

# Historical processes and their diffusion limits for modelling populations with past dependence

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# Motivation

★ **Structured populations:** individuals are characterized by variables that affect their reproducing and survival capacities. Here: trait  $x \in \mathcal{X} \subset \mathbb{R}^d$  that is inherited from a parent to its offspring.

★ Continuous time birth-death processes, stochastic evolution based on individual dynamics **with past dependence** and **competition**.

★ **Purpose here: Modelling of genealogies and ancestral paths**  
Ex: Application to the modelling of social interactions based on kin relations (cooperative breeding).

# The biological assumptions

- ★ Large population,
- ★ Fixed amount of resources: small individuals with density dependence,
- ★ Fast births and deaths: allometric demographics (lifetimes and gestation lengths are proportional to individual biomass), however the demographic balance is preserved.
- ★ Asexual reproduction,
- ★ Small mutation steps: mutant offspring look like their parent.

Introduction

**Genealogies and ancestral paths**

Individual dynamics

Population evolution and historical superprocess limit

Numerical examples

# Births and ancestral lineages

## ★ Trait at birth:

- ▶ With probability  $1 - p$ , the trait of the parent  $x$  is inherited.
- ▶ With probability  $p$ , there is a mutation. The new trait is  $x + h$  where  $h \rightsquigarrow \pi^n(h)dh$ ,  $\pi^n$  being a Gaussian kernel with expectation 0 and variance  $(\sigma^2/n)\text{Id}$ .

We define:

$$K^n(dh) = p \pi^n(h)dh + (1 - p) \delta_0(dh).$$

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★ We consider the ancestral path or lineage:

$y_t$  = trait of the ancestor living at time  $t$

$y \in \mathbb{D}_{\mathbb{R}^d} = \mathbb{D}(\mathbb{R}_+, \mathbb{R}^d)$  embedded with the Skorohod topology.

**Notation:**  $y_t, y^t = y_{\cdot \wedge t}, (y|s|w)$

# Particle system

★ Recall:  $y \in \mathbb{D}_{\mathbb{R}^d} = \mathbb{D}(\mathbb{R}_+, \mathbb{R}^d)$

**Notation:**  $y_t, y^t = y_{\cdot \wedge t}, (y|s|w)$

★ Population:

$$X_t^n(dy) = \frac{1}{n} \sum_{i=1}^{N_t^n} \delta_{y_{i \wedge t}}(dy)$$

in  $\mathcal{M}(\mathbb{D}_{\mathbb{R}^d})$  embedded with the weak convergence topology. Thus  $X^n \in \mathbb{D}(\mathbb{R}_+, \mathcal{M}_F(\mathbb{D}_{\mathbb{R}^d}))$ , embedded with the Skorohod topology.

## Related works

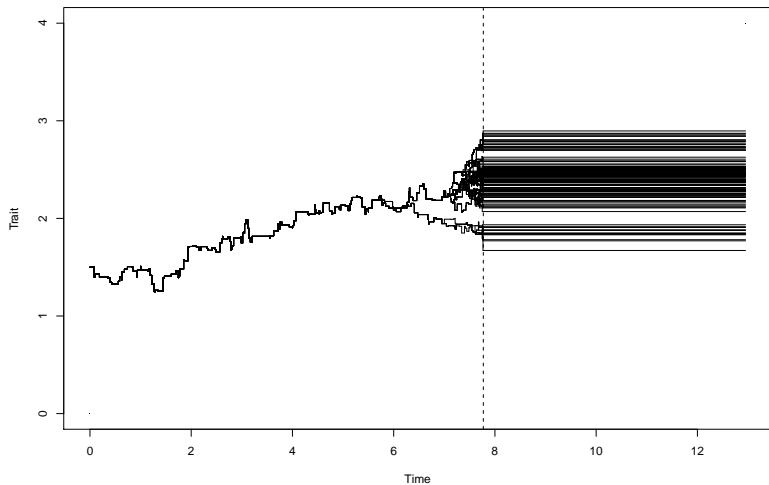
★ Historical Processes: Dawson-Perkins (1991), Perkins (1995), Etheridge (2000)

★ Coalescent: Berestycki N. (book: 2009), Schweinsberg (2000), Möhle Sagitov (2001)

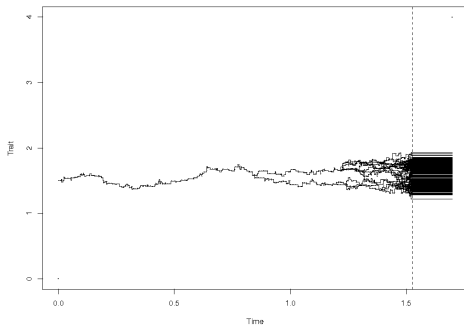
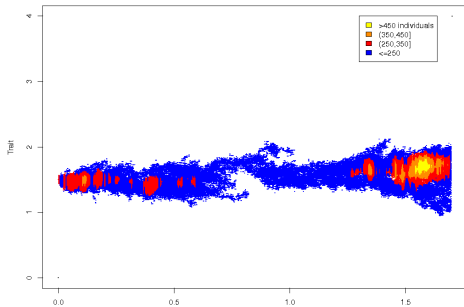
★ Tree-valued processes: Greven Pfaffelhuber Winter (2009,2010)

★ Superprocess renormalization: Dynkin (1991), Dawson (1991).

# An example of evolving genealogies







Introduction

Genealogies and ancestral paths

**Individual dynamics**

Population evolution and historical superprocess limit

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# Birth and death rates: examples

★ Allometric birth and death rates:

$$nr(t, y) + b(t, y)$$

$$nr(t, y) + d(t, y, X_t^n)$$

★ Birth rate:  $nr(t, y) + b(t, y)$  with

$$b(t, y) = B\left(\int_{[0, t)} y_{t-s} \nu_b(ds)\right)$$

▶  $\nu_b(ds) = \delta_0(ds)$

▶  $\nu_b(ds) = e^{-\alpha s} ds$

★ Death rate:  $nr(t, y) + d(t, y, X)$  with

$$d(t, y, X) = d_0(t, y) + \int_0^t \int_{\mathbb{D}} U(t, y, y') X_{t-s}(dy') \nu_d(ds)$$

# Examples

★ **Dieckmann-Doebeli:**  $r(t, y) = 1$  and

$$b(t, y) = \exp\left(-\frac{(y_t - 2)^2}{2\sigma_b^2}\right), \quad d(t, y, X) = \int_{\mathbb{D}} \exp\left(-\frac{(y_t - y'_t)^2}{2\sigma_U^2}\right) X(dy')$$

★ **Adler's fattened goats:**

$$U(t, y, y') = K_\varepsilon(y_t - y'_t),$$

$$d(t, y, X) = \int_0^t \int_{\mathbb{D}_{\mathbb{R}^d}} K_\varepsilon(y_t - y'_s) X_s(dy') e^{-\alpha(t-s)} ds.$$

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# Evolution equation

★  $\sup_{n \in \mathbb{N}^*} \mathbb{E}(\langle X_0^n, 1 \rangle^3) < +\infty, \Rightarrow \sup_{n \in \mathbb{N}^*} \mathbb{E}(\sup_{t \in [0, T]} \langle X_t^n, 1 \rangle^3) < +\infty.$

★ For bounded test functions  $\varphi$  of  $y \in \mathbb{D}_{\mathbb{R}^d}$ :

$$\begin{aligned} M_t^{n, \varphi} = & \langle X_t^n, \varphi \rangle - \langle X_0^n, \varphi \rangle - \int_0^t \int_{\mathbb{D}_{\mathbb{R}^d}} X_s^n(dy) ds \left[ \right. \\ & nr(s, y) \int_{\mathbb{R}^d} (\varphi(y|s|y_s + h) - \varphi(y)) K^n(y_s, dh) \\ & \left. + b(s, y) \int_{\mathbb{R}^d} \varphi(y|s|y_s + h) K^n(y_s, dh) - d(s, y, (X^n)^s) \varphi(y) \right] \end{aligned}$$

is a square integrable martingale starting from 0 with quadratic variation:

$$\begin{aligned} \langle M^{n, \varphi} \rangle_t = & \frac{1}{n} \int_0^t \int_{\mathbb{D}_{\mathbb{R}^d}} X_s^n(dy) ds \left[ \right. \\ & (nr(s, y) + b(s, y)) \int_{\mathbb{R}^d} \varphi^2(y|s|y_s + h) K^n(y_s, dh) \\ & \left. + (nr(s, y) + d(s, y, (X^n)^s)) \varphi^2(y) \right]. \end{aligned}$$

## Test functions

★ Dawson, Dynkin, Perkins use the following class of test functions:

$$\varphi(y) = \prod_{j=1}^m g_j(y_{t_j})$$

for  $m \in \mathbb{N}^*$ ,  $0 \leq t_1 < \dots < t_m$  and  $\forall j \in \llbracket 1, m \rrbracket$ ,  $g_j \in \mathcal{C}_b^2(\mathbb{R}^d, \mathbb{R})$ .  
**However these functions are not necessarily continuous for discontinuous  $y$ 's.**

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**However these functions are not necessarily continuous for discontinuous  $y$ 's.**

★ For a real  $\mathcal{C}_b^2$ -function  $g$  on  $\mathbb{R}_+ \times \mathbb{R}^d$  and a real  $\mathcal{C}_b^2$ -function  $G$  on  $\mathbb{R}$ , we define the continuous function  $G_g$  as

$$G_g(y) = G\left(\int_0^T g(s, y_s) ds\right).$$



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★ **Lemma:** Let  $\varphi$  be a test function of the 1st form. Then, there exists a sequence of test functions of the second form  $(\varphi_q)_{q \in \mathbb{N}^*}$  such that for every  $y \in \mathbb{D}_{\mathbb{R}^d}$  and every  $t \in \mathbb{R}_+$  at which  $y$  is continuous,

$$\lim_{q \rightarrow +\infty} \varphi_q(y) = \varphi(y).$$

(choose  $G(x) = e^x$  and  $g_q(s, y_s) = \sum_{j=1}^m \log g_j(y_s) k^q(t_j - s)$ )

# Superprocess limit

★ **Prop 1:** The sequence  $(X^n)_{n \in \mathbb{N}^*}$  converges in law in  $\mathbb{D}(\mathbb{R}_+, \mathcal{M}_F(\mathbb{D}_{\mathbb{R}^d}))$  to the superprocess  $\bar{X} \in \mathcal{C}(\mathbb{R}_+, \mathcal{M}_F(\mathbb{D}_{\mathbb{R}^d}))$  characterized as follows, for test functions  $\varphi$  of  $y \in \mathbb{D}_{\mathbb{R}^d}$ :

$$M_t^\varphi = \langle \bar{X}_t, \varphi \rangle - \langle \bar{X}_0, \varphi \rangle - \int_0^t \int_{\mathbb{D}_{\mathbb{R}^d}} \left( pr(s, y) \frac{\sigma^2}{2} D^2 \varphi_{G, g}(s, y) + [b(s, y) - d(s, y, \bar{X}_s)] \varphi(y) \right) \bar{X}_s(dy) ds$$

is a square integrable martingale where:

$$D^2 \varphi_{G, g}(t, y) = G' \left( \int_0^T g(s, y_s) ds \right) \int_t^T \Delta_x g(s, y_t) ds + G'' \left( \int_0^T g(s, y_s) ds \right) \sum_{i=1}^d \left( \int_t^T \partial_{x_i} g(s, y_t) ds \right)^2.$$

with quadratic variation:

$$\langle M^{\varphi_{G, g}} \rangle_t = \int_0^t \int_{\mathbb{D}_{\mathbb{R}^d}} 2 r(s, y) \sigma^2 \varphi_{G, g}^2(y) \bar{X}_s(dy) ds.$$

# Martingale problem for the tests functions of Dawson

★ For the Laplacian  $\Delta$  of  $\mathbb{R}^d$ , a path  $y \in \mathbb{D}_{\mathbb{R}^d}$ , a time  $t > 0$  and a test function  $\varphi$  of the product form:

$$\tilde{\Delta}\varphi(t, y) = \sum_{k=0}^{m-1} \mathbf{1}_{[t_k, t_{k+1}[}(t) \left( \prod_{j=1}^k g_j(y_{t_j}) \Delta \left( \prod_{j=k+1}^m g_j \right) (y_t) \right)$$

with  $t_0 = 0$  and  $t_{m+1} = t$ .

★ **Prop 2:** The solutions of the MP of Prop 1 satisfy the MP:

$$M_t^\varphi = \langle \bar{X}_t, \varphi \rangle - \langle \bar{X}_0, \varphi \rangle - \int_0^t \int_{\mathbb{D}_{\mathbb{R}^d}} \left( pr(s, y) \frac{\sigma^2}{2} \tilde{\Delta}\varphi(s, y) + \left[ b(s, y) - d(s, y, \bar{X}_s) \right] \varphi(y) \right) \bar{X}_s(dy) ds,$$

the bracket being as in Prop 1.

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the bracket being as in Prop 1.

★ **Idea of the proof of the Prop 1:**

Tightness of the sequence  $(X^n)$ .

Uniqueness of the solution of the MP of Prop 2.

# Tightness criterion

**Prop: from [Dawson-Perkins, (Ethier-Kurtz)]**  $(X^n)_{n \in \mathbb{N}^*}$  is tight in  $\mathbb{D}(\mathbb{R}_+, \mathcal{M}_F(\mathbb{D}_{\mathbb{R}^d}))$  if:

(i)  $\forall T > 0, \forall \varepsilon > 0, \exists K \subset \mathbb{D}_{\mathbb{R}^d}$  compact,

$$\sup_{n \in \mathbb{N}^*} \mathbb{P}(\exists t \in [0, T], X_t^n(K_T^c) > \varepsilon) \leq \varepsilon,$$

where

$$K_T = \{y^t, y^{t-} \mid y \in K, t \in [0, T]\} \subset \mathbb{D}_{\mathbb{R}^d}. \quad (1)$$

(ii)  $\forall \varphi \in \mathcal{C}_b(\mathbb{D}_{\mathbb{R}^d}, \mathbb{R}_+)$ , the family  $(\langle X^n, \varphi \rangle)_{n \in \mathbb{N}^*}$  is tight in  $\mathbb{D}_{\mathbb{R}_+}$ .

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★ Let us define  $S_\varepsilon^n = \inf\{t \geq 0, X_t^n(K_T^c) > \varepsilon\}$ .

$$\mathbb{P}(S_\varepsilon^n < T) = \mathbb{P}\left(S_\varepsilon^n < T, X_T^n((K^T)^c) > \frac{\varepsilon}{2}\right) + \mathbb{P}\left(S_\varepsilon^n < T, X_T^n((K^T)^c) \leq \frac{\varepsilon}{2}\right)$$

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★ Let us define  $S_\varepsilon^n = \inf\{t \geq 0, X_t^n(K_T^c) > \varepsilon\}$ .

$$\begin{aligned} \mathbb{P}(S_\varepsilon^n < T) &= \mathbb{P}\left(S_\varepsilon^n < T, X_T^n((K^T)^c) > \frac{\varepsilon}{2}\right) + \mathbb{P}\left(S_\varepsilon^n < T, X_T^n((K^T)^c) \leq \frac{\varepsilon}{2}\right) \\ &\leq \frac{2}{\varepsilon} \mathbb{E}(X_T^n((K^T)^c)) + \mathbb{P}(S_\varepsilon^n < T)(1 - \eta) \end{aligned}$$

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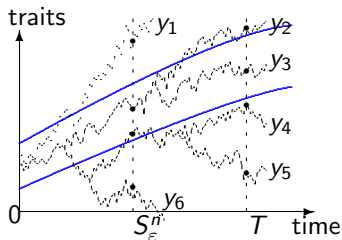
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Then:

$$\mathbb{P}(S_\varepsilon^n < T) \leq \frac{2\mathbb{E}(X_T^n((K^T)^c))}{\varepsilon\eta}.$$



Upperbound of  $\mathbb{P}\left(S_\varepsilon^n < T, X_T^n((K^T)^c) \leq \frac{\varepsilon}{2}\right)$



★ The mass of particles **started at  $S_\varepsilon^n$**  and corresponding to trajectories  $y^{S_\varepsilon^n} \notin K^{S_\varepsilon^n}$  is approximated by:

$$\mathcal{Y}_t = \mathcal{Y}_0 + \int_0^t (\bar{b} - \underline{d}) \mathcal{Y}_s ds + \int_0^t \sqrt{\rho(s)} \mathcal{Y}_s dB_s$$

where  $2\underline{r} \leq \rho(s) \leq 2\bar{r}$  is defined by the limit of the quadratic variation.

★  $\mathbb{P}_\varepsilon(\inf_{s \in [0, T]} \mathcal{Y}_s > \varepsilon/2) > 0$ .

# Uniqueness

★ By Dawson-Girsanov's theorem, we can find a probability measure  $\mathbb{Q}$  on  $\mathcal{C}([0, T], \mathcal{M}_F(\mathbb{D}_{\mathbb{R}^d}))$  under which:

$$\tilde{M}_t^\varphi = \langle \bar{X}_t, \varphi \rangle - \langle \bar{X}_0, \varphi \rangle - \int_0^t \int_{\mathbb{D}_{\mathbb{R}^d}} \frac{pr(s, y)\sigma^2}{2} \tilde{\Delta}\varphi(s, y) \bar{X}_s(dy) ds$$

is a martingale with the same bracket as above.

★ Pathwise existence and uniqueness for the SDE in  $\mathbb{R}^d$ :

$$Y_t = Y_0 + \int_0^t \sqrt{\sigma^2 pr(s, Y^s)} dB_s.$$

$$W_t = Y_t^t \text{ and } S_{s,t}\varphi(y) = \mathbb{E}^{\mathbb{Q}}(\varphi(W_t) | W_s = y^s).$$

★ We have that

$$\mathbb{E}^{\mathbb{Q}}(\exp(-\langle \bar{X}_t, \varphi \rangle) | \bar{X}_s = \delta_{y^s}) = e^{-V_{s,t}\varphi(y)}$$

where  $V_{s,t}\varphi(y)$  is the unique solution of:

$$V_{s,t}\varphi(y) = S_{s,t}\varphi(y) - \int_s^t \frac{p\sigma^2}{2} S_{s,u} \left( r(u, \cdot) (V_{u,t}\varphi(\cdot))^2 \right) (y) du.$$

# Lineages' distributions

★ Perkins' representation:

Under  $\mathbb{Q}$ , we have in distribution:

$$Y_t(\mathbf{y}) = Y_0(\mathbf{y}) + \int_0^t \sqrt{\sigma^2 p_r(s, Y^s(\mathbf{y}))} d\mathbf{y}_s$$
$$\bar{X}_0, \quad \langle \bar{X}_t, \varphi \rangle = \int_{\mathbb{D}_{\mathbb{R}^d}} \varphi(Y(\mathbf{y})^t) H_t(d\mathbf{y})$$

where  $(H_t(d\mathbf{y}))_{t \in \mathbb{R}_+}$  is under  $\mathbb{Q}$  a historical Brownian superprocess.

## Lineages' distributions: case of constant $r$ and $b - d$ 's

★  $\langle \mu_t, \varphi \rangle = \langle \bar{X}_t, \varphi \rangle / \langle \bar{X}_t, 1 \rangle$ . When  $r$  and  $b - d$  are constant:

$$\langle \mathbb{E}(\mu_t), \varphi \rangle = \langle \mathbb{E}(\mu_0), \varphi \rangle + \int_0^t \langle \mathbb{E}(\mu_s), pr\sigma^2 \tilde{\Delta} \varphi(s, \cdot) \rangle ds.$$

$b - d = 0$ : historical super Brownian motion (Dawson Perkins 91).

★ For the historical super Brownian motion, we have a very precise description of the probabilistic structure of the genealogies.

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★ Let  $\phi(\mu) = \langle \mu \otimes \mu, \varphi \rangle = \int_{\mathbb{D}_{\mathbb{R}^d}} \int_{\mathbb{D}_{\mathbb{R}^d}} \varphi(t, y, z) \mu_t(dy) \mu_t(dz)$  and  $\tilde{\Delta}^{(2)} \varphi(y, z) = \tilde{\Delta}(y \mapsto \varphi(y, z)) + \tilde{\Delta}(z \mapsto \varphi(y, z))$ . We recover Fleming-Viot generator:

$$\begin{aligned} L^{FV} \phi(X) &= \frac{pr\sigma^2}{2} \left\langle \frac{X}{\langle X, 1 \rangle} \otimes \frac{X}{\langle X, 1 \rangle}, \tilde{\Delta}^{(2)} \varphi \right\rangle \\ &+ \frac{2r\sigma^2}{\langle X, 1 \rangle} \left( \int_{\mathbb{D}_{\mathbb{R}^d}} \varphi(y, y) \frac{X(dy)}{\langle X, 1 \rangle} - \left\langle \frac{X}{\langle X, 1 \rangle} \otimes \frac{X}{\langle X, 1 \rangle}, \varphi \right\rangle \right) \end{aligned}$$

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$$\text{and } d(t, y, X) = \int_0^t \int_{\mathbb{R}^d} \frac{K_\varepsilon(y'(s) - y(t))}{K} X_s(dy', dc') e^{-\alpha(t-s)} ds$$

