CEMRACS 2018: Horizontal Gene Transfer

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Motivation

Horizontal Gene Transfer (HGT) -

exchange of genetic material between unicellular/multicellular organisms not through a vertical transmission.

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



Figure 1: Unilateral HGT. 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: evolutionary rescue



Goal

Model

The demography of the population is regulated by:

- $X_i(t) \in \mathbb{R}^d$ is the trait of *i*-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..).

Structure of project



Objective:

- Grasp the evolutionary rescue with the help of a deterministic model
- Develop a stable scheme to deal with asymptotically vanishing values
- Analyze the setting which leads to such a rescue both numerically and theoretically

Stochastic model

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

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

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 $X^0 := \mathcal{N}(x^0_{mean}, \sigma^0) \times N^0$

1 Set:
$$b \equiv const$$
, $d = d_r x^2 + C \frac{N^i}{K}$, $\alpha(x) = heav(x)$

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 $\mathbf{T}_{\mathbf{d}} \leq \Delta$: remove *x*-th individual * If $\mathbf{T}_{\mathbf{b}} \leq \Delta$: add a new individual with a trait from $\mathcal{N}(x, \sigma^2)$ * If $\mathbf{T}_{\mathbf{HGT}} \leq \Delta$: pick a trait $y \in X^i$ according to the law $\frac{h_K(x, y, N^{i-1})}{\sum_{u \in X^i} h_K(x, y, N^{i-1})}$

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, $(b_r = d_r = 1, \sigma = 0.01, T_{max} = 1000, \Delta = 0.01)$.

Stochastic simulations



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All codes and more pictures:

https://github.com/melnyashka/horizontal_gene_transfer

PDE: Model and notations

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

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

- $f(t,x) := \lim_{K \to +\infty} \nu^K$: density of the population at time t with trait x,
- b(x), d(x), C: birth, death and competition rate,
- m(x-y): mutation kernel,
- $\tau(y-x) := \tau_0 \left[\alpha(x-y) \alpha(y-x) \right]$: HT kernel

Further reading:

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

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Explicit Euler scheme, (the integrals are computed with a left-point quadrature rule).

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

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

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• Death rate term

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 $N_r - 1$ • Competition term: $\Delta x \sum_{i=0} f_j^n$ $\frac{f_i^{n+1} - f_i^n}{\Delta t} = \left(-\frac{\rho^n}{\rho^n} - \frac{D_i}{D_i} + \frac{T_i^n}{D_i}\right)f_i^n + \frac{1}{2}\left(-\frac{\rho^n}{\rho^n} - \frac{D_i}{D_i} + \frac{T_i^n}{D_i}\right)f_i^n + \frac{T_i^n}{D_i}\left(-\frac{\rho^n}{\rho^n} - \frac{T_i^n}{D_i} + \frac{T_i^n}{D_i}\right)f_i^n + \frac{T_i^n}{D_i}\left(-\frac{P_i^n}{\rho^n} - \frac{T_i^n}{D_i} + \frac{T_i^n}{D_i}\right)f_i^n + \frac{T_i^n}{D_i}\left(-\frac{P_i^n}{\rho^n} - \frac{T_i^n}{D_i} + \frac{T_i^n}{D_i}\right)f_i^n + \frac{T_i^n}{D_i}\left(-\frac{P_i^n}{D_i} + \frac{T_i^n}{D_i}\right)f_i^n + \frac{T_i^n}{D_i}\left(-\frac{P_i^n$ B_i^n Death rate term • Transfer rate term: $\Delta x \sum_{i=1}^{N_x-1} \tau(x_i - x_j) \frac{f_j^n}{\rho^n}$ $N_z - 1$ • Birth rate term: $[m * (bf)]_i^n = \Delta z \sum_{i=1}^{n} m(z_k)b(x_i + z_k)f^n(x_i + z_k)$.



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

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$$m(y-y')$$
 : $\longrightarrow \quad \frac{1}{\varepsilon}m\left(\frac{y-y'}{\varepsilon}\right)$: \square

Evolutionary scale

Counterpart: large time

 $\partial_t \longleftrightarrow \varepsilon \partial_t$

 $\stackrel{\varepsilon}{\leftrightarrow}$

t

Ecological scale

PDE: The rescaled model

$$\begin{split} \varepsilon \partial_t f_{\varepsilon}(t,x) &= -(d(x) + C\rho_{\varepsilon}(t))f_{\varepsilon}(t,x) + \int_{\mathbb{R}} \underbrace{\overline{m(z)b(x + \varepsilon z)f_{\varepsilon}(t,x + \varepsilon z)dz}}_{+f_{\varepsilon}(t,x)\int_{\mathbb{R}} \tau(x-y)\frac{f_{\varepsilon}(t,y)}{\rho_{\varepsilon}(t)}dy, \\ \rho_{\varepsilon}(t) &= \int_{\mathbb{R}} f_{\varepsilon}(t,x)dx, \quad \text{+ init. conditions.} \end{split}$$

Hopf-Cole transformation

$f_{\varepsilon} \approx \text{Gaussian of variance } \varepsilon.$

 \implies Hopf-Cole transformation:

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

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

•
$$f_{\varepsilon}(t,x) = e^{\frac{u_{\varepsilon}(t,x)}{\varepsilon}}.$$

• (Formally) $u_{\varepsilon} \underset{\varepsilon \to 0}{\longrightarrow} u$ (viscosity) solution of:

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

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 $\bullet \ \sup_{x \in \mathbb{R}} u(t, \cdot) \leq 0, \quad \text{ with "} < " \Leftrightarrow \text{ extinction}.$

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

Hamilton-Jacobi: convenient framework for concentration phenomenon. Formally :

•
$$\rho(t) = \max(0, b - d\bar{x}(t)^2).$$

Adaptative dynamics:

$$\frac{\mathrm{d}}{\mathrm{d}t}\bar{x}(t) = \frac{1}{-\partial_x^2 u(t,\bar{x}(t))} \left[b - d\bar{x}(t)^2\right] \quad \text{+ possible jumps}$$

• Evolutionary Equilibrium:

$$\bar{x}_{\star} = \frac{\tau'(0)}{2d}.$$

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Evolutionary Equilibrium:

$$\bar{x}_{\star} = \frac{\tau'(0)}{2d}.$$

Threshold:

Oscillations iff
$$\frac{\tau'(0)^2}{\|\tau\|_{\infty}} \ge 4d.$$

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• Threshold:

Extinction "iff"
$$\|\tau\|_{\infty} \ge 2\sqrt{bd}$$
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Asymptotic Preserving (AP) scheme (Jin, 1999, Klar, 1998, 1999)

- avoid the increase of computational cost,
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Asymptotic Preserving (AP) scheme (Jin, 1999, Klar, 1998, 1999)

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

$$\begin{array}{cccc}
P_{\varepsilon} & \xrightarrow{\varepsilon \to 0} & P_{0} \\
 & & & & \\ \uparrow & & & \uparrow \\
S_{\varepsilon}^{h} & \xrightarrow{\varepsilon \to 0} & S_{0}^{h} \\
\end{array}$$

Hamilton-Jacobi simulations: numerical AP scheme

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

• Competition term (Implicit). Recall: $\rho^{n+1} = \sum_{i} e^{\frac{u_i^{n+1}}{\varepsilon}}$.

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

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Remarking that for the exponential computations we make

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

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

Rho T max=10, dT=0.001, tau=0.4, eps=0.01 Population dynamics Population dynamics Rho 2.0 Population dynamics Rho 1.5 1.5 1.0 1.0 -1.0 1.0 0.5 -0.5 0.5 0.5 trait ò 10 trait 10 0.5 rait. Mean trait Mean trait Mean trait 0.0 0.0 0.0 0.75 0.50 0.2 -0.5 -0.5-0.50.1 0.25 -1.0-1.0ò ŝ 10 15 20 25 30 20 ó à 10 ò 10 ż 10 10 time time (a) Stabilization: $\tau = 0.1$ (b) Cycles: $\tau = 0.4$ (c) Extinction: $\tau = 0.9$

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

T max=10. dT=0.001. tau=0.1. eps=0.01

T max=30, dT=0.001, tau=0.9

Conclusion



- After two limiting procedures, Hamilton-Jacobi model is still able to grasp the qualitative properties of the stochastic model.
- H-J is convenient to describe where the population concentrates. Our numerics shows that it is also able to describe *small population*.
- H-J framework allows a rigorous and rich description.

Evolutionary rescue



Open questions

- Rigorous proofs.
- Pormula for the period of oscillations.

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- Pormula for the period of oscillations.
- Reconstruction of lineages with the characteristics of Hamilton-Jacobi.



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