processes**

- **Random environment**

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Marked model inconsistency :

roles of synapses can change at every spike

Diffusive scaling, random environment, dimension 1

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Limit system $W \sim \mathcal{N}(0, \sigma^2)$

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Heuristics for the limit system

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CLT coupling from KMT result

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Then there exist $W^{[N]}$ i.d. $\sim \mathcal{N}(0, \sigma^2)$ and K such that :

$$\left| \frac{1}{\sqrt{N}} \sum_{j=1}^N U_j - W^{[N]} \right| \leq K \frac{\ln N}{\sqrt{N}} \text{ and } \mathbb{E} \left[e^{\gamma K} \right] < \infty \text{ for some } \gamma > 0$$

Sketch of proof of CLT coupling

[Komlós, Major, Tusnády (1976)] :

there exist BM β and constants Γ, Λ, λ , such that $\forall N \geq 2, x > 0$,

$$\mathbb{P} \left(\max_{k \leq N} \left| \sum_{j=1}^k U_j - \sigma \beta_k \right| > \Gamma \ln N + x \right) \leq \Lambda e^{-\lambda x}$$

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with $W^{[N]} := \sigma \beta_N / \sqrt{N} \sim \mathcal{N}(0, \sigma^2)$

Conditional stochastic calculus

$$dX_t^N = b(X_t^N)dt + N^{-1/2} \sum_{j=1}^N U_j \int_0^\infty \mathbb{1}_{\{z \leq f(X_{t-}^N)\}} d\pi^j(t, z)$$

Control of moment of $\sup |X_t^N|^2$:

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Control of moment of $\sup |X_t^N|^2$: if f, b bounded,

$$\mathbb{E}_{\mathcal{E}} \left[\sup_{s \leq t} |X_s^N|^2 \right] \leq C \left(t^2 + t \left(N^{-1} \sum_{j=1}^N U_j^2 \right) + t^2 \left(N^{-1/2} \sum_{j=1}^N U_j \right)^2 \right)$$

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Theorem

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- For all $t > 0, g \in C_b^3(\mathbb{R})$,

$$\left| \mathbb{E} \left[g(X_t^N) \right] - \mathbb{E} \left[g(\bar{X}_t) \right] \right| \leq C_{g,t} \left(\frac{\ln N}{\sqrt{N}} + d_{KR}(\nu_0^N, \bar{\nu}_0) \right)$$

with $\nu_0^N := \mathcal{L}(X_0^N)$ and $\bar{\nu}_0 := \mathcal{L}(\bar{X}_0)$

Remarks :

- $d_{KR} = \text{Kantorovich-Rubinstein} = \text{1st order Wasserstein}$

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Theorem

- X^N converges to \bar{X} in distribution in $D(\mathbb{R}_+, \mathbb{R})$
- For all $t > 0, g \in C_b^3(\mathbb{R})$,

$$\left| \mathbb{E} [g(X_t^N)] - \mathbb{E} [g(\bar{X}_t)] \right| \leq C_{g,t} \left(\frac{\ln N}{\sqrt{N}} + d_{KR}(\nu_0^N, \bar{\nu}_0) \right)$$

with $\nu_0^N := \mathcal{L}(X_0^N)$ and $\bar{\nu}_0 := \mathcal{L}(\bar{X}_0)$

Remarks :

- d_{KR} = Kantorovich-Rubinstein = 1st order Wasserstein
- same convergence speed for FIDI distribution

Assumptions and example

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- for $1 \leq k \leq 4$, $b^{(k)}, f^{(k)}, \sqrt{f}^{(k)}$ are bounded

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$$b(x) := -\alpha x \text{ and } f(x) := \frac{\theta}{1 + e^{-\lambda(x-x_0)}} \quad [\text{Velichko, Boriskov (2020)}]$$

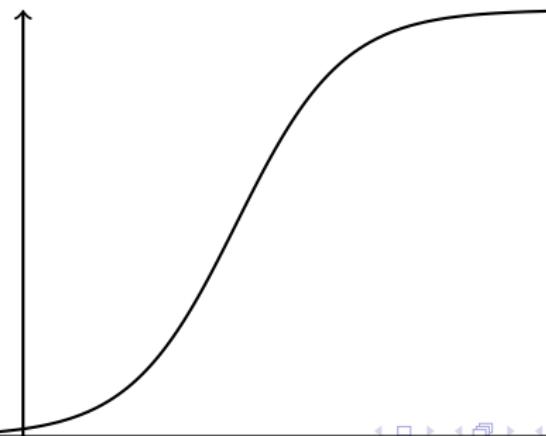
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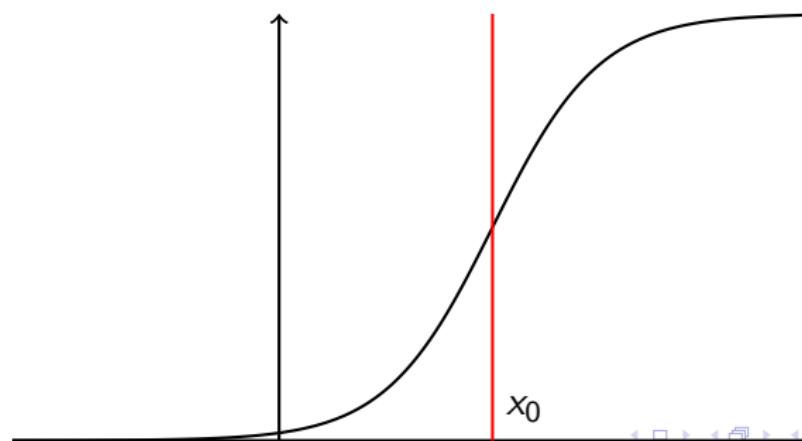
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Infinitesimal generator

N -particle system

$$dX_t^N = b(X_t^N)dt + N^{-1/2} \sum_{j=1}^N U_j \int_0^\infty \mathbb{1}_{\{z \leq f(X_{t-}^N)\}} d\pi^j(t, z)$$

Limit system

$$d\bar{X}_t^N = b(\bar{X}_t^N)dt + W^{[N]}f(\bar{X}_t^N)dt + \sigma \sqrt{f(\bar{X}_t^N)} dB_t$$

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Difference of generators

$$\left| A_{\mathcal{E}}^N g(x) - \bar{A}_{\mathcal{E}}^N g(x) \right| \leq f(x) \left(\left| \frac{1}{\sqrt{N}} \sum_{j=1}^N U_j - W^{[N]} \right| \cdot |g'(x)| \right. \\ \left. + \frac{1}{2} \left| \frac{1}{N} \sum_{j=1}^N U_j^2 - \sigma^2 \right| \cdot |g''(x)| \right. \\ \left. + \frac{1}{6N\sqrt{N}} \sum_{j=1}^N |U_j|^3 \cdot \|g'''\|_{\infty} \right)$$

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Semigroup

$$\left(\bar{P}_{\mathcal{E},t}^N - P_{\mathcal{E},t}^N \right) g(x) = \int_0^t P_{\mathcal{E},t-s}^N \left(\bar{A}_{\mathcal{E}}^N - A_{\mathcal{E}}^N \right) \bar{P}_{\mathcal{E},s}^N g(x) ds$$

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$$= \int_0^t \left[-\frac{d}{du} \left(P_{\mathcal{E},u}^N \bar{P}_{\mathcal{E},s}^N g(x) \right) \Big|_{u=t-s} + \frac{d}{du} \left(P_{\mathcal{E},t-s}^N \bar{P}_{\mathcal{E},u}^N g(x) \right) \Big|_{u=s} \right] ds$$

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Semigroup convergence

$$\left| \left(\bar{P}_{\mathcal{E},t}^N - P_{\mathcal{E},t}^N \right) g(x) \right| \leq \int_0^t \left| P_{\mathcal{E},t-s}^N \left(\bar{A}_{\mathcal{E}}^N - A_{\mathcal{E}}^N \right) \bar{P}_{\mathcal{E},s}^N g(x) \right| ds$$

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Control of $\|\bar{P}_{\mathcal{E},s}^N g(x)\|_{3,\infty}$

$$\bar{P}_{\mathcal{E},s}^N g(x) = \mathbb{E}_{\mathcal{E}, \bar{X}_0^N = x} [g(\bar{X}_s^N)]$$

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$$\partial_x \bar{P}_{\mathcal{E},s}^N g(x) = \mathbb{E}_{\mathcal{E}} \left[(\partial_x \bar{X}_s^N(x)) g'(\bar{X}_s^N(x)) \right]$$

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$$|\partial_x \bar{P}_{\mathcal{E},s}^N g(x)| \leq \|g'\|_{\infty} \sup_x \mathbb{E}_{\mathcal{E}} \left[|\partial_x \bar{X}_s^N(x)| \right] \leq C_s \|g'\|_{\infty} e^{C_s |W^{[N]}|}$$

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Control of $\|\bar{P}_{\mathcal{E},s}^N g(x)\|_{3,\infty}$

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One-dimensional convergence

$$\left| \mathbb{E}_{\mathcal{E}} \left[g(X_t^N) \right] - \mathbb{E}_{\mathcal{E}} \left[g(\bar{X}_t^N) \right] \right|$$

One-dimensional convergence

$$\begin{aligned} & \left| \mathbb{E}_{\mathcal{E}} \left[g(X_t^N) \right] - \mathbb{E}_{\mathcal{E}} \left[g(\bar{X}_t^N) \right] \right| \\ &= \left| \int d\nu_0^N(x) P_{\mathcal{E},t}^N g(x) - \int d\bar{\nu}_0(x) \bar{P}_{\mathcal{E},t}^N g(x) \right| \end{aligned}$$

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One-dimensional convergence

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Model in dimension N

Random environment iid U_{ji} =synaptic strength $j \rightarrow i$

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Problem : not explicit, not (conditional) McKean-Vlasov

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Girsanov's theorem gives $\mathcal{L}((X^{N,i})_{1 \leq i \leq N}) / \mathcal{L}((\tilde{X}^{N,i})_{1 \leq i \leq N})$

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Thank you for your attention !

Questions ?