

Symmetric Particle Model

A Brownian Particle System with Local Time Interaction

Kevin A. Buhr

Thomas G. Kurtz

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Consider a K -density collection of particles located in \mathbb{R} with types in E .

Start them at:

$$\sum \delta_{(X_j(0), Z_j(0))} \sim PPP(K\nu)$$

where ν is a measure on $\mathbb{R} \times E$ with $\nu(\cdot, E) = \ell_{\mathbb{R}}$.

Evolve them as:

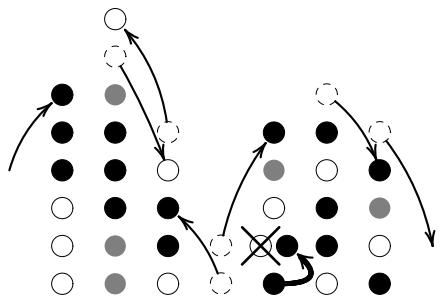
$$\begin{aligned} \text{(Locations)} \quad X_j(t) &= X_j(0) + \sqrt{\theta} W_j(t) \\ \text{(Interactions)} \quad \tilde{V}_{ij}(t) &= N_{ij} \left(\frac{\lambda}{2} L_t^0(X_i - X_j) \right) \\ \text{(Types)} \quad \tilde{Z}_j(t) &= Z_j(0) \\ &\quad + \sum_{i \neq j} \int_0^t (\tilde{Z}_i(s-) - \tilde{Z}_j(s-)) d\tilde{V}_{ij}(s) \\ &\quad + \text{Mutation}(t) \end{aligned}$$

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Genetic Stepping-Stone Model

- one-dimensional lattice $n^{-1}\mathbb{Z}$ of sites;
- initially distributed iid Poisson mean $n^{-1}K$;
- site-to-site migration (rate θn^2);
- Moran dynamics (rate n) at each site.



Genetic Stepping-Stone Model

Consider a K -density collection of particles living in $n^{-1}\mathbb{Z}$ with types in E .

Start them at:

$$\sum \delta_{(X_j^n(0), Z_j^n(0))} \sim PPP(K\nu^n)$$

where ν^n is a measure on $n^{-1}\mathbb{Z} \times E$ with $\nu^n(\cdot, E) = \sum_{x \in n^{-1}\mathbb{Z}} n^{-1} \delta_x$.

Evolve them as:

$$\begin{aligned} \text{(Locations)} \quad X_j^n(t) &= X_j^n(0) + \frac{1}{n} W_j^{\mathbb{Z}}(\theta n^2 t) \\ \text{(Interactions)} \quad \tilde{V}_{ij}^n(t) &= N_{ij} \left(\frac{\lambda}{2} \int_0^t n \cdot 1_{\{X_i^n(s) = X_j^n(s)\}} 2\theta ds \right) \\ \text{(Types)} \quad \tilde{Z}_j^n(t) &= Z_j^n(0) \\ &\quad + \sum_{i \neq j} \int_0^t (\tilde{Z}_i^n(s-) - \tilde{Z}_j^n(s-)) d\tilde{V}_{ij}^n(s) \\ &\quad + \text{Mutation}(t) \end{aligned}$$

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Brownian Particle System

Stepping-Stone Limit

Instead of

We have

$$((X_j^n)_j, (\tilde{V}_{ij}^n)_{i \neq j}) \Rightarrow ((X_j)_j, (V_{ij})_{i \neq j})$$

in J_1 topology.

Under $\nu^n \rightarrow \nu$ and some regularity conditions on mutation, we will have

$$(X_j^n, \tilde{Z}_j^n)_j \Rightarrow (X_j, \tilde{Z}_j)_j$$

Types evolve as:

$$\begin{aligned} Z_j(t) &= Z_j(0) \\ &+ \sum_{i \neq j} \int_0^t (Z_i(s-) - Z_j(s-)) dV_{ij}(s) \\ &+ \text{Mutation}(t) \end{aligned}$$

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Infinite-Density System ξ

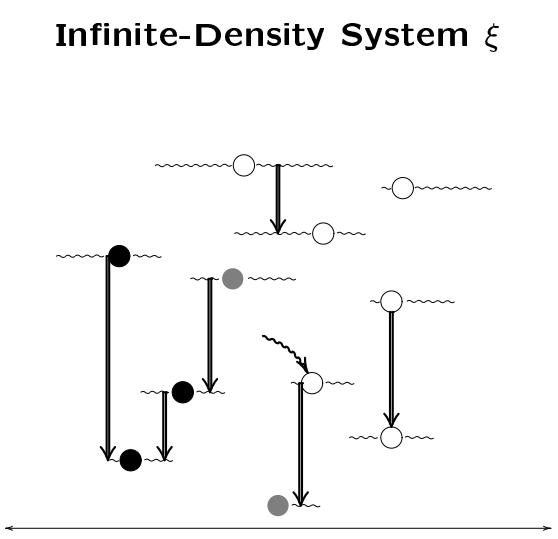
Start particles at:

$$\sum \delta_{(X_j(0), Z_j(0), U_j)} \sim PPP(\nu \times \ell_{\mathbb{R}^+})$$

Evolve them as:

$$\begin{aligned} \text{(Locations)} \quad X_j(t) &= X_j(0) + \sqrt{\theta} W_j(t) \\ \text{(Interactions)} \quad V_{ij}(t) &= N_{ij} \left(\mathbf{1}_{\{U_i < U_j\}} \lambda L_t^0 (X_i - X_j) \right) \\ \text{(Types)} \quad Z_j(t) &= Z_j(0) \\ &+ \sum_{i \neq j} \int_0^t (Z_i(s-) - Z_j(s-)) dV_{ij}(s) \\ &+ \text{Mutation}(t) \end{aligned}$$

Write $\xi_t = \sum_j \delta_{(X_j(t), Z_j(t), U_j)}$.



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An Intermediate Model

LTFBI:

- $\sum_j \delta_{(X_j(0), Z_j(0))} \sim PPP(K\nu)$;
- W_j iid Brownian motions on \mathbb{R} ;
- $N_{\{i,j\}}$ iid rate 1 Poisson counters;
- $\pi_{\{i,j\},k}$ iid uniform random $\{i,j\} \leftrightarrow \{i,j\}$;
- U_j iid $U[0, K]$.

Define Brownian locations

$$\tilde{X}_j(t) = X_j(0) + \sqrt{\theta} W_j(t)$$

and directionless interactions

$$V_{\{i,j\}}(t) = N_{\{i,j\}}(\lambda L_t^0(\tilde{X}_i - \tilde{X}_j))$$

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Ordering the Model

Some notation:

- Let $\{T_{\{i,j\},k}\}_{k \in \mathbb{N}}$ be the ordered jump times of $V_{\{i,j\}}$;
- Let $\{(T_{j,k}, \pi_{j,k})\}$ be the strict ordering of $\{(T_{\{i,j\},k}, \pi_{\{i,j\},k}) : \forall i \neq j, \forall k\}$ by first component.

That is, j interacts at $T_{j,1} < T_{j,2} < \dots$, and at $T_{j,k}$, there is a $\pi_{j,k} : \{i,j\} \leftrightarrow \{i,j\}$.

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Ordering the Model

Theorem 1. There exist $[0, K]$ -valued, left-continuous, jump processes \tilde{U}_j satisfying

$$\tilde{U}_j(t) = \begin{cases} U_j, & 0 \leq t \leq T_{j,1}; \\ \tilde{U}_{\pi_{j,l}(j)}(T_{j,l}), & T_{j,l} < t \leq T_{j,l+1}. \end{cases}$$

and \mathbb{N} -valued, left-continuous jump processes Φ_j satisfying

$$\tilde{U}_{\Phi_j(t)}(t) = U_j$$

For each fixed $t \geq 0$, conditioned on

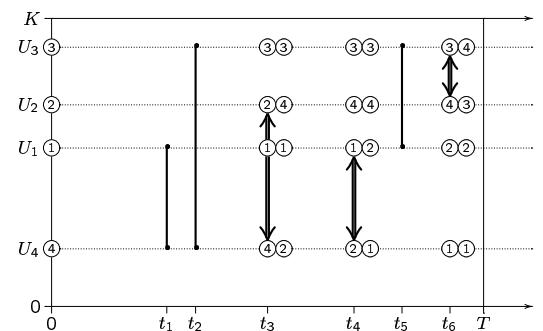
$$\sigma \left\{ T_{\{i,j\},k}, 1_{\{\tilde{U}_i(T_{\{i,j\},k}) < \tilde{U}_j(T_{\{i,j\},k}\}} : T_{\{i,j\},k} < t \right\}$$

the $\tilde{U}_j(t)$ are iid $U[0, K]$.

(Thus, conditioned on $\sigma\{T_{\{i,j\},k}\}$, the $1_{\{\tilde{U}_i(T_{\{i,j\},k}) < \tilde{U}_j(T_{\{i,j\},k}\}}$ are iid coin flips.)

Ordered Intermediate Model

① = level of particle j



j	$\Phi_j(0+)$	$\Phi_j(t_3+)$	$\Phi_j(t_4+)$	$\Phi_j(t_6+)$	$\tilde{U}_{\Phi_j(t)}(t)$
1	1		1	2	U_1
2	2	4	4	3	U_2
3	3	3	3	4	U_3
4	4	2	1	1	U_4

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Deriving the Symmetric Particle Model

Define \tilde{V}_{ij} (started at 0) by

$$\Delta \tilde{V}_{ij}(t) = \sum_{k=1}^{\infty} 1_{\{t=T_{\{i,j\},k}\}} 1_{\{\tilde{U}_i(t) < \tilde{U}_j(t)\}}$$

By Theorem 1,

$$\tilde{V}_{ij} =^d N_{ij} \left(\frac{\lambda}{2} L_t^0 (\tilde{X}_i - \tilde{X}_j) \right)$$

If we define

$$\begin{aligned} \tilde{Z}_j(t) &= Z_j(0) \\ &+ \sum_{i \neq j} \int_0^t (\tilde{Z}_i(s-) - \tilde{Z}_j(s-)) d\tilde{V}_{ij}(s) \\ &+ \text{Mutation}(t) \end{aligned}$$

then $(\tilde{X}_j, \tilde{Z}_j)$ is the K -density symmetric model.

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Deriving the Infinite-Density System ξ

Define Brownian locations

$$X_j(t) = \tilde{X}_{\Phi_j(t)}(t)$$

Define V_{ij} (started at 0) by

$$\Delta V_{ij}(t) = 1_{\{U_i < U_j\}} \sum_{k=1}^{\infty} 1_{\{t=T_{\{\Phi_i(t), \Phi_j(t)\},k}\}}$$

If we define

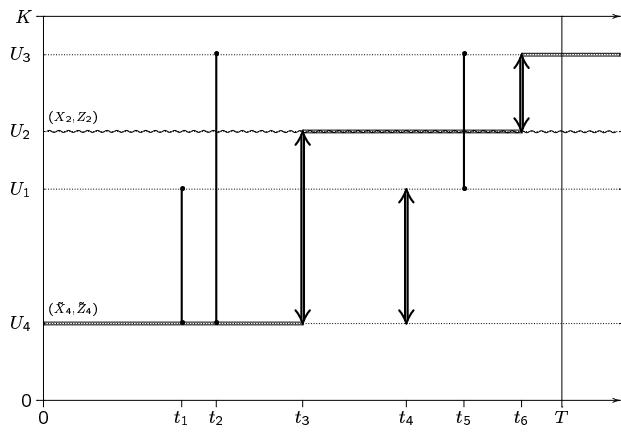
$$\begin{aligned} Z_j(t) &= Z_j(0) \\ &+ \sum_{i \neq j} \int_0^t (Z_i(s-) - Z_j(s-)) dV_{ij}(s) \\ &+ \text{Mutation}(t) \end{aligned}$$

then

$$\sum \delta_{(X_j, Z_j, U_j)} =^d \xi|_{\mathbb{R} \times E \times [0, K]}$$

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Symmetric and ξ Particles



Consequence: $\sum \delta_{(\tilde{X}_j, \tilde{Z}_j)} = \sum \delta_{(X_j, Z_j)}$

Some Notation

Consider the infinite density model on $\mathbb{R} \times E \times \mathbb{R}^+$:

$$\xi_t = \sum_j \delta_{(X_j(t), Z_j(t), U_j)}$$

Write

$$\langle u^K_t, g \rangle = \sum_{U_j \leq K} g(X_j(t), Z_j(t))$$

and define

$$\begin{aligned} \mathfrak{F}_t^K &= \sigma \left\{ \xi|_{\mathbb{R} \times E \times (K, \infty)}(r), \sum_{U_j \leq K} \delta_{(X_j, Z_j)}(r), r \leq t \right\} \\ \mathfrak{F}_t^\infty &= \bigcap_{K>0} \mathfrak{F}_t^K \end{aligned}$$

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Limits Location-Type Measure

We are interested in $\langle u_t, g \rangle \equiv \lim_{K \rightarrow \infty} \frac{1}{K} \langle u_t^K, g \rangle$.

Theorem 2. For $g \in B_c(\mathbb{R} \times E)$, we have

$$\frac{1}{K} \langle u_t^K, g \rangle = \mathbb{E}[\langle u_t^1, g \rangle \mid \mathfrak{F}_t^K] \xrightarrow[K \rightarrow \infty]{} \mathbb{E}[\langle u_t^1, g \rangle \mid \mathfrak{F}_t^\infty]$$

almost surely and in L_1 .

Proof. By the coupling,

$$\begin{aligned} & \mathbb{E}[\langle u_t^1, g \rangle \mid \mathfrak{F}_t^K] \\ &= \mathbb{E}\left[\sum_{U_j \leq K} 1_{\{U_j \leq 1\}} g(X_j(t), Z_j(t)) \mid \mathfrak{F}_t^K\right] \\ &= \mathbb{E}\left[\frac{1}{K} \sum_{U_j \leq K} g(X_j(t), Z_j(t)) \mid \mathfrak{F}_t^K\right] \end{aligned}$$

Convergence follows as $\mathbb{E}[\langle u_t^1, g \rangle \mid \mathfrak{F}_t^K]$ is a backwards martingale in K . \square

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Poisson Structure

Why is $\langle u_t, g \rangle \equiv \lim_{K \rightarrow \infty} \frac{1}{K} \langle u_t^K, g \rangle$ interesting?

Theorem 3. For all $t \geq 0$, conditioned on \mathfrak{F}_t^∞ , the process ξ_t is $PPP(\nu_t \times \ell_{\mathbb{R}^+})$ where $\nu_t(F) = \langle u_t, 1_F \rangle$.

Remark 1. Note that $\nu_t(\cdot, E) = \ell_E$. By Morando's Theorem, we may (with abuse of notation) write:

$$\nu_t(dx, dz) = \nu_t(x, dz)dx$$

An Itô Identity

Take the mutation to satisfy

$$g(Y(t)) = g(y) + \int_0^t Bg(Y(s))ds + M^g(t)$$

For $f \in C_c^2(\mathbb{R})$ and $g \in \mathfrak{D}(B)$, we claim

$$\begin{aligned} & \langle u_t^1, fg \rangle - \langle u_0^1, fg \rangle - \int_0^t \left\langle u_s^1, \frac{\theta}{2} f'' g + fBg \right\rangle ds \\ &= \sqrt{\theta} \sum_{U_j \leq 1} \int_0^t f'(X_j(s))g(Z_j(s-))dW_j(s) \\ &+ \sum_{U_j \leq 1} \int_0^t f(X_j(s))dM_j^g(s) \\ &+ \sum_{U_i < U_j \leq 1} \int_0^t (f(X_i(s))g(Z_i(s-)) - \\ &\quad f(X_j(s))g(Z_j(s-)))dV_{ij}(s) \end{aligned}$$

is an (\mathfrak{F}_t^1) -martingale.

A Martingale Problem

Lemma 4. If $\mathfrak{F}_t \subseteq \mathfrak{G}_t$ then

$$H(t) - \int_0^t K(s)ds$$

a (\mathfrak{G}_t) -martingale implies

$$\mathbb{E}[H(t) \mid \mathfrak{F}_t] - \int_0^t \mathbb{E}[K(s) \mid \mathfrak{F}_s]ds$$

an (\mathfrak{F}_t) -martingale.

Therefore,

$$\langle u_t^1, fg \rangle - \langle u_0^1, fg \rangle - \int_0^t \left\langle u_s^1, \frac{\theta}{2} f'' g + fBg \right\rangle ds$$

an (\mathfrak{F}_t^1) -martingale implies

$$\langle u_t, fg \rangle - \langle u_0, fg \rangle - \int_0^t \left\langle u_s, \frac{\theta}{2} f'' g + fBg \right\rangle ds$$

is an (\mathfrak{F}_t^∞) -martingale.

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The Angle-Brackets Process $\langle M \rangle$

Consider the (\mathfrak{F}_t^∞) - and (\mathfrak{F}_t^K) -martingales:

$$M_t = \langle u_t, fg \rangle - \langle u_0, fg \rangle - \int_0^t \langle u_s, \frac{\theta}{2} f'' g + f B g \rangle ds$$

$$M_t^K = \frac{1}{K} \left\{ \langle u_t^K, fg \rangle - \langle u_0^K, fg \rangle - \int_0^t \langle u_s^K, \frac{\theta}{2} f'' g + f B g \rangle ds \right\}$$

Lemma 5. For all $t \geq 0$, $M_t^K \xrightarrow{L_2} M_t$.

Lemma 6. If $\langle M^K \rangle_t \xrightarrow{L_1} A_t$ for predictable A , then $\langle M \rangle = A$.

Proof. For $0 \leq s < t$,

$$0 = \mathbb{E} \left[\left((M_u^K)^2 - \langle M^K \rangle_u \right) \Big|_{u=s}^{u=t} \mid \mathfrak{F}_s^\infty \right]$$

$$\xrightarrow{L_1} \mathbb{E} \left[\left((M_u)^2 - A_u \right) \Big|_{u=s}^{u=t} \mid \mathfrak{F}_s^\infty \right]$$

□

By the same Itô identity,

$$M_t^K = \frac{1}{K} \left\{ \langle u_t^K, fg \rangle - \langle u_0^K, fg \rangle - \int_0^t \langle u_s^K, \frac{\theta}{2} f'' g + f B g \rangle ds \right\}$$

$$= \frac{1}{K} \left\{ \sqrt{\theta} \sum_{U_j \leq K} \int_0^t f'(X_j(s)) g(Z_j(s-)) dW_j(s) \right.$$

$$+ \sum_{U_j \leq K} \int_0^t f(X_j(s)) dM_j^g(s)$$

$$+ \sum_{U_i < U_j \leq K} \int_0^t (f(X_i(s)) g(Z_i(s-)) - f(X_j(s)) g(Z_j(s-))) dV_{ij}(s) \right\}$$

Thus,

$$\langle M^K \rangle_t = O_p(\frac{1}{K})$$

$$+ \frac{\lambda}{K^2} \sum_{U_i < U_j \leq K} \int_0^t (f(X_i(s)) g(Z_i(s-)) - f(X_j(s)) g(Z_j(s-)))^2 dL_t^0(X_i - X_j)(s)$$

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Calculating $\langle M \rangle$

Write

$$h_{ij} = (f(X_i(s)) g(Z_i(s-)) - f(X_j(s)) g(Z_j(s-)))^2$$

Then

$$\begin{aligned} & \frac{\lambda}{K^2} \sum_{U_i < U_j \leq K} \int_0^t h_{ij} dL_t^0(X_i - X_j)(s) \\ & \approx \frac{\lambda}{K^2} \sum_{U_i < U_j \leq K} \int_0^t h_{ij} \int_{\mathbb{R}} n^2 \mathbf{1}_{\{X_i(s), X_j(s) \in (x, x + \frac{1}{n})\}} dx 2\theta ds \\ & \xrightarrow{L_1} 2\theta \lambda \int_0^t \int_{\mathbb{R}} \left(n \int_x^{x + \frac{1}{n}} \int_E f^2(y) g^2(z) \nu_s(y, dz) dy \right. \\ & \quad \left. - \left(n \int_x^{x + \frac{1}{n}} \int_E f(y) g(z) \nu_s(y, dz) dy \right)^2 \right) dx ds \\ & \approx 2\theta \lambda \int_0^t \int_{\mathbb{R}} \left(\int_E f^2(x) g^2(z) \nu_s(x, dz) \right. \\ & \quad \left. - \left(\int_E f(x) g(z) \nu_s(x, dz) \right)^2 \right) dx ds \\ & = \theta \lambda \int_0^t \int_{\mathbb{R}} \int_{E \times E} f^2(x) (g(z) - g(z'))^2 \nu_s(x, dz) \nu_s(x, dz') dx ds \end{aligned}$$

Complete Martingale Problem

For $f \in C_c^2(\mathbb{R})$ and $g \in \mathfrak{D}(B)$, we have

$$\langle u_t, fg \rangle - \langle u_0, fg \rangle - \int_0^t \langle u_s, \frac{\theta}{2} f'' g + f B g \rangle ds$$

an (\mathfrak{F}_t^∞) -martingale with angle-brackets process (and quadratic variation)

$$\theta \lambda \int_0^t \int_{\mathbb{R}} \int_{E \times E} f^2(x) (g(z) - g(z'))^2 \nu_s(x, dz) \nu_s(x, dz') dx ds$$

Is the solution unique?

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Mueller-Tribe SPDE

- Two types $E = \{0, 1\}$;
- No mutation.

Then, for $g = \delta_1$ and $u(s, x) = \nu_s(x, \delta_1)$, we have

$$\int_{\mathbb{R}} f(x)u(t, x)dx - \int_{\mathbb{R}} f(x)u(0, x)dx - \frac{\theta}{2} \int_0^t f''(x)u(s, x)dx ds$$

a martingale with quadratic variation

$$2\theta\lambda \int_0^t \int_{\mathbb{R}} f^2(x)u(s, x)(1 - u(s, x))dx ds$$

Thus, u is a weak solution of:

$$\dot{u} = \frac{\theta}{2}\Delta u + \sqrt{2\theta\lambda u(1 - u)}\dot{W}$$