Biological context		A stochastic approach	

Large population scalings of stochastic population dynamics in ecology and evolution Lecture 3: large population scaling of adaptive dynamics

Nicolas Champagnat



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

Sac

Biological context ●○○		A stochastic approach	
Adaptive dynamics			

Adaptive dynamics

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 the interactions between individuals and their environment, including the rest of the population (ecology).

Adaptive dynamics (since the 90s): Hofbauer and Sigmund (1990), Metz, Geritz et al. (1992,1996), Dieckmann and Law (1996)...

- Focus on the interplay between ecology and evolution
- Ecological interactions modeled in detail
- Heredity is simplified as much as possible: asexual (clonal) reproduction



Biological context ○●○		A stochastic approach	
Adaptive dynamics			

Adaptive dynamics

 \rightsquigarrow Density-dependent individual-based models where no fitness is given. The fitness landscape has to be constructed from the parameters of the model.

 \rightsquigarrow New phenomenon of evolutionary branching (Metz et al., 1996)

- Transition from a population concentrated around a single phenotype to a population concentrated around several distinct phenotypes, still under ecological interaction
- Mechanism of diversification
- Can lead to sympatric speciation (Dieckmann and Doebeli, 1999)
- \leadsto Three biological main assumptions (Metz et al., 1996):
 - large populations
 - rare mutations
 - small mutation steps



Biological context		
000		
Adaptive dynamics		

Evolutionary banching





Biological context	The model ●0000000	A stochastic approach	
The model			

Individual-based model

Birth-death-competition-mutation process (Metz et al. 1996, Bolker-Pacala 97, Kisdi 99, Dieckmann-Law 00, Doebeli-Dieckmann 01, Fournier-Méléard 04, C.-Ferrière-Méléard 06...).

- Each individual characterized by a continuous phenotypic trait $x \in \mathcal{X} \subset \mathbb{R}$ (individual size, age at maturity, rate of food intake...).
- K scales the size of the population
- μ scales the probability of mutation
- σ scales the size of mutation steps
- At time t, the population is composed of $N_K(t)$ individuals with weights $\frac{1}{K}$ and traits $x_1, \ldots, x_{N_K(t)} \in \mathcal{X}$:

$$\nu_t^K = \frac{1}{K} \sum_{i=1}^{N_K(t)} \delta_{x_i}.$$

 $\mathcal{O} \mathcal{O} \mathcal{O}$

Biological context	The model ○●○○○○○○	A stochastic approach	
The model			

Transition rates for an individual with trait x

- Reproduction at rate b(x):
 - With probability 1μ , clonal reproduction (offspring with trait x).
 - With probability μ , mutation, and the mutant trait is $x + \sigma H$, where $H \sim m(h)dh$, symmetric w.r.t. 0 (e.g. Gaussian distribution).
- Death without competition at rate d(x).
- Death from competition with any other individual of trait y at rate $\frac{1}{K}c(x, y)$.

 \leadsto an individual with trait x dies at density dependent rate

$$\begin{aligned} d(x) &+ \frac{1}{K} \sum_{i=1}^{N_K(t)} c(x, x_i) - c(x, x) \\ &= d(x) + \int_{\mathcal{X}} c(x, y) \left(\nu_t^K(dy) - \frac{1}{K} \delta_x(dy) \right). \end{aligned}$$

500

Biological context	The model ○○●○○○○○	A stochastic approach	
The model			

On the limit $K \to +\infty$

Assume $b(x) \equiv b$, $d(x) \equiv d$ and $c(x, y) \equiv c$ (neutral case). Then the total number of individuals N_t^K is a Markov birth and death process with

- birth rate **bn**
- death rate $\frac{dn + cn \frac{n-1}{K}}{K}$ when $N_t^K = n$.

In this case, N_t^K/K converges when $K \to +\infty$ to the solution of the logistic equation

$$\dot{n} = n(b - d - cn).$$

Remark: also true if $\nu_0^K \to n_0 \delta_x$ and $\mu = 0$, with b = b(x), d = d(x) and c = c(x, y) (monomorphic case). We will use the notation

$$\bar{n}(x) = \frac{b(x) - d(x)}{c(x, x)}$$

500

the equilibrium of the logistic equation.

Biological context	The model	The PDE approach	A stochastic approach	
	0000000			
Two examples				

Example 1

Arm-race competition (Kisdi 1999, Kisdi and Geritz 2000)

- $\mathcal{X} = [0, 4], \quad d(x) \equiv 0, \quad p(x) \equiv p$
- $M(x,h)dh = \mathcal{N}(0,\sigma^2)$ (conditioned on $x + h \in \mathcal{X}$)
- b(x) = 4 x decreasing
- $\alpha(x,y) = \alpha(x-y)$ with



Asymetric competition



Biological context	The model ○○○○●○○○	A stochastic approach	
Two examples			

Simulations 1



 $\mu = 0.1 \quad \sigma = 0.03 \quad K = 50 \qquad \mu = 0.1 \quad \sigma = 0.03 \quad K = 1000$



Biological context	The model ○○○○○●○○	A stochastic approach	
Two examples			

Example 2

Roughgarden (1976,1979), Dieckmann-Doebeli (1999): symmetric competition.

- $\mathcal{X} = [-2, 2]$ $d(x) \equiv 0$ $u_K = 1$ p(x) = p.
- $m(h)dh = \mathcal{N}(0,1)$ (conditioned on $x + h \in \mathcal{X}$).
- $b(x) = \exp\left(-\frac{x^2}{2\sigma_b^2}\right)$, maximum at 0.
- Symmetric competition for resources:

$$\alpha(x,y) = \alpha(x-y) = \exp\left(-\frac{(x-y)^2}{2\sigma_{\alpha}^2}\right).$$



Biological context	The model ○○○○○○●○	A stochastic approach	
Two examples			

Simulations 2



$$\begin{split} \mu &= 0.1, \ K = 1000, \ \sigma = 0.01, \qquad \mu = 0.1, \ K = 1000, \ \sigma = 0.01, \\ \sigma_b &= 0.9, \ \sigma_\alpha = 1.0. \qquad \qquad \sigma_b = 0.9, \ \sigma_\alpha = 0.7. \end{split}$$

Biological context	The model ○○○○○○●	A stochastic approach	
Two examples			

Comments

We observe quite complex phenomena (directional evolution, diversification...).

Our goals:

- use mathematical approaches to analyse these phenomena
- using "unrealistic" assumptions
- but enlightening about the phenomena, the building blocks, the effects of small mutations...

Sac

 \leadsto Mathematical modeling and analysis to give a qualitative understanding of the biological phenomenon

Biological context		The PDE approach ●○○○○	A stochastic approach	
Hamilton- lacobi equation with o	onstraints			

Example 1: large K limit





Biological context		The PDE approach ○●○○○	A stochastic approach	
Hamilton-Jacobi equation with c	constraints			

Large population limit

Fournier and Méléard, 2004: assuming that ν_0^K converges in law to the measure $u_0(x) dx$ for the weak topology when $K \to +\infty$, then $(\nu_t^K, t \ge 0)$ converges in law to $(u(t, x) dx, t \ge 0)$, where u(t, x) is solution to the PDE

$$\begin{aligned} \partial_t u(t,x) &= u(t,x) \left((1-\mu)b(x) - d(x) - \int_{\mathcal{X}} c(x,y)u(t,y) \, dy \right) \\ &+ \int_{\mathcal{X}} b(y)\mu u(t,y)m(\frac{x-y}{\sigma}) \, \frac{dy}{\sigma}. \end{aligned}$$

Assuming $\mu = 1$ and $\sigma = \varepsilon$, this PDE can be written as

$$\begin{split} \partial_t u(t,x) &= \quad u(t,x) \left(r(x) - \int_{\mathbb{R}^\ell} c(x,y) u(t,y) \, dy \right) \\ &+ \quad \int_{\mathbb{R}^\ell} m(h) (u(t,x+\varepsilon h) - u(t,x)) \, dh, \end{split}$$

Sar

Biological context		The PDE approach ○●○○○	A stochastic approach	
Hamilton-Jacobi equation with o	onstraints			

Large population limit

Fournier and Méléard, 2004: assuming that ν_0^K converges in law to the measure $u_0(x) dx$ for the weak topology when $K \to +\infty$, then $(\nu_t^K, t \ge 0)$ converges in law to $(u(t, x) dx, t \ge 0)$, where u(t, x) is solution to the PDE

$$\begin{aligned} \partial_t u(t,x) &= u(t,x) \left((1-\mu)b(x) - d(x) - \int_{\mathcal{X}} c(x,y)u(t,y) \, dy \right) \\ &+ \int_{\mathcal{X}} b(y)\mu u(t,y)m(\frac{x-y}{\sigma}) \, \frac{dy}{\sigma}. \end{aligned}$$

Assuming $\mu = 1$ and $\sigma = \varepsilon$, this PDE can be written as

$$\begin{split} \partial_t u(t,x) &= \frac{1}{\varepsilon} u(t,x) \left(r(x) - \int_{\mathbb{R}^\ell} c(x,y) u(t,y) \, dy \right) \\ &\quad + \frac{1}{\varepsilon} \int_{\mathbb{R}^\ell} m(h) (u(t,x+\varepsilon h) - u(t,x)) \, dh, \end{split}$$

Sar

scaling time as t/ε (large time, small mutations)

Biological context		The PDE approach ○○●○○	A stochastic approach	
Hamilton-Jacobi equation with c	onstraints			

Simulation



Competition for two resources (Diekmann, Jabin, Mischler, Perthame, 2005)



Biological context		The PDE approach ○○○●○	A stochastic approach	
Hamilton-Jacobi equation with	constraints			

Limit Hamilton-Jacobi equation (1)

Diekmann et al., 2005: defining (WKB ansatz)

$$u_{\varepsilon}(t,x) = \exp\left(rac{arphi_{\varepsilon}(t,x)}{arepsilon}
ight), \qquad \partial_t u_{arepsilon} = rac{u_{arepsilon}}{arepsilon} \partial_t arphi_{arepsilon},$$

the PDE becomes

$$\begin{split} \partial_t \varphi_{\varepsilon}(t,x) &= r(x) - \int_{\mathbb{R}^\ell} c(x,y) u_{\varepsilon}(t,y) \, dy \\ &+ \int_{\mathbb{R}^\ell} m(h) \left[\exp\left(\frac{\varphi_{\varepsilon}(t,x+\varepsilon h) - \varphi_{\varepsilon}(t,x)}{\varepsilon}\right) - 1 \right] \, dh. \end{split}$$

This suggests the convergence of φ_{ε} to the solution of

$$\partial_t \varphi(t,x) = r(x) - \int_{\mathbb{R}^\ell} c(x,y) \mu_t(dy) + \beta H(\nabla_x \varphi(t,x)),$$

where

$$H(p) = \int_{\mathbb{R}^{\ell}} \overline{m}(h)(e^{p \cdot h} - 1) \, dh$$

500

and μ_t is (in some sense) the limit of $u_{\varepsilon}(t, \cdot)$.

Limit Hamilton-Jacobi equation (2)

- The total population mass remains bounded $\Rightarrow \max_{x} \varphi(t, x) = 0$ for all $t \ge 0$.
- The limit population density at time t is 0 except at the points x where $\varphi(t, x) = 0 \quad \rightsquigarrow \quad \mu_t$ has support in $\{\varphi(t, \cdot) = 0\}$.
- The measure μ_t has to be metastable, i.e.

•
$$r(x) - \int c(x, y)\mu_t(dy) \leq 0$$
 for all x such that $\varphi(t, x) = 0$,

• $r(x) - \int c(x, y) \mu_t(dy) = 0$ for all x in the support of μ_t .

• Under the assumption that the kernel c(x, y) is positive, these two conditions are satisfied for a unique measure μ_t , and

$$\mu_t = \mu(\{\varphi(t, \cdot) = 0\}),$$

< 口 > < 行 >

< 三) 三 の Q (や

for some well-defined function μ

 \rightsquigarrow closed Hamilton-Jacobi equation (C., Jabin, 2011).

Biological context		A stochastic approach ●○○○○○○○○○○○○○○	
Rare mutations			

Example 2: rare mutations



 $\begin{array}{ll} \mu = 0.0001, \, K = 1000, & \mu = \\ \sigma = 0.08, \, \sigma_b = 0.9, \, \sigma_\alpha = 1.0. & \sigma = 0.0 \end{array}$

$$\mu = 0.0001, \ K = 1000,$$

$$\sigma = 0.08, \ \sigma_b = 0.9, \ \sigma_\alpha = 0.7.$$

Biological context		A stochastic approach	
Adaptive walk			

Limit of rare mutations: Metz et al. 1996

- The selection process has sufficient time between two mutations to eliminate disadvantaged traits.
- Large population assumption: (nearly) deterministic population dynamics between mutations, so that one can predict the outcome of competition between the traits.

 \rightsquigarrow Succession of phases of (random) mutant invasion, and phases of (fast, deterministic) competition between traits.

Adaptive walk in a fitness landscape that depends on the current state of the population: fitness of a mutant trait y in a population x at equilibrium

$$f(y,x) = b(y) - d(y) - c(y,x)\overline{n}(x)$$

(C., 2006, C. and Méléard 2011)



Biological context		A stochastic approach ○○●○○○○○○○○○○○	
Adaptive walk			



< 一 二 二 二 二 一 二) へ つ へ つ つ へ つ

Biological context		A stochastic approach	
Adaptive walk			



日本の

Biological context		A stochastic approach	
Adaptive walk			



Biological context		A stochastic approach	
Adaptive walk			



Biological context		A stochastic approach	
Adaptive walk			



「日日」の

Biological context		A stochastic approach	
Adaptive walk			

Large population limit without mutation

• Monomorphic case

If $p \equiv 0$ and $\nu_0^K = n_0^K \delta_x$ with $n_0^K \to n_0$, then $\nu_t^K \to n(t)\delta_x$, with $n(0) = n_0$ and

$$\dot{n} = (b(x) - d(x) - \alpha(x, x)n)n.$$

Logistic equation: one stable equilibrium

$$\bar{n}(x) = \frac{b(x) - d(x)}{\alpha(x, x)}.$$



Biological context	The PDE approach	A stochastic approach	
		000000000000000000000000000000000000000	
Adaptive walk			

Large population limit: dimorphic case

• If $\nu_0^K = n_x^K(0)\delta_x + n_y^K(0)\delta_y$, then $\nu_t^K \to n_x(t)\delta_x + n_y(t)\delta_y$, with $\dot{n}_x = (h(x) - d(x)) - n_x(x-x)n_y - n_y(x-x)n_y(x-x$

$$n_x = (b(x) - d(x) - \alpha(x, x)n_x - \alpha(x, y)n_y)n_x$$

$$\dot{n}_y = (b(y) - d(y) - \alpha(y, x)n_x - \alpha(y, y)n_y)n_y.$$

- Equilibria: (0,0) (unstable), $(\bar{n}(x),0)$, $(0,\bar{n}(y))$ and possibly $(\bar{n}_1(x,y),\bar{n}_2(x,y))$ in $(0,\infty)^2$.
- The stability of the equilibria is governed by the invasion fitness of the mutant trait y in a resident population of trait x:

$$f(y;x) = b(y) - d(y) - \alpha(y,x)\bar{n}(x).$$

- $(\bar{n}(x), 0)$ is unstable iff f(y; x) > 0.
- If f(y; x) > 0 and f(x; y) > 0, there is a non-trivial equilibrium, globally asymptotically stable (coexistence).
- Note that f(x; x) = 0.

Lotka-Volterra system $LV(d, x_1, \ldots, x_d)$

For *d*-morphic initial conditions $(x_1, \ldots, x_d) \in \mathcal{X}^d$ we define the *d*-dimensional competitive Lotka-Volterra system $LV(d, x_1, \ldots, x_d)$

$$\dot{n}_i(t) = n_i(t) \Big(r(x_i) - \sum_{j=1}^d \alpha(x_i, x_j) n_j(t) \Big), \quad \forall 1 \le i \le d.$$

Definition

- The traits x_1, \ldots, x_d coexist if $LV(d, x_1, \ldots, x_d)$ has a unique equilibrium $\mathbf{\bar{n}}(\mathbf{x})$ in $(\mathbb{R}^*_+)^d$ locally strongly stable.
- Given x_1, \ldots, x_d which coexist, the fitness of trait y is defined as

$$f(y;\mathbf{x}) = f(y;x_1,\cdots,x_d) = r(y) - \sum_{i=1}^d \alpha(y,x_i)\bar{n}_i(\mathbf{x}).$$

Its sign governs the possibility of invasion of the mutant trait y, i.e. the stability of the eq. $(\bar{\mathbf{n}}(\mathbf{x}), 0)$ of $LV(d+1, x_1, \ldots, x_d, y)$.

Biological context		A stochastic approach	
Result			

Main assumption (A)

For all x_1, \ldots, x_d which coexist,

- (A1) for a.e. y s.t. $f(y; x_1, \ldots, x_d) > 0$, there exists a neighborhood \mathcal{N} of $(\bar{\mathbf{n}}(\mathbf{x}), 0)$ s.t. all solutions of $LV(d+1, x_1, \ldots, x_d, y)$ starting from $\mathcal{N} \cap (\mathbb{R}^*_+)^{d+1}$ converges to a unique equilibrium \mathbf{n}^* .
- (A2) **n**^{*} is locally strongly stable (the eigenvalues of the Jacobian matrix all have negative real part).

Not so restrictive:

- (A) is satisfied until the first time where there is coexistence of 3 traits (see below).
- (A) is satisfied if the competition kernel is symmetric and positive (C., Jabin, Raoul, 2010).



Biological context		A stochastic approach ○○○○○○○○●○○○○○	
Result			

Main assumption (A)

For all x_1, \ldots, x_d which coexist,

- (A1) for a.e. y s.t. $f(y; x_1, \ldots, x_d) > 0$, there exists a neighborhood \mathcal{N} of $(\bar{\mathbf{n}}(\mathbf{x}), 0)$ s.t. all solutions of $LV(d+1, x_1, \ldots, x_d, y)$ starting from $\mathcal{N} \cap (\mathbb{R}^*_+)^{d+1}$ converges to a unique equilibrium \mathbf{n}^* .
- (A2) **n**^{*} is locally strongly stable (the eigenvalues of the Jacobian matrix all have negative real part).

Not so restrictive:

- (A) is satisfied until the first time where there is coexistence of 3 traits (see below).
- (A) is satisfied if the competition kernel is symmetric and positive (C., Jabin, Raoul, 2010).

Let
$$\mathcal{M}_{eq}(\mathcal{X}) = \left\{ \sum_{i=1}^{d} \bar{n}_i \delta_{x_i}, \ d \ge 1, \ (x_1, \dots, x_d) \in \mathcal{X}^d \text{ coexist} \right\}.$$

Biological context	The PDE approach	A stochastic approach	
		000000000000000000000000000000000000000	
Result			

The Polymorphic Evolution Sequence (PES)

Theorem

Assume (A) and that $\nu_0^K = n_K \delta_x$ for $x \in \mathcal{X}$, with $n_K \to \bar{n}(x)$ in probability when $K \to +\infty$. If

$$\forall C > 0, \quad \log K \ll \frac{1}{Ku_K} \ll \exp(CK),$$

then, the process $(\nu_{t/Ku_{\kappa}}^{K}, t \geq 0)$ converges for f.d.d. to a process $(\Lambda_t, t \geq 0)$ which is a Markov jump process on the set $\mathcal{M}_{eq}(\mathcal{X})$, with jumps

from
$$\sum_{i=1}^{d} \bar{n}_i \delta_{x_i}$$
 to $\sum_{i=1}^{d} n_i^*(x_1, \dots, x_d, x_j + h) \delta_{x_i} + n_{d+1}^* \delta_{x_j + h}$

with infinitesimal rate

$$p(x_j)b(x_j)\bar{n}_j(\mathbf{x})\frac{[f(x_j+h;\mathbf{x})]_+}{b(x_j+h)}m(x_j,h)dh, \quad \forall 1 \le j \le d.$$



Biological context		A stochastic approach	
Idea of the proof			

Idea of the proof: (1) Mutation phase

Before the first mutation in a monomorphic population of trait x:

- the population size is close to the solution of $\dot{n} = (b(x) d(x) \alpha(x, x)n)n.$
- the population size reaches any neighborhood of $\bar{n}(x)$ in finite time.
- Large deviations: the exit time from $[\bar{n}(x) \varepsilon, \bar{n}(x) + \varepsilon]$ behaves as $\exp(KC)$, with C > 0.
- therefore, the rate of mutation is (close to) $u_K p(x)b(x)K\bar{n}(x)$.

Biological context		A stochastic approach ○○○○○○○○○○○●○○	
Idea of the proof			

(2) Competition phase

- Between 0 and t_1 : the number of mutant individuals is close to a branching process with birth rate b(y) and death rate $d(y) + \alpha(y, x)\overline{n}(x)$.
- Survival probability : $[f(y;x)]_+/b(y)$.
- Between t_1 and t_2 : close to the 2-dim Lotka-Volterra system.
- After t₂: the number of resident is close to a sub-critical branching process.



naa

Biological context		A stochastic approach	
Idea of the proof			

Monomorphic case: Trait Substitution Sequence

Until the first coexistence time

 $\Lambda_t = \bar{n}(X_t)\delta_{X_t}$

where the Markov jump process $(X_t, t \ge 0)$ on \mathcal{X} satisfies $X_0 = x$ and has infinitesimal generator

$$A\varphi(x) = \int (\varphi(x+h) - \varphi(x))p(x)b(x)\bar{n}(x)\frac{[f(x+h;x)]_+}{b(x+h)}m(x,h)dh$$

The first coexistence time is the first time where $f(X_t, X_{t-}) > 0$ and $f(X_{t-}, X_t) > 0$.

(日)

Canonical Equation of Adaptive Dynamics (first form)

Adaptive walk with small mutations:

When $\sigma \to 0$, on the time scale $\frac{t}{\sigma^2}$, the TSS converges to x(t) solution to $\frac{dx}{dt} = \int dx \, dx \, dx \, dx$

$$\frac{dx}{dt} = \int h^2 m(h) dh \,\bar{n}(x) \partial_1 f(x;x).$$

- "hill-climbing" process in the fitness landscape (Dieckmann and Law, 1996).
- evolutionary branching can also be described with this approach (C., Méléard, 2011)
- Criticism (Waxman, Gavrilets, 2005)
 - mutations are too rare (real populations are never monomorphic)

< 三) 三 の Q (や

- evolution on a too long time-scale $t/\mu K\sigma^2$
- \leadsto PDE analysts proposed a second approach.

Biological context		A stochastic approach	Conclusion

Conclusion

- Alternative approach to study limits of "concentration" in evolution
- The concentration limits provide simpler tools to study the long term evolution of the population
- Two main phenomena: directional evolution following the fitness gradient (canonical equation) and evolutionary branching
- It is possible to obtain a criterion for evolutionary branching following the stochastic approach (C., Méléard, 2011)
- The deterministic approach suffers from well-posedness problems for the limiting Hamilton-Jacobi equation
- Both approaches suffer from biologically unrealistic assumptions \rightsquigarrow many open problems

Sac