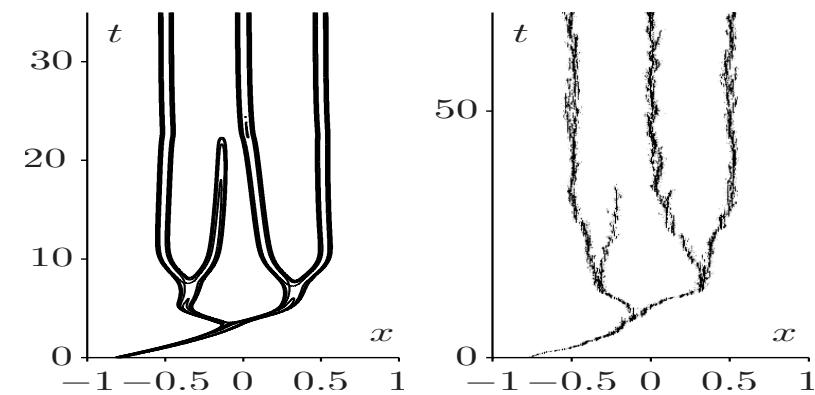
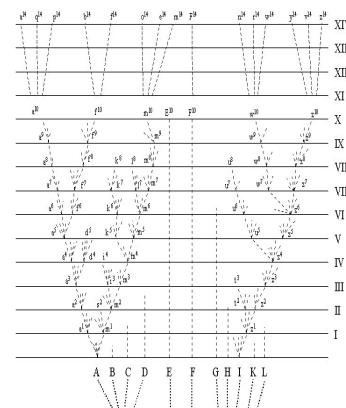
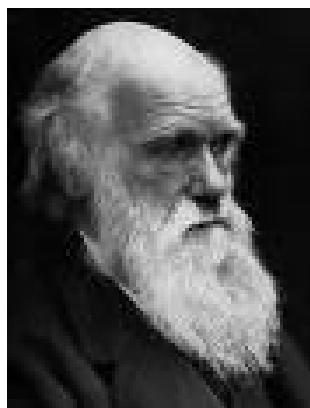


Adaptive evolution : A population point of view

Benoît Perthame





Population formalism

$$\underbrace{\frac{\partial}{\partial t} n(x, t)}_{\text{variation of individuals}} = \overbrace{\int b(y) M(x, y) n(y, t)}^{\text{birth with mutations}} + \underbrace{n(x, t) R(x, I(t))}_{\text{growth rate}}$$

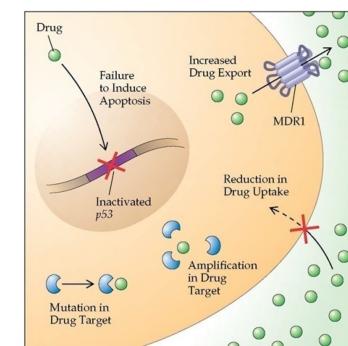
- $n(x, t)$ = number of individuals with trait x
- x = phenotypical trait
- $I(t) = (I_1(t), \dots, I_J(t))$ = environmental unknowns
- $R(x, I)$ of Lotka-Volterra type, can be negative

- Standard : Calsina, Cuadrado, Desvillettes, Raoul, Jabin, Mirrahimi, ...

Population formalism

The variable x can be

- Size of the adult individuals
- Cannibalism rate (and evolutionary suicide)
- Cooperative behaviour
- Dispersal rate
- Resistance to therapy



Chisholm,... Clairambault, *Emergence of reversible drug tolerance...*, Cancer Research, 2015



Population formalism

$$\underbrace{\frac{\partial}{\partial t} n(x, t)}_{\text{variation of individuals}} = \overbrace{\int b(y) M(x, y) n(y, t)}^{\text{birth with mutations}} + \underbrace{n(x, t) R(x, I(t))}_{\text{growth rate}}$$

- $n(x, t)$ = number of individuals with trait x
- $I(t) = (I_1(t), \dots, I_J(t))$ = environmental unknowns
- interplay between population and environment



Rescaling

$$\varepsilon \frac{\partial}{\partial t} n_\varepsilon(x, t) = \int b(y) M_\varepsilon(x, y) n_\varepsilon(y, t) dy + n_\varepsilon(x, t) R(x, I_\varepsilon(t)),$$

- $M_\varepsilon(x, y)$ means mutations are rare/have small effect



Rescaling

$$\varepsilon \frac{\partial}{\partial t} n_\varepsilon(x, t) = \int b(y) M_\varepsilon(x, y) n_\varepsilon(y, t) dy + n_\varepsilon(x, t) R(x, I_\varepsilon(t)),$$

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- $\varepsilon \frac{\partial}{\partial t} n_\varepsilon(x, t)$ means we consider a long time scale

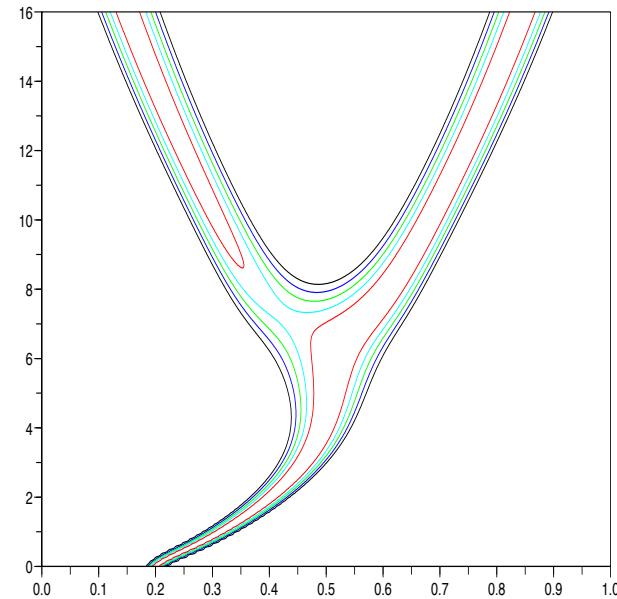
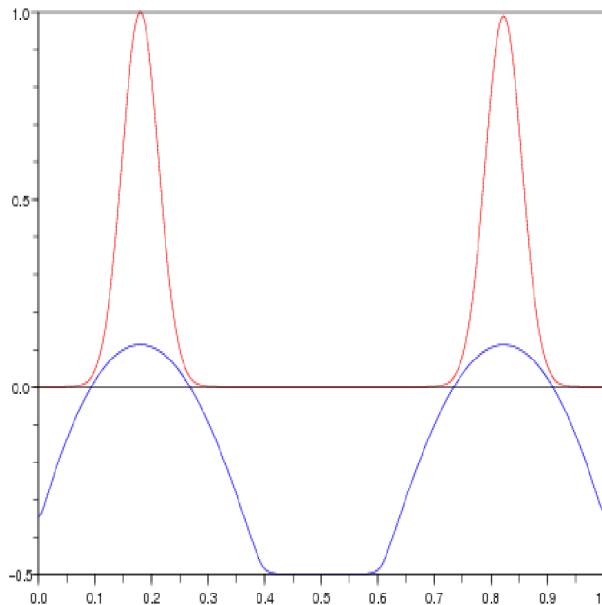


Rescaling

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- $M_\varepsilon(x, y)$ means mutations are rare/have small effect
- $\varepsilon \frac{\partial}{\partial t} n_\varepsilon(x, t)$ means we consider a long time scale
- $M_\varepsilon(x, y) = \frac{1}{\varepsilon^d} M\left(\frac{x-y}{\varepsilon}\right)$

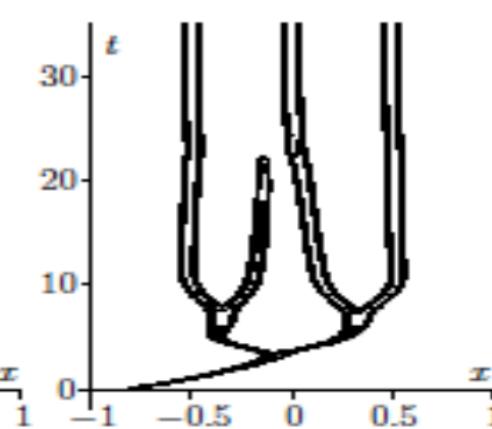
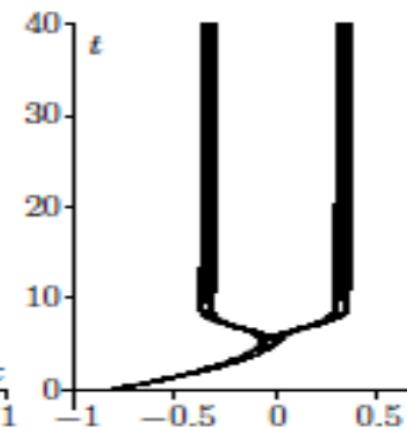
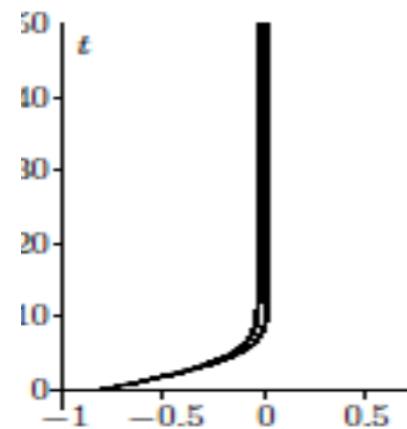
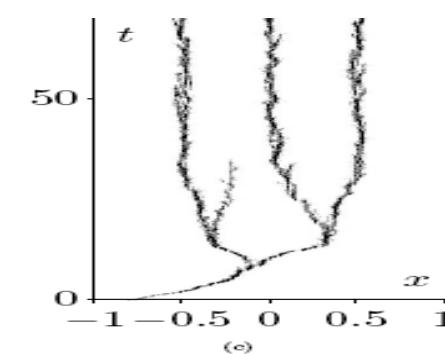
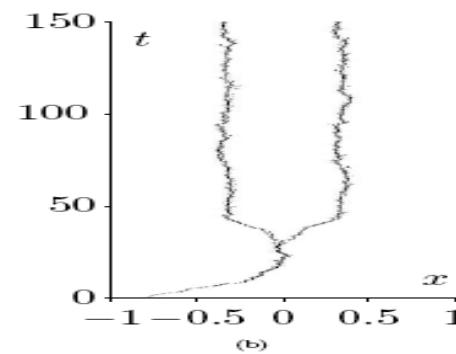
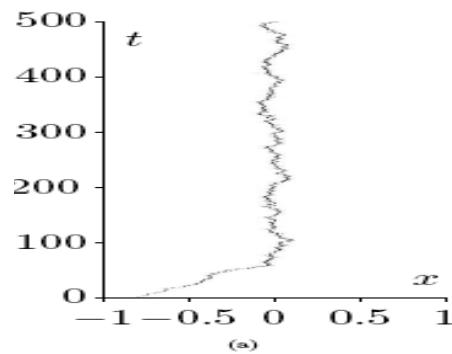
Examples of behaviors



Branching can occur for more general right hand sides (convolution)

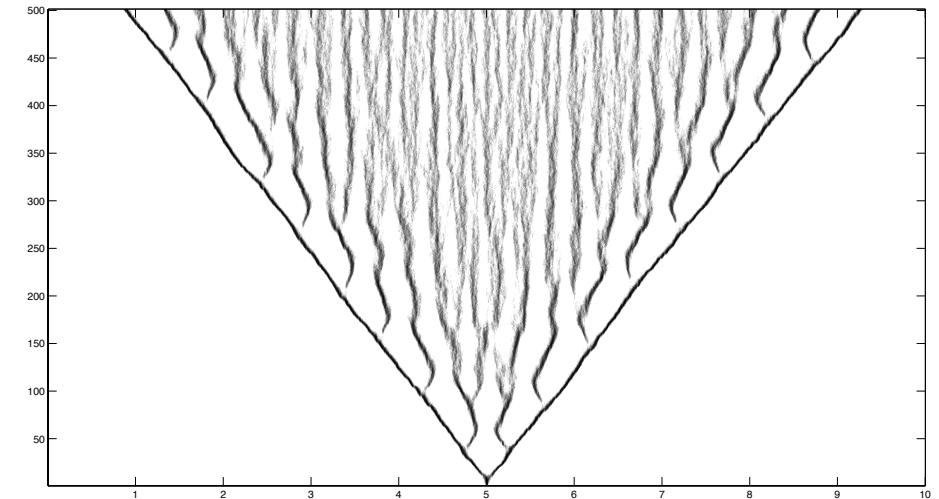
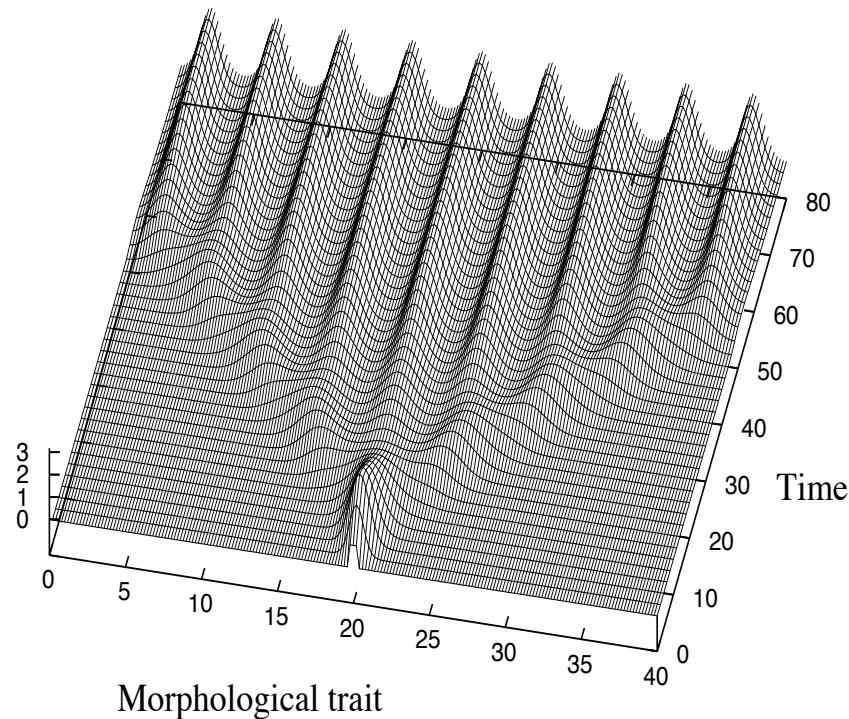


Examples of behaviors



Branching for a Gaussian convolution

Examples of behaviors



Branching for a non-Gaussian convolution



Rescaling

$$\varepsilon \frac{\partial}{\partial t} n_\varepsilon(x, t) = \int b(y) M_\varepsilon(x, y) n_\varepsilon(y, t) dy + n_\varepsilon(x, t) R(x, I_\varepsilon(t)),$$

- $M_\varepsilon(x, y)$ means mutations are rare/have small effect
- $\varepsilon \frac{\partial}{\partial t} n_\varepsilon(x, t)$ means we consider a long time scale
- Simple case $I_\varepsilon(t)$ is reduced to the knowledge of

$$\varrho_\varepsilon(t) = \int_{\mathbb{R}^d} n_\varepsilon(x, t) dx$$

Concentration phenomena

$$\begin{cases} \varepsilon \frac{\partial}{\partial t} n_\varepsilon(x, t) - \varepsilon^2 \Delta n_\varepsilon = n_\varepsilon(x, t) R(x, \varrho_\varepsilon(t)), & x \in \mathbb{R}, \\ \varrho_\varepsilon(t) = \int_{\mathbb{R}^d} n_\varepsilon(x, t) dx. \end{cases}$$

- $\exists \varrho_M > 0$ s.t. $\max_x R(x, \varrho_M) = 0$
- $R_\varrho < 0$ ■ $R_x > 0$

Theorem (d=1) For well-prepared initial data, we have

$$n_\varepsilon(x, t) \xrightarrow[\varepsilon_k \rightarrow 0]{} \bar{\varrho}(t) \delta(x = \bar{x}(t)), \quad \bar{x}(t), \bar{\varrho}(t) \in BV_{loc}(0, \infty)$$

$$R(\bar{x}(t), \bar{\varrho}(t)) = 0 \quad \text{for a.e. } t > 0$$

$\bar{x}(t)$ is the fittest trait



Concentration phenomena

$$\begin{cases} \varepsilon \frac{\partial}{\partial t} n_\varepsilon(x, t) - \varepsilon^2 \Delta n_\varepsilon = n_\varepsilon(x, t) R(x, \varrho_\varepsilon(t)), & x \in \mathbb{R}, \\ \varrho_\varepsilon(t) = \int_{\mathbb{R}^d} n_\varepsilon(x, t) dx. \end{cases}$$

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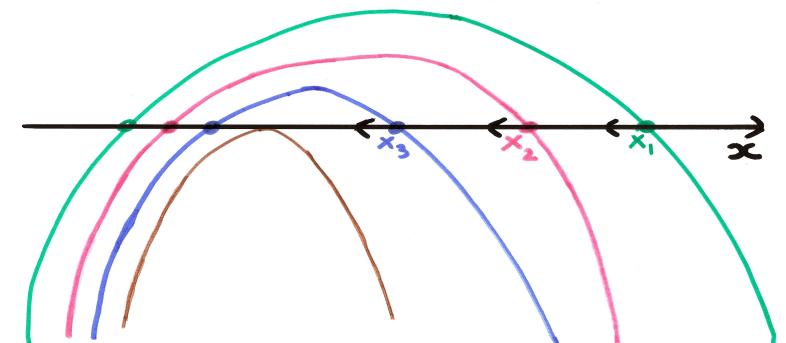
$$R(\bar{x}(t), \bar{\varrho}(t)) = 0 \quad \text{for a.e. } t > 0$$

$$\text{as } t \rightarrow \infty \quad R(\bar{x}_\infty, \bar{\varrho}_\infty) = 0 = \max_x R(x, \bar{\varrho}_\infty)$$

Concentration phenomena, $d \geq 1$

$$\begin{cases} \varepsilon \frac{\partial}{\partial t} n_\varepsilon(x, t) - \varepsilon^2 \Delta n_\varepsilon = n_\varepsilon(x, t) R(x, \varrho_\varepsilon(t)), & x \in \mathbb{R}^d \\ \varrho_\varepsilon(t) = \int_{\mathbb{R}^d} n_\varepsilon(x, t) dx. \end{cases}$$

- $R_\varrho < 0$
- $\exists \varrho_M > 0$ s.t. $\max_x R(x, \varrho_M) = 0$
- $D_x^2 R \leq -K I d,$



Theorem (Any dim.) For well-prepared initial data, we have

$$n_\varepsilon(x, t) \rightarrow \bar{\varrho}(t) \delta(x = \bar{x}(t)), \quad \bar{x}(t), \bar{\varrho}(t) \in C^1([0, \infty))$$

$$R(\bar{x}(t), \bar{\varrho}(t)) = 0 \quad \text{for all } t > 0$$

$$\text{as } t \rightarrow \infty \quad R(\bar{x}_\infty, \bar{\varrho}_\infty) = 0 = \min_\rho \max_x R(x, \varrho)$$



Concentration phenomena

Why is mathematics interesting ?

- Nonlocal nonlinearity drastically changes the picture
- Control in L^1 only
- Constrained Hamilton-Jacobi eq.
- Is there a simple rule for the dynamics of $\bar{x}(t)$?

Related approaches

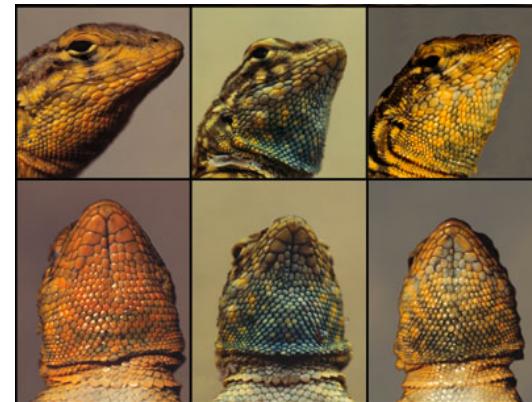
- **Evolutionary game theory**

Blue (stronger),

Orange (middle size),

Yellow (smaller)

compensate by mating **strategies**



from B. Sinervo. <http://bio.research.ucsc.edu/barrylab>

NATURE VOL. 246 NOVEMBER 2 1973

The Logic of Animal Conflict

J. MAYNARD SMITH

School of Biological Sciences, University of Sussex, Falmer, Sussex BN1 9QH

G. R. PRICE

Galton Laboratory, University College London, 4 Stephenson Way, London NW1 2HE

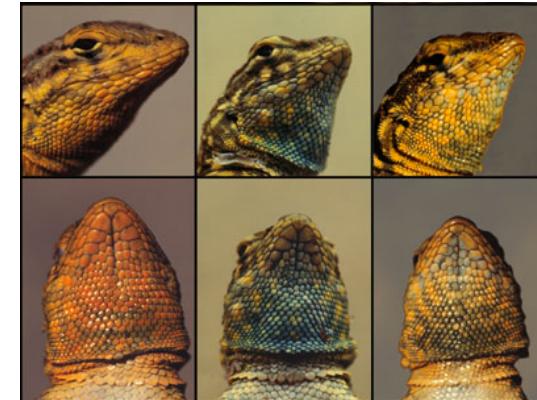
J. Hofbauer- M. Nowak- K. Zigmund

Related approaches

- Evolutionary game theory

Blue (stronger),
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compensate by mating **strategies**

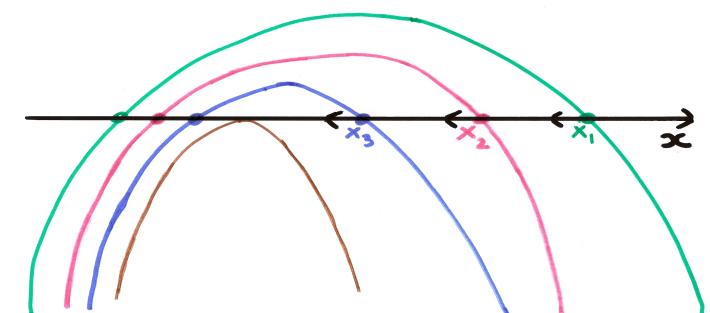


from B. Sinervo. [http : //bio.research.ucsc.edu/barrylab](http://bio.research.ucsc.edu/barrylab)

The relation can be seen by

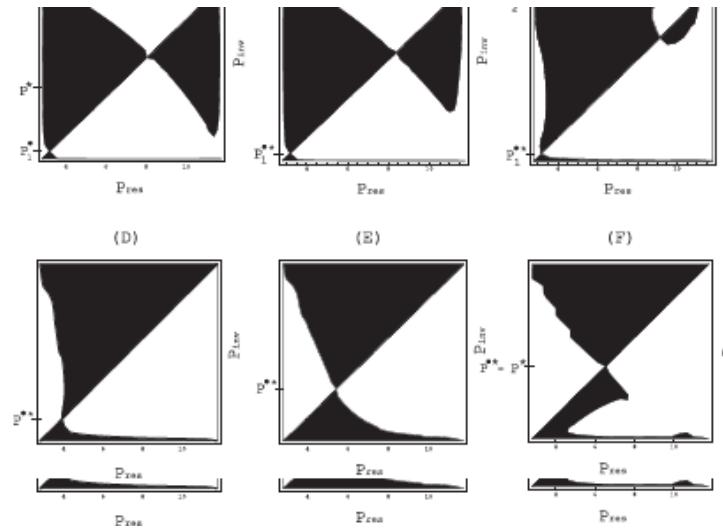
$$\max_S R(x, \bar{\varrho}_\infty) = 0 = R(\bar{x}_\infty, \bar{\varrho}_\infty)$$

$$\min_{\varrho} \max_S R(x, \varrho) = 0 = R(\bar{x}_\infty, \bar{\rho}_\infty)$$



Related approaches

- **Dynamical systems**



H. Metz, S. Geritz, G. Meszena,
S. Kisdi, O. Diekmann

Can a mutant invade the resident population ?

Related approaches

- Stochastic models, Individual Based Models

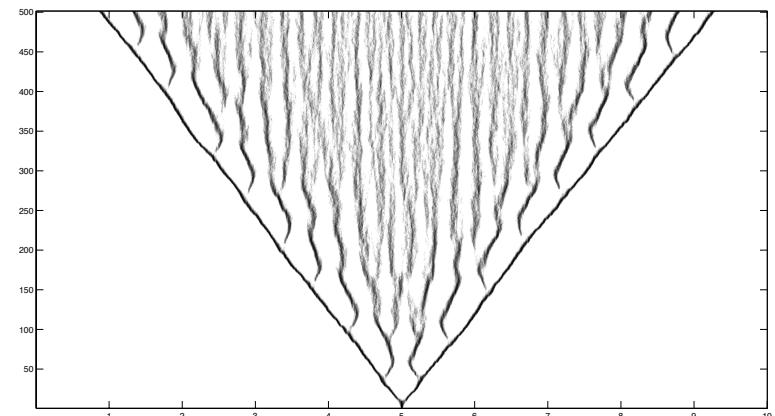
N individuals,

rescale mutation, birth, death rates

U. Dieckmann-R. Law, R. Ferriere

S. Billard, N. Champagnat

S. Méléard, V. C Tran





Asymptotics with mutations

$$\begin{cases} \varepsilon \frac{\partial}{\partial t} n_\varepsilon(t, x) - \varepsilon^2 \Delta n_\varepsilon = n_\varepsilon(t, x) R(x, \varrho_\varepsilon(t)), \\ \varrho_\varepsilon(t) = \int_{\mathbb{R}^d} n_\varepsilon(t, x) dx. \end{cases}$$



Asymptotics with mutations

$$\begin{cases} \varepsilon \frac{\partial}{\partial t} n_\varepsilon(t, x) - \varepsilon^2 \Delta n_\varepsilon = n_\varepsilon(t, x) R(x, \varrho_\varepsilon(t)), \\ \varrho_\varepsilon(t) = \int_{\mathbb{R}^d} n_\varepsilon(t, x) dx. \end{cases}$$

In the limit one can expect

$$0 = n(t, x) R(x, \varrho(t)),$$

$$n(t, x) = \rho \delta_{\Gamma(t)}, \quad \Gamma(t) \subset \{R(\cdot, \rho(t)) = 0\}.$$

Proof



Step 1. $\varrho_\varepsilon(t) \in_b L^\infty, \quad n_\varepsilon \in_b L_t^\infty(L_x^1)$

Step 2. A BV estimate

Step 3. Represent

$$n_\varepsilon(t, x) = \exp \frac{\varphi_\varepsilon(t, x)}{\varepsilon}$$

the 'fittest' trait $\bar{x}(t)$ is characterised by the Eikonal equation with constraints

$$\begin{cases} \frac{\partial}{\partial t} \varphi(t, x) = R(x, \bar{\varrho}(t)) + |\nabla \varphi(t, x)|^2 \\ \max_x \varphi(t, x) = 0 \quad \left(= \varphi(t, \bar{x}(t)) \right). \end{cases}$$

Proof



Uniqueness

- $R(x, \varrho) = b(x)a(\varrho) - d(x)$
- J.-M. Roquejoffre et S. Mirrahimi
- P. E. Jabin Approach by modulation



Canonical equation

Any concentration point $\bar{x}_i(t)$ will satisfy

$$(i) \quad R(\bar{x}_i(t), \bar{I}(t)) = 0$$

$$(ii) \quad \frac{d}{dt} \bar{x}_i(t) = \left(-D^2 \varphi(\bar{x}_i(t), t) \right)^{-1} \cdot \nabla R(\bar{x}_i(t), \bar{I}(t))$$

Canonical equation

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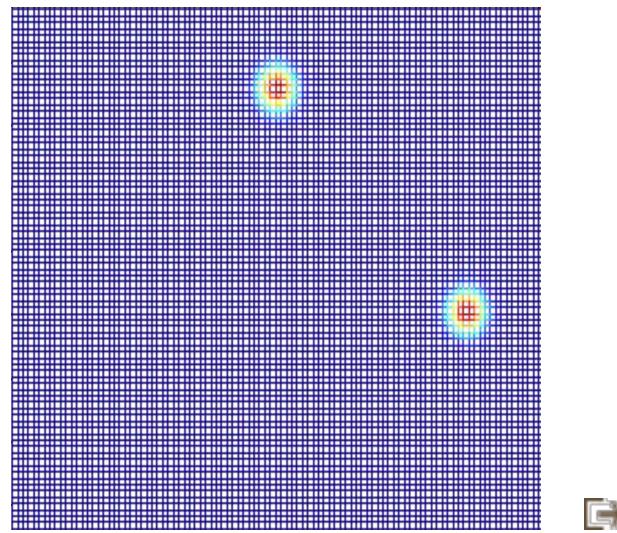
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Conclusions :

- Gause's competitive exclusion principle
- $n_\varepsilon = \exp(\varphi/\varepsilon)$ the shape of φ plays a role

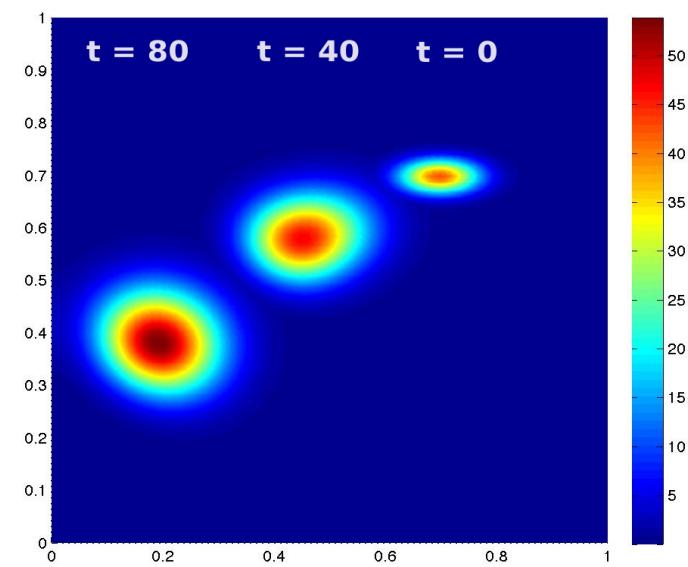
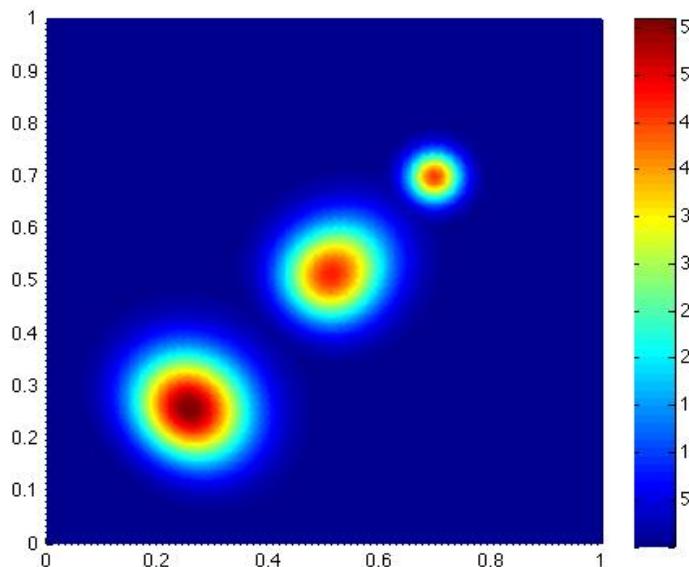
Canonical equation



Canonical equation

$$\frac{d}{dt}\bar{x}(t) = \left(-D^2\varphi(\bar{x}(t), t) \right)^{-1} \cdot \nabla R(\bar{x}(t), \bar{\varrho}(t))$$

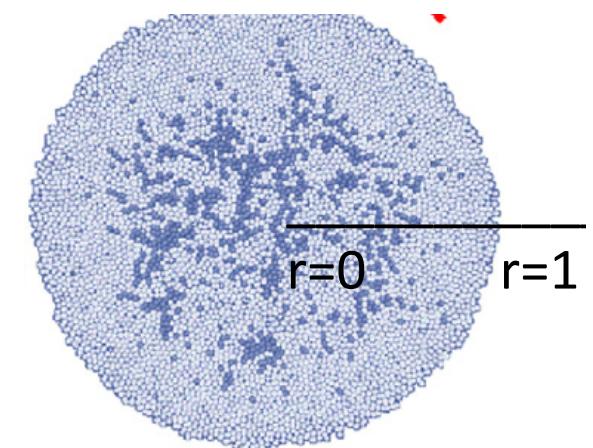
Effect of the matrix $\left(-D^2\varphi(\bar{x}(t), t) \right)$ (microstructure of the Dirac)



Space-trait concentration

Let $y \in \mathbb{R}$ a space variable

$$\begin{cases} \varepsilon \partial_t n_\varepsilon(y, x, t) = [r(x)c_\varepsilon(y, t) - d(x)\varrho_\varepsilon(y, t) - \mu(x)]n_\varepsilon(y, x, t) \\ -\Delta_y c_\varepsilon(y, t) + [\varrho_\varepsilon(y, t) + \lambda]c_\varepsilon(y, t) = \lambda c_B, \\ \varrho_\varepsilon(y, t) = \int n_\varepsilon(y, x, t)dx \end{cases}$$



Interpretation

- Nutrients/drugs are diffused and consumed by cells
- Local conditions select space-dependent traits

Space-trait concentration

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Theorem : For well-prepared initial data, as $\varepsilon_k \rightarrow 0$, we have

$$n_\varepsilon(y, x, t) \rightarrow \bar{\rho}(y, t)\delta(x - \bar{X}(y, t))$$

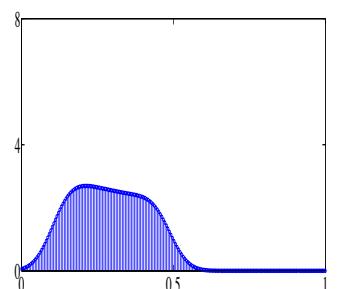
Difficulty : Space works well with L^∞ . Traits with L^1

Outcome : Explains heterogeneity

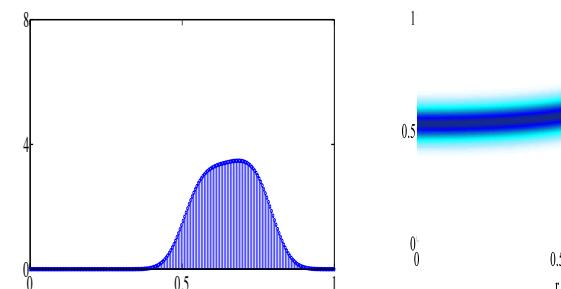
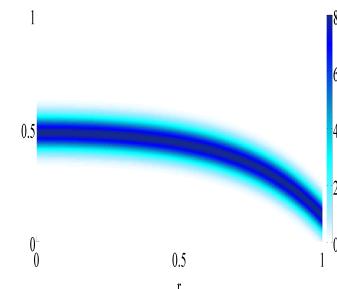
Space-trait concentration

Let x = resistance to drugs

$$\begin{cases} \varepsilon \partial_t n_\varepsilon(y, x, t) = [r(x)c_\varepsilon(y, t) - d(x)\varrho_\varepsilon(y, t) - \mu(x)]n_\varepsilon(y, x, t) \\ -\Delta_y c_\varepsilon(y, t) + [\varrho_\varepsilon(y, t) + \lambda]c_\varepsilon(y, t) = \lambda c_B, \\ \varrho_\varepsilon(y, t) = \int n_\varepsilon(y, x, t)dx \end{cases}$$



Without cytotoxic drug
High heterogeneity



With cytotoxic drug
Lower heterogeneity





Evolution of Dispersal

Selection without a proliferative advantage ?

- motility/dispersal of individuals is subject to variability
- no advantage regarding their reproductive rate
- $R(x, \rho)$ = Operator acting on the space variable

Hastings, *Theor. Popul. Biol.* 1983



Evolution of Dispersal

We model it for $y \in \Omega, x > 0$ + Neuman BC

$$\partial_t n(t, x, y) = \underbrace{x \partial_{yy}^2 n(t, x, y)}_{=R(x, \cdot)} + \underbrace{n(t, x, y) (K(y) - \rho(t, y))}_{\text{reproduction}} + \underbrace{\varepsilon^2 \partial_{xx}^2 n(t, x, y)}_{\text{mutations on motility}}$$

$$\rho(t, y) = \int_0^\infty n(t, x, y) dy$$



Evolution of Dispersal

$$\partial_t n(t, x, y) = \overbrace{x \partial_{yy}^2 n(t, x, y)}^{\text{dispersion/motility}} + \overbrace{n(t, x, y) (K(y) - \rho(t, y))}^{\text{reproduction}} + \overbrace{\varepsilon^2 \partial_{xx}^2 n(t, x, y)}^{\text{mutations on motility}}$$
$$\rho(t, y) = \int_0^\infty n(t, x, y) dy$$

Theorem (P. E. Souganidis, BP and K. Y. Lam, Y. Lou) The ESS are of the form

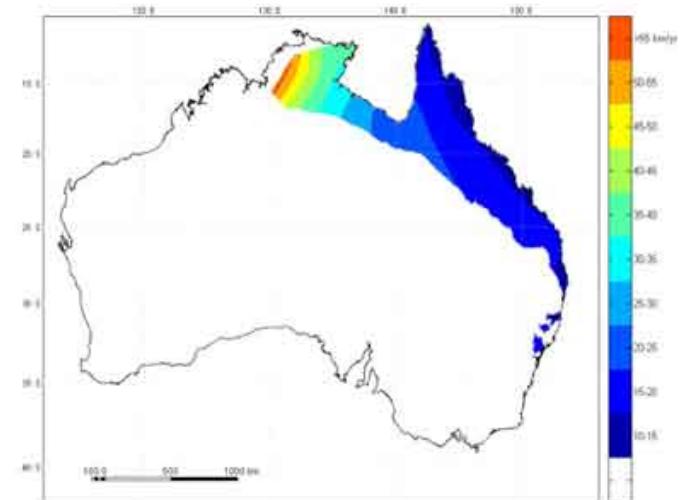
$$n(t, x, y) \approx \bar{\rho}_\infty(y) \delta(x = 0) \quad \varepsilon \rightarrow 0, \quad t \rightarrow \infty$$

and the constrained H.-J. eq.

$$\begin{cases} \frac{\partial}{\partial t} u(x, t) = \Lambda(x, \varrho(\cdot, t)) + |\nabla u|^2 \\ \max_x u(x, t) = 0 = u(\bar{X}(t), t), \end{cases}$$

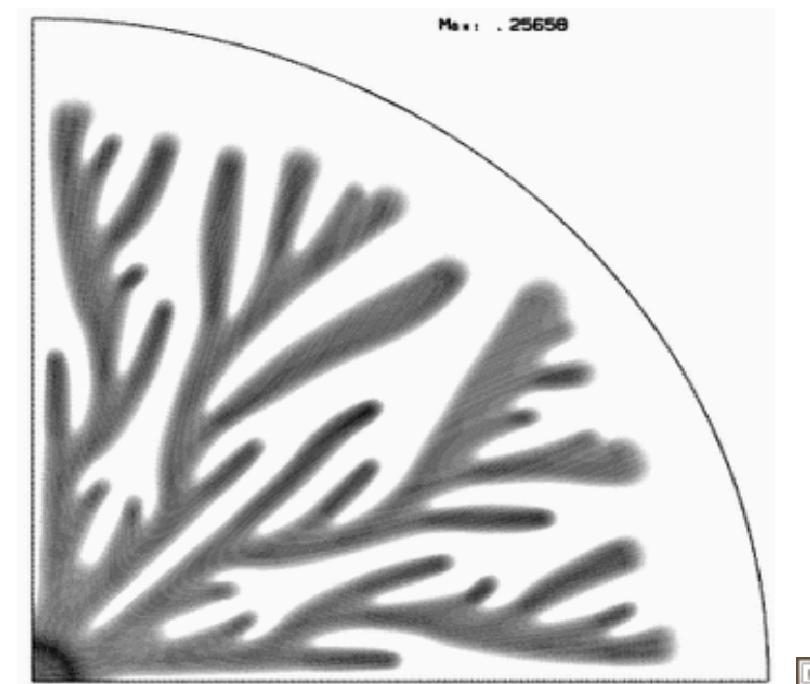
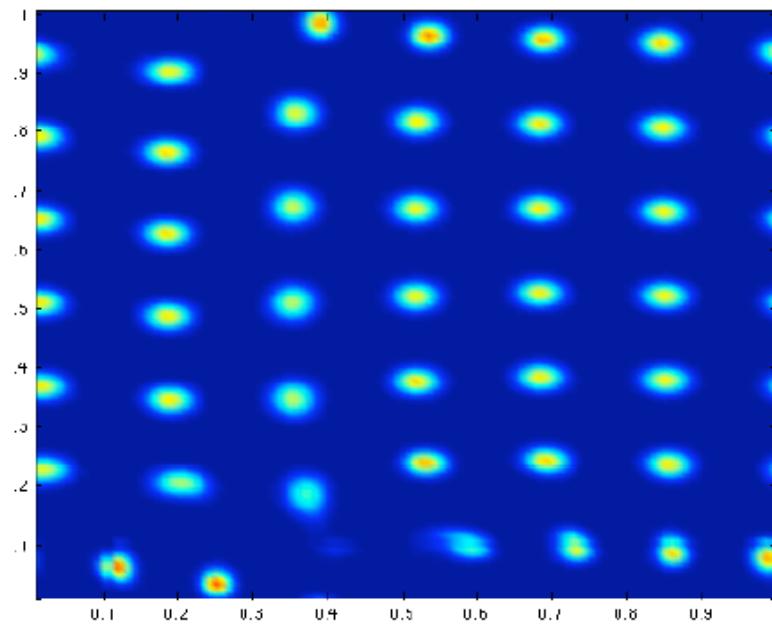
Evolution of Dispersal

- Same question for traveling waves
- Accelerating waves
- Example cane toads invasion in Australia



J. Berestycki, E. Bouin, V. Calvez, C. Mouhot, G. Raoul, L. Ryzhik., C. Henderson

Turing (dendritic) patterns



Thanks to my collaborators

O. Diekmann, P.-E. Jabin, S. Mischler,

M. Gauduchon, J. Clairambault, A. Escargueil,

G. Barles, S. Mirrahimi, P. E. Souganidis, A. Lorz, T. Lorenzi,

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THANK YOU ALL