

Large population scalings of stochastic population dynamics in ecology and evolution

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Workshop/School on Stochastic PDEs, Mean Field Games and
Biology, L'Aquila, 6–8 Sept. 2017

Darwinian evolution

Three main ingredients:

- **Heredity**: transmissions of individual characteristics from a generation to the next one.
- **Mutation**: cause of the variability in individual characteristics.
- **Selection**: consequence of interactions between individuals and their environment, including the rest of the population (**ecology**).

Adaptive dynamics (AD)

Adaptive dynamics (Hofbauer and Sigmund 1990, Marrow et al. 1992, Metz et al. 1992):

- describe the evolution of a population by putting emphasis on the **ecological interactions**
↪ density-dependent selection modelled in detail
- heredity (in a first approach) is simplified as much as possible:
asexual (clonal) reproduction
- individual-based
- stochastic
- interactions are modelled in a realistic way
- population size can fluctuate

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Grounded on models that are

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- stochastic
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- population size can fluctuate

Biological motivations

Evolutionary time-scale is not always slow w.r.t. ecological time-scale

- evolution of resistance in pathogens
- genetic adaptation to harvesting
- experimental evolution in microorganisms

↪ Makes sense to study the interplay between ecology and evolution in models

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Implications in biodiversity management

- rapid evolutions usually involve human pressure
- adaptive evolution does not necessarily “rescue” populations
- how can management and restoration practice account for/use the evolutionary process?

Adaptive dynamics scales

The theory of adaptive dynamics (Metz et al., 1996, Dieckman and Law, 1996) proposes simple models approaching the evolution under several assumptions:

- Large populations
- Rare mutations
- Small mutation steps

Ecological models of dispersal

The models of adaptive dynamics can also have a spatial interpretation

- mutations can be seen as spatial dispersion, or other motions (Bolker, Pacala, 1997, Champagnat, Méléard, 2007)
- classical ecological question: links between local interaction and spatial dispersion
- invasion, survival, extinction
- competition between species
- similar scalings can be considered (spatial scaling, dispersal probability/range, time...)

Outline of the lectures

- 1 Description of the stochastic individual-based ecological model; first properties
- 2 Several large population scalings \rightsquigarrow recover classical or original macroscopic models under various biological assumptions and scales, including superprocesses
- 3 Basic properties of the class of SPDE obtained this way
- 4 Properties of local extinction and persistence of these SPDE
- 5 The case of age-dependent evolutionary dynamics

Microscopic model

A general birth-and-death measure-valued process with competition and mutation (already studied in Bolker and Pacala 1997, Dieckmann and Law 2000, Fournier and Méléard 2004,...)

- each individual is characterized by a phenotypic **trait** x (individual size, age at maturity,...) in a closed subset \mathcal{X} of \mathbb{R}^k
- a population of $N(t)$ individuals holding traits $x_1, \dots, x_{N(t)} \in \mathcal{X}$

is represented by $\nu_t = \sum_{i=1}^{N(t)} \delta_{x_i}$

- state space: $\mathcal{M} = \left\{ \sum_{i=1}^n \delta_{x_i} : n \geq 0, x_i \in \mathcal{X} \right\}$

Transitions

- as in the pure multitype branching process:
 - each individual with trait x gives birth at rate $b(x)$ to a single individual of trait x
 - each individual of trait x dies at rate $d(x)$
- in addition,
 - each individual of trait y picks any given individual of trait x at rate $\alpha(x, y)$ and then kills him
 - \rightsquigarrow an individual with trait x dies at rate

$$d(x) + \sum_{i=1}^{N_t} \alpha(x, x_i) = d(x) + \int_{\mathcal{X}} \alpha(x, y) \nu_t(dy)$$

- at each birth from an individual with type x
 - $\mu(x)$ mutation probability
 - $x + h$ mutant trait, where $h \sim m(x, dh)$

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Generator

↪ Markov jump process $(\nu_t, t \geq 0)$ on \mathcal{M} with generator

$$\begin{aligned}
 L\phi(\nu) &= \int_{\mathcal{X}} [\phi(\nu + \delta_x) - \phi(\nu)](1 - \mu(x))b(x)\nu(dx) \\
 &+ \int_{\mathcal{X}} \int_{\mathbb{R}^d} [\phi(\nu + \delta_{x+h}) - \phi(\nu)]\mu(x)b(x)m(x, h)dh \nu(dx) \\
 &+ \int_{\mathcal{X}} [\phi(\nu - \delta_x) - \phi(\nu)] \left(d(x) + \int_{\mathcal{X}} \alpha(x, y)\nu(dy) \right) \nu(dx)
 \end{aligned}$$

Biological comments

- Logistic interaction = competition
Easy generalization to more general interactions (Champagnat, Ferrière, Méléard, 2008)
 - birth rate $b(x, U * \nu_t(x))$
 - death rate $d(x, V * \nu_t(x))$

Example:

$$b(x, U * \nu_t(x)) = b(x) + U * \nu_t(x), \quad d(x, V * \nu_t(x)) = d(x) + V * \nu_t(x)$$

$U \geq V$ corresponds to mutualistic interaction

- Multispecific (prey-predator, host-parasite, ressource exploitation, mutulistic community,...) generalization

Assumptions

$$(A1) \quad 0 \leq \alpha(\cdot, \cdot) \leq \bar{\alpha} < +\infty$$

$$(A1) \quad 0 \leq b(\cdot) \leq \bar{b} < +\infty$$

$$(A1) \quad 0 \leq d(\cdot) \leq \bar{d} < +\infty$$

(A2) $m(x, dh)$ has a density $m(x, h)$ w.r.t. the Lebesgue measure such that $m(x, h) \leq m(h)$ with $\int m(h) dh < +\infty$

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↪ Total jump rate less than $\langle \nu_t, 1 \rangle (\bar{b} + \bar{d} + \bar{\alpha}(\langle \nu_t, 1 \rangle - 1))$

Construction as a SDE driven by Poisson point measures

Given independent PPM M_1, M_3 (resp. M_2) on $\mathbb{R}_+ \times \mathbb{N} \times \mathbb{R}_+$ (resp. $\mathbb{R}_+ \times \mathbb{N} \times \mathbb{R}^d \times \mathbb{R}_+$) with intensity $ds(\sum_{k \geq 1} \delta_k(di))d\theta$ (resp. $ds(\sum_{k \geq 1} \delta_k(di))\bar{m}(h)dh d\theta$),

$$\begin{aligned} \nu_t = & \nu_0 + \int_0^t \int_{\mathbb{N}} \int_0^\infty \delta_{H_{s-}^i} \mathbb{1}_{i \leq \langle \nu_{s-}, 1 \rangle} \mathbb{1}_{\theta \leq b(1-\mu)(H_{s-}^i)} M_1(ds, di, d\theta) \\ & + \int_0^t \int_{\mathbb{N}} \int_{\mathbb{R}^d} \int_0^\infty \delta_{x+h} \mathbb{1}_{i \leq \langle \nu_{s-}, 1 \rangle} \mathbb{1}_{\theta \leq b\mu(H_{s-}^i)m(H_{s-}^i, h)/\bar{m}(H_{s-}^i)} M_2(ds, di, dh, d\theta) \\ & - \int_0^t \int_{\mathbb{N}} \int_0^\infty \delta_{H_{s-}^i} \mathbb{1}_{i \leq \langle \nu_{s-}, 1 \rangle} \mathbb{1}_{\theta \leq d(H_{s-}^i) + \int \alpha(H_{s-}^i, y)\nu_{s-}(dy)} M_3(ds, di, d\theta), \end{aligned}$$

where H_t^i is the i -th atom in ν_t (for some arbitrary order).

Martingale properties (Fournier, Méléard, 2004)

- Bounded birth rate: for $p \geq 1$,
 $\mathbf{E}[\langle \nu_0, \mathbf{1} \rangle^p] < +\infty \Rightarrow \mathbf{E}[\sup_{t \leq T} \langle \nu_t, \mathbf{1} \rangle^p] < +\infty$
- for ϕ with appropriate growth, $\phi(\nu_t) - \phi(\nu_0) - \int_0^t L\phi(\nu_s) ds$ is a càdlàg martingale
- In particular, for $\phi(\nu) = \langle \nu, f \rangle$, assuming $\mathbf{E}[\langle \nu_0, \mathbf{1} \rangle^2] < +\infty$

$$\begin{aligned} \langle \nu_t, f \rangle &= \langle \nu_0, f \rangle + M_t^f \\ &+ \int_0^t \int_{\mathcal{X}} \left\{ [(1 - \mu(x))b(x) - d(x) - \int \alpha(x, y)(\nu_s(dy) - \delta_x(dy))]f(x) \right. \\ &\quad \left. + b(x)\mu(x) \int f(x+z)M(x, z)dz \right\} \nu_s(dx) ds, \end{aligned}$$

with

$$\begin{aligned} \langle M^f \rangle_t &= \int_0^t \int_{\mathcal{X}} \left\{ [(1 - \mu(x))b(x) - d(x) - \int \alpha(x, y)(\nu_s(dy) - \delta_x(dy))]f^2(x) \right. \\ &\quad \left. + b(x)\mu(x) \int f^2(x+z)M(x, z)dz \right\} \nu_s(dx) ds. \end{aligned}$$

Proof of the moments bound

Introducing $\tau_n = \inf\{t \geq 0 : \langle \nu_t, 1 \rangle \geq n\}$, using $(x+1)^p - x^p \leq C_p(1+x^{p-1})$ and

$$\begin{aligned} \sup_{s \leq t \wedge \tau_n} \langle \nu_s, 1 \rangle^p &\leq \langle \nu_0, 1 \rangle^p + \int_0^{t \wedge \tau_n} \int_{\mathbb{N}} \int_{\mathbb{R}^d} \int_0^\infty [(\langle \nu_{s-}, 1 \rangle + 1)^p - \langle \nu_{s-}, 1 \rangle^p] \\ &\quad \mathbb{1}_{i \leq \langle \nu_{s-}, 1 \rangle} \mathbb{1}_{\theta \leq \bar{b}} M_2(ds, di, dh, d\theta) \\ &\quad + \text{similar term for } M_1, \end{aligned}$$

taking expectation, we deduce that

$$\mathbb{E} \sup_{s \leq t \wedge \tau_n} \langle \nu_s, 1 \rangle^p \leq C_p + C_p \mathbb{E} \int_0^t (1 + \langle \nu_{s \wedge \tau_n}, 1 \rangle^p) ds$$

and the result follows from Gronwall.

Example

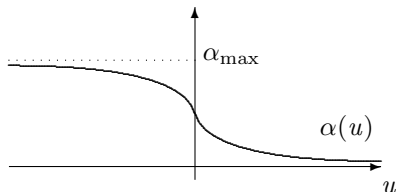
Parameters from Kisdi (1999)

$$\mathcal{X} = [0, 4] \quad d(x) \equiv 0 \quad \mu(x) \equiv \mu$$

$$m(x, h)dh = \mathcal{N}(0, \sigma^2)$$

(conditioned on $x + h \in \mathcal{X}$)

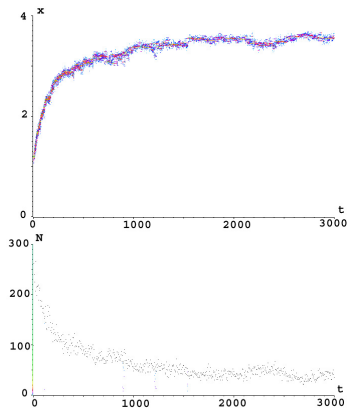
$$b(x) = 4 - x \quad \alpha(x, y) = \alpha(x - y) \quad \text{with}$$



Asymmetric competition

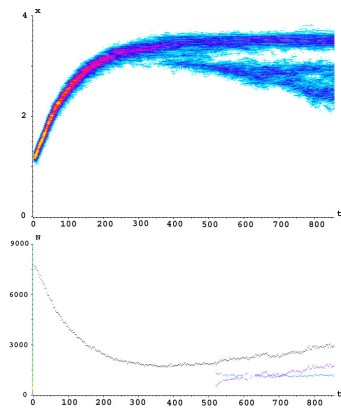
- arm-race competition
- evolution of the cell size at division

Simulations



$$\mu = 0.1 \quad \sigma = 0.03$$

$$\alpha_{\max} = 0.02$$



$$\mu = 0.1 \quad \sigma = 0.03$$

$$\alpha_{\max} = 0.001$$

Large population scalings (C., Ferrière, Méléard, 2008)

Parameter K : b_K , d_K , μ_K , M_K and $\alpha_K(x, y) = \frac{\alpha(x, y)}{K}$

Biological interpretations: K scales the amount of ressources available (carrying capacity, or “system size”), or the size of individuals (w.r.t. their competitive pressure).

$$X_t^K = \frac{1}{K} \sum_{i=1}^{I(t)} \delta_{x_t^i} = \frac{\nu_t^K}{K}$$

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$$\begin{aligned} L^K \phi(X) &= \int_{\mathcal{X}} [\phi(X + \frac{\delta_x}{K}) - \phi(X)] (1 - \mu_K(x)) b_K(x) KX(dx) \\ &+ \int_{\mathcal{X}} \int_{\mathbb{R}^d} [\phi(X + \frac{\delta_{x+z}}{K}) - \phi(X)] \mu_K(x) b_K(x) M_K(x, z) dz KX(dx) \\ &+ \int_{\mathcal{X}} [\phi(X - \frac{\delta_x}{K}) - \phi(X)] \left(d_K(x) + \int_{\mathcal{X}} \frac{\alpha(x, y)}{K} KX(dy) \right) KX(dx) \end{aligned}$$

Simplest large population limit

$$b_K = b, d_K = d, \mu_K = \mu, M_K = M.$$

Only the competitive kernel is modified: limit of large population size.

Theorem

Assume that $X_0^K \Rightarrow \xi_0$, $\sup_K \mathbf{E}[\langle X_0^K, \mathbf{1} \rangle^3] < +\infty$
and smooth parameters.

Then $X^K \Rightarrow \xi \in \mathcal{C}([0, T], M_F(\mathcal{X}))$ deterministic, where

$$\begin{aligned} \langle \xi_t, f \rangle &= \langle \xi_0, f \rangle \\ &+ \int_0^t \int_{\mathcal{X}} \left\{ [(1 - \mu(x))b(x) - d(x) - \int_{\mathcal{X}} \alpha(x, y)\xi_s(dy)]f(x) \right. \\ &\quad \left. + b(x)\mu(x) \int f(x+z)M(x, z)dz \right\} \xi_s(dx) ds. \end{aligned} \quad (1)$$

Kimura's equation for "continuum of alleles", extended to density-dependent selection.

Remark

- If $\xi_0(dx) = u_0(x)dx$, then $\xi_t(dx) = u(t, x)dx$, $\forall t > 0$ and $u(t, x)$ is weak solution to

$$\begin{aligned} \partial_t u = & [(1 - \mu(x))b(x) - d(x) - \int \alpha(x, y)u(t, y)dy]u(t, x) \\ & + \int \mu(y)b(y)M(y, x - y)u(t, y)dy \end{aligned}$$

Sketch of the proof (1)

- Martingale problem

$$\begin{aligned}
 \langle \nu_t, f \rangle &= \langle \nu_0, f \rangle + M_t^f \\
 &+ \int_0^t \int_{\mathcal{X}} \left\{ [(1 - \mu(x))b(x) - d(x) - \int_{\mathcal{X}} \alpha(x, y)\nu_s(dy)]f(x) \right. \\
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 \langle X_t^K, f \rangle &= \langle X_0^K, f \rangle + M_t^{f,K} \\
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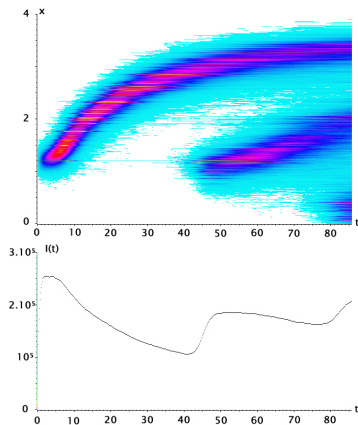
with

$$\begin{aligned} \langle M^{f,K} \rangle_t &= \frac{1}{K^2} \int_0^t \int_{\mathcal{X}} \left\{ [(1 - \mu(x))b(x) - d(x) - \int_{\mathcal{X}} \alpha(x, y) X_s^K(dy)] f^2(x) \right. \\ &\quad \left. + b(x)\mu(x) \int f^2(x+z)M(x, z)dz \right\} K X_s^K(dx) ds. \end{aligned}$$

Idea of the proof (2)

- Since $\sup_K \mathbf{E}[\sup_{t \geq T} \langle X_t^K, \mathbf{1} \rangle^3] < +\infty$,
 $\langle X^K, f \rangle$ is tight (Aldous-Rebolledo criterion) $\rightsquigarrow X^K$ is tight
 (Roelly, 1986)
- $\sup_{t \leq T} \sup_{\|f\|_\infty \leq 1} |\langle X_t^K, f \rangle - \langle X_{t-}^K, f \rangle| \leq 1/K$
 \rightsquigarrow continuity of the limit process
- Since $\langle M^{f,K} \rangle \leq \frac{C}{K}$, any accumulation point is deterministic and must satisfy (1)
- Uniqueness of ξ (Gronwall lemma for the total variation distance between two solutions)

Simulation



$$\mu = 0.1 \quad \sigma = 0.03$$
$$K = 100000$$

Large population limit with accelerated births and deaths

Here, the limit of large system size is combined with an acceleration of births and deaths $\mathcal{X} = \mathbb{R}^d$, $\alpha_K(x, y) = \alpha(x, y)/K$,

$$b_K(x) = K^\eta r(x) + b(x), \quad d_K(x) = K^\eta r(x) + d(x), \quad \eta \in (0, 1].$$

Biological interpretation: fast births and deaths but slow demography

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$$b_K(x) = K^\eta r(x) + b(x), \quad d_K(x) = K^\eta r(x) + d(x), \quad \eta \in (0, 1].$$

Biological interpretation: fast births and deaths but slow demography

$$\begin{aligned} \langle X_t^K, f \rangle &= \langle X_0^K, f \rangle + M_t^{f, K} \\ &+ \int_0^t \int_{\mathcal{X}} \left\{ [K^\eta r(x) + b(x) - K^\eta r(x) - d(x) - \int_{\mathcal{X}} \alpha(x, y) X_s^K(dy)] f(x) \right. \\ &\left. + (K^\eta r(x) + b(x)) \mu_K(x) \int (f(x+z) - f(x)) M_K(x, z) dz \right\} X_s^K(dx) ds, \end{aligned}$$

Since births are accelerated, the effect of mutation (either the mutation probability or the mutation amplitude) must be rescaled accordingly: $\mu_K = \mu$, $M_K(x, z) dz \sim \mathcal{N}(0, \sigma^2(x) \text{Id}/K^\eta)$.

$$\rightsquigarrow \langle M^{K, f} \rangle_t \leq C \frac{K^\eta}{K}.$$

Small mutation step

Case $\eta < 1$

- $X^K \Rightarrow \xi \in \mathcal{C}([0, T], M_F)$ where

$$\begin{aligned} \langle \xi_t, f \rangle &= \langle \xi_0, f \rangle \\ &+ \int_0^t \int_{\mathcal{X}} \left\{ (b(x) - d(x) - \int_{\mathcal{X}} \alpha(x, y) \xi_s(dy)) f(x) \right. \\ &\quad \left. + \frac{1}{2} r(x) \mu(x) \sigma^2(x) \Delta f(x) \right\} \xi_s(dx) ds. \end{aligned}$$

↪ Generalization of Fisher's models in ecology (Kimura's approximation for small mutation steps)

Case $\eta = 1$

$X^K \Rightarrow Z \in \mathcal{C}([0, T], M_F)$ where Z is defined by the 3 conditions:

- $\sup_{t \leq T} \mathbf{E}[\langle Z_t, \mathbf{1} \rangle^3] < \infty$
- $\langle Z_t, f \rangle = \langle Z_0, f \rangle + \bar{M}_t^f$

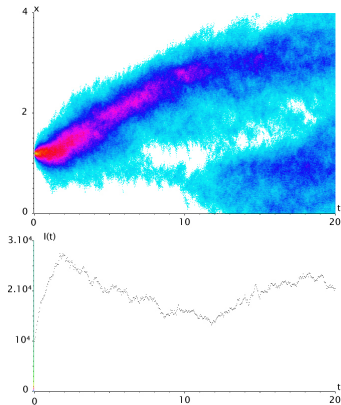
$$+ \int_0^t \int_{\mathbb{R}^d} \left\{ (b(x) - d(x) - \int_{\mathcal{X}} \alpha(x, y) Z_s(dy)) f(x) + \frac{1}{2} r(x) \mu(x) \sigma^2(x) \Delta f(x) \right\} Z_s(dx) ds$$

- $\langle \bar{M}^f \rangle_t = 2 \int_0^t \int_{\mathbb{R}^d} r(x) f^2(x) Z_s(dx) ds.$

↪ Microscopic justification of superprocesses with density-dependent interaction, recently proposed and studied in population genetics (Etheridge 06)

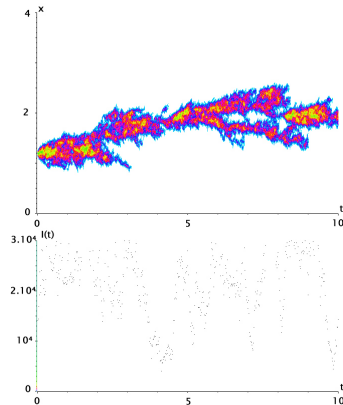
- birth and death stochasticity reflect on the demographic time-scale
- diversification vs extinction

Simulations



$$\mu = 0.3 \quad \sigma = 0.3$$

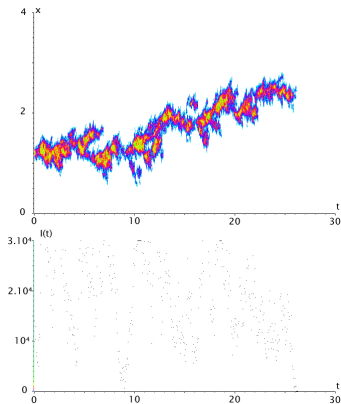
$$K = 10000 \quad \eta = 0.5$$



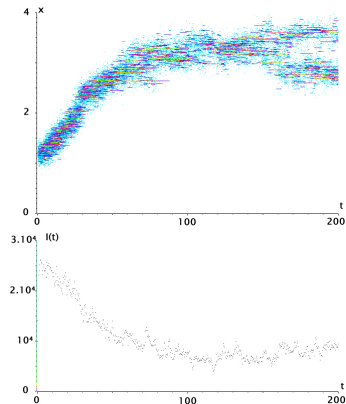
$$\mu = 0.3 \quad \sigma = 0.3$$

$$K = 10000 \quad \eta = 1$$

Simulations



$$\begin{aligned} \mu &= 0.3 & \sigma &= 0.3 \\ K &= 10000 & \eta &= 1 \end{aligned}$$



$$\begin{aligned} \mu &= 0.1/K^\eta & \sigma &= 0.1 \\ K &= 10000 & \eta &= 0.5 \end{aligned}$$

Conclusion

- Mathematical justification of several (old and new) macroscopic evolutionary models
- Precising the biological assumptions and scales underlying each macroscopic model (large resources, different scales for individual births and deaths and for demography, . . .)
- Unifying these models from the same microscopic model