Horizontal Gene Transfer:

numerical comparison between stochastic and deterministic approaches

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Seminar GdT MathBio, 12 November, 2018

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Introduction

Definition

Horizontal Gene Transfer (HGT) — exchange of genetic material between unicellular/multicellular organisms not through a vertical transmission.

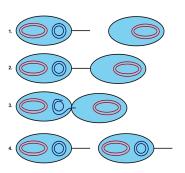


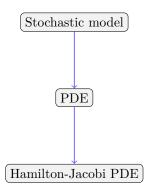
Figure 1: Unilateral HGT

HGT plays a key role in:

- ► the evolution of organisms
- ► transmission of pathogenes
- ► resistance to antibiotics in bacteria

Picture from Raz, Y. & Tannenbaum, E. (2010). The Influence of Horizontal Gene Transfer on the Mean Fitness of Unicellular Populations in Static Environments. Genetics, 185(1), 327–337.

Motivation



Our goal:

Study in silico the population dynamics using:

- ► Individual-based model (stochastic jump process)
- ► Large population limit (PDE)
- ► Large population on evolutionary time scale (Hamilton-Jacobi PDE)

Model

The demography of the population is regulated by:

- $ightharpoonup x_j^t \in \mathbb{R}^d$ is the trait of j-th individual living at t
- ▶ K: scale parameter (carrying capacity), N^t size of the population at time t
- ▶ Birth: b(x) with a mutation kernel m(x,y).
- ▶ Death: $d(x) + C\frac{N^t}{K}$, where C is a competition rate
- ➤ Horizontal Gene Transfer (HGT):

$$h_K(x, y, N^t) = \tau_0 \alpha(x - y) \frac{K}{N^t}$$

where α a smooth bounded function (for example: heaviside, arctan, etc..).

Stochastic model

For a population described by point measure $\nu^t(dx)=\frac{1}{K}\sum_{i=0}^N\delta_{X_i(t)}(dx)$ the generator of the process is:

$$L^{K}F(\nu) = \sum_{i=1}^{N} b(x_{i}) \int_{\mathbb{R}^{d}} \left(F\left(\nu + \frac{1}{K}\delta_{y}\right) - F(\nu) \right) m(x_{i}, dy)$$

$$+ \sum_{i=1}^{N} \left(\frac{d(x_{i}) + C\frac{N}{K}}{K} \right) \left(F\left(\nu - \frac{1}{K}\delta_{x_{i}}\right) - F(\nu) \right)$$

$$+ \sum_{i=1}^{N} h_{K}(x_{i}, x_{j}, \nu) \left(F\left(\nu + \frac{1}{K}\delta_{x_{i}} - \frac{1}{K}\delta_{x_{j}}\right) - F(\nu) \right).$$

Further reading:

Billiard et al. (2016a, 2015)

Stochastic simulations: algorithm

Algorithm of simulation on $[0, \Delta, \dots, i\Delta, \dots, N\Delta = T]$:

- 0 Randomly initialize the population $X^0 := \mathcal{N}(x_{mean}^0, \sigma^0) \times N^0$
- 1 Set: $b \equiv const$, $d = d_r x^2 + C \frac{N^t}{K}$, $\alpha(x) = heav(x)$
- 2 For $i \in [1, N-1]$:
 - (i) Copy X^{i-1} —th population to X^i
 - (ii) Compute exponential arrival times for each individual:

$$T_b := \lambda(b), T_d := \lambda(d), T_{HGT} := \lambda \left(\sum_{y \in X^i} h_K(x, y, N^{i-1}) \right)$$

- (iii) $\forall x \in X^i$:
 - * If $T_d \leq \Delta$: remove x-th individual
 - * If $T_b \leq \Delta$: add a new individual with a trait from $\mathcal{N}(x, \sigma^2)$
 - * If $T_{HGT} \leq \Delta$: pick a trait $y \in X^i$ according to the law

$$\frac{h_K(x, y, N^{i-1})}{\sum_{y \in X^i} h_K(x, y, N^{i-1})}$$

then remove individual with trait x and add a new individual with trait y.

(iv) Return X^i

Stochastic simulations

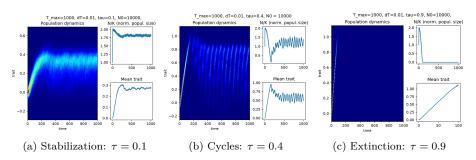


Figure 2: Behavior of the population dynamics as the mutation rate τ is changing, $(b_r=d_r=1,\,\sigma=0.01,T_{max}=1000,\Delta=0.01).$

All codes and more pictures:

https://github.com/melnyashka/horizontal_gene_transfer

Stochastic model

Advantages

- + Very precise
- + Allows to track the heritage

Limitations

- Computational cost
- Hard to analyze from theoretical point of view

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Solution

Pass to the limit with PDE!

PDE: Model and notations

The sequence of stochastic processes gives a macroscopic approximation when $K \to +\infty$.

$$\begin{cases} \partial_t f(t,x) &= -(\frac{d(x)}{t}) + \frac{C\rho(t)}{t} + \int_{\mathbb{R}^d} \frac{m(x-y)b(y)f(t,y)dy}{m(x-y)b(y)f(t,y)dy} \\ &+ f(t,x) \int_{\mathbb{R}^d} \tau(x-y) \frac{f(t,y)}{\rho(t)} dy, \\ &\rho(t) = \int_{\mathbb{R}^d} f(t,x)dx, \qquad f(0,x) = f^0(x) > 0. \end{cases}$$

- $\blacktriangleright f(t,x) := \lim_{K \to +\infty} \nu^K$: density of the population at time t with trait x,
- ▶ b(x), d(x), C: birth, death and competition rate,
- ightharpoonup m(x-y): mutation kernel,
- $ightharpoonup au(y-x) := au_0 \left[\alpha(x-y) \alpha(y-x) \right]$: HT kernel

Further reading:

Billiard et al. (2016b,a), Ferrière and Tran (2009)

Explicit Euler scheme: the integrals are computed with a left-point quadrature rule.

Competition term:
$$\Delta_x \sum_{j=0}^{N_x-1} f_j^n$$

$$\frac{f_i^{n+1} - f_i^n}{\Delta_t} = \left(-\frac{C\rho^n}{-D_i} - \frac{D_i}{-D_i} + \frac{T_i^n}{-D_i} \right) f_i^n + \frac{B_i^n}{-D_i}$$

- ▶ Death rate term
- ▶ Transfer rate term: $\Delta_x \sum_{j=0}^{N_x-1} \tau(x_i x_j) \frac{f_j^n}{\rho^n}$
- ▶ Birth rate term: $[m * (bf)]_i^n = \Delta_z \sum_{k=0}^{N_z-1} m(z_k) b(x_i + z_k) f^n(x_i + z_k)$.

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Death rate term

- ► Transfer rate term: $\Delta_x \sum_{j=0}^{N_x-1} \tau(x_i x_j) \frac{f_j^n}{\rho^n}$
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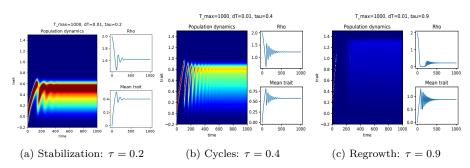


Figure 3: Behavior of the population dynamics as the mutation rate τ is changing.

PDE model

- + Fast simulation
 - Not very well adapted to small values

	$\Delta = 0.1, T = 10$	$\Delta = 0.01, T = 10$
SM (N = 1000)	3.883s	38.145s
SM (N = 10000)	15.805s	153.255s
PDE	0.186s	1.673s

Table 1: Elapsed time for simulation of population dynamics for stochastic and PDE model.

Limit of PDE model

Evolutionary scale:

- ightharpoonup Time scale $T \to \infty$
- ▶ Mutation probability is small: $m(y y') \to \mathcal{N}(0, \sigma^2)$, where $\sigma \to 0$

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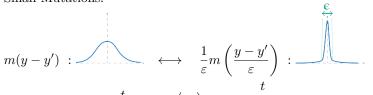
Solution:

Introduce a rescaling parameter $\varepsilon > 0$:

$$\blacktriangleright \ t \longrightarrow \frac{t}{\varepsilon}$$

Shape of solutions

► Small Mutations:



► Large time:

Ecological scale

Evolutionary scale

 $\partial_t \longleftrightarrow \varepsilon \partial_t$

- ▶ Competition \longrightarrow Saturation: total population $\rho(t)$ is bounded.
- ▶ Selection of the fittest trait $\bar{x} \Longrightarrow f(t,x)$ converges to a Gaussian centered at \bar{x} , with same variance as m (mutation kernel)

PDE: The rescaled model

Rescaled PDE model is given by:

$$\begin{cases} \varepsilon \partial_t f_{\varepsilon}(t,x) &= -(d(x) + C\rho_{\varepsilon}(t)) f_{\varepsilon}(t,x) + \int_{\mathbb{R}} \underbrace{\frac{z = \frac{x - y}{\varepsilon}}{m(z)b(x + \varepsilon z)} f_{\varepsilon}(t,x + \varepsilon z) dz} \\ &+ f_{\varepsilon}(t,x) \int_{\mathbb{R}} \tau(x - y) \frac{f_{\varepsilon}(t,y)}{\rho_{\varepsilon}(t)} dy, \end{cases}$$

$$\rho_{\varepsilon}(t) &= \int_{\mathbb{R}} f_{\varepsilon}(t,x) dx, \quad + \text{ init. conditions.}$$

Hopf-Cole transformation

Main assumption:

 f_{ε} is Gaussian with a variance ε .

$$\begin{split} \left[f_{\varepsilon}(t,x) &= e^{\frac{u_{\varepsilon}(t,x)}{\varepsilon}}. \right] \\ & \downarrow \\ \partial_t u_{\varepsilon} &= -(d(x) + \rho_{\varepsilon}(t)) + \int_{\mathbb{R}^d} m(z)b(x + \varepsilon z)e^{\frac{u_{\varepsilon}(t,x + \varepsilon z) - u_{\varepsilon}(t,x)}{\varepsilon}} dz \\ &+ \int_{\mathbb{R}} \tau(x - y) \frac{f_{\varepsilon}(t,y)}{\rho_{\varepsilon}(t)} dy. \end{split}$$

The limiting Hamilton-Jacobi equation

$$\blacktriangleright \left| f_{\varepsilon}(t,x) = e^{\frac{u_{\varepsilon}(t,x)}{\varepsilon}}. \right|$$

▶ $u_{\varepsilon} \xrightarrow[\varepsilon \to 0]{} u$, where u is the viscosity solution of:

$$\partial_t u = -(d(x) + \rho(t)) + b(x) \int_{\mathbb{R}} M(z) e^{z \cdot \nabla_x u} dz + \tau(x - \overline{x}(t))$$

- ▶ $\sup_{x \in \mathbb{R}} u(t, \cdot) \le 0$, with " < " \Leftrightarrow extinction.
- ▶ Population concentrates on $\bar{x}(t) = \operatorname{argmax} u(t, \cdot)$
- ► Non-standard drift term

Hamilton-Jacobi simulations

Target equation:

$$\partial_t u_{\varepsilon} = -(d(x) + \rho_{\varepsilon}(t)) + \int_{\mathbb{R}^d} m(z)b(x + \varepsilon z)e^{\frac{u_{\varepsilon}(t, x + \varepsilon z) - u_{\varepsilon}(t, x)}{\varepsilon}} dz + \int_{\mathbb{R}} \tau(x - y) \frac{f_{\varepsilon}(t, y)}{\rho_{\varepsilon}(t)} dy.$$

$$\varepsilon \to 0$$



Refine grid in $x: \Delta_x \to 0$

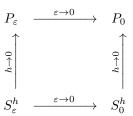


Explicit scheme not consistent

Hamilton-Jacobi simulations

Asymptotic Preserving (AP) scheme (Jin, 1999, Klar, 1998, 1999)

- ▶ avoid the increase of computational cost,
- lacktriangle ensure the scheme approaches the limit H-J equation for small arepsilon



For $u(t,x) = \varepsilon \ln f(t,x)$ we compute:

Competition term:
$$\rho$$
 is implicit. Recall: $\rho^{n+1} = \sum_{i} e^{\frac{u_i^{n+1} + i}{\varepsilon}}$.
$$\frac{u_i^{n+1} - u_i^n}{\Delta t} = -\frac{\rho^{n+1}}{\delta t} - \frac{D_i}{\delta t} + \frac{B_i^n}{\delta t} + \frac{T_i^n}{\delta t}$$

- ▶ Death rate term: explicit
- ▶ Birth rate term: linear interpolation
- ► Transfer rate term

$$\frac{f^{\varepsilon}(t^n,y)}{\rho^{\varepsilon}(t^n)} = \frac{\mathrm{e}^{u^{\varepsilon}(t^n,y)/\varepsilon}}{\int_{\mathbb{R}} \mathrm{e}^{u^{\varepsilon}(t^n,z)/\varepsilon}\mathrm{d}z} = \frac{\mathrm{e}^{(u^{\varepsilon}(t^n,y) - \max_x u^{\varepsilon}(t^n,x))/\varepsilon}}{\int_{\mathbb{R}} \mathrm{e}^{(u^{\varepsilon}(t^n,z) - \max_x u^{\varepsilon}(t^n,x))/\varepsilon}\mathrm{d}z},$$

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$$\frac{f^\varepsilon(t^n,y)}{\rho^\varepsilon(t^n)} = \frac{\mathrm{e}^{u^\varepsilon(t^n,y)/\varepsilon}}{\int_{\mathbb{D}} \mathrm{e}^{u^\varepsilon(t^n,z)/\varepsilon}\mathrm{d}z} = \frac{\mathrm{e}^{(u^\varepsilon(t^n,y) - \max_x u^\varepsilon(t^n,x))/\varepsilon}}{\int_{\mathbb{D}} \mathrm{e}^{(u^\varepsilon(t^n,z) - \max_x u^\varepsilon(t^n,x))/\varepsilon}\mathrm{d}z},$$

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$$\frac{u_i^{n+1} - u_i^n}{\Delta t} = -\rho^{n+1} - D_i + B_i^n + T_i^n$$

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Hamilton-Jacobi equation: computation 7 of ρ

- 1. Recall: $\rho^{n+1} = \sum_{i} e^{\frac{u_i^{n+1}}{\varepsilon}}$
- 2. Define: $A_i^n := u_i^n + \Delta_t(-d(x_i) + B_i^n + T_i^n)$ and $A_{i_0}^n = \max A_i^n$
- 3. By definition of a scheme: $\rho^{n+1} = \Delta_x e^{-\Delta_t \rho^{n+1/\varepsilon}} \sum_{i=0}^{N_x-1} e^{A_i^n/\varepsilon}$
- 4. Note that ρ^{n+1} is a solution of the following equivalent equations:

$$g_1(y) = ye^{\Delta_t y/\varepsilon} - \Delta_x e^{A_i^n/\varepsilon} \sum_{i=0}^{N_x - 1} e^{(A_i^n - A_{i_0}^n)/\varepsilon}$$

$$g_2(y) = -\varepsilon \ln(y) - \Delta_t y + \varepsilon \ln(\Delta_x) + A_{i_0}^n + \varepsilon \ln\left(\sum_{i=0}^{N_x - 1} e^{(A_i^n - A_{i_0}^n)/\varepsilon}\right)$$

5. Then we find ρ^{n-1} by solving either g_1 or g_2 by a Newton's method (with derivatives computed analytically).

⁷Courtesy of Hélène Hivert Susy, Hélène, Anya, Sam

Hamilton-Jacobi simulations (PDE for $\varepsilon \ll 1$):

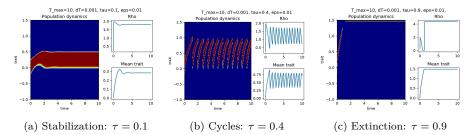


Figure 4: Behavior of the population dynamics as the mutation rate τ is changing.

Evolutionary rescue

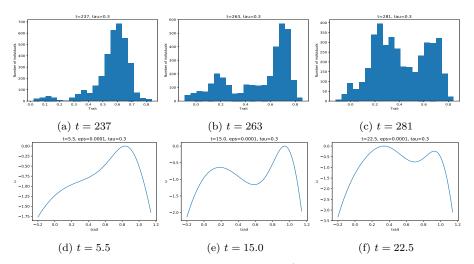
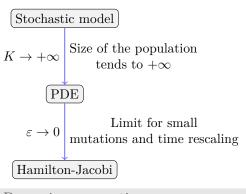


Figure 5: Stochastic/HJ. $\varepsilon = 10^{-4}$ and $\tau = 0.3$

Conclusion



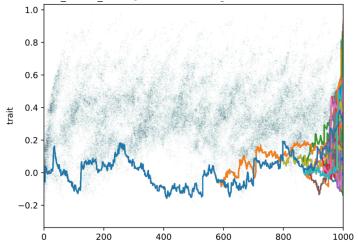
- ► H-J is convenient to describe the concentration phenomenon.
- ► H-J framework allows a rigorous and rich description.

Paper in preparation:

V. Calvez, S.F. Iglesias, H. Hivert, S. Méléard, A. Melnykova, S. Nordmann (2018) "Horizontal gene transfer: numerical comparison between stochastic and deterministic approaches"

Open questions

- 1. Theoretical results: threshold for oscillation, extinction, stabilization, computations of period of oscillations etc.
- 2. Reconstruction of lineages.



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This project has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation program (grant agreement No. 639638).

Thank you for your attention!