Random walks in dynamic random environments and ancestry under local population regulation

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based on joint work, in part in progress, with Jiří Černý, Andrej Depperschmidt, Nina Gantert and Sebastian Steiber

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General aim

Study/understand the space-time embedding of ancestral lineages in spatial models for populations with local density regulation (in particular, with non-constant local population sizes).

A step towards combining ecological and population genetics aspects in a stochastic spatial population model

Caveat: Most results so far are more of conceptual than practical interest.

Outline

Introduction

- Logistic branching random walks and 'relatives'
 Coupling
- Spatial embedding of an ancestral line



M. Lamotte's grove snail data (cepaea nemoralis)





(c) Wikipedia user Mad Max



Frequency of the b+ gene in 108 colonies in a region in Aquitaine, southwestern $\ensuremath{\mathsf{France}}$

Maxime Lamotte, Recherches sur la structure génétique des populations naturelles du *Cepaea nemoralis*, Bulletin biologique de France et de Belgique, Suppl. 35, 1–239, (1951)

M. Lamotte's grove snail data



distance [km]

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Let $\eta(\mathbf{x}) =$ frequency of gene b+ in colony at $\mathbf{x} \in \mathbb{R}^2$

Question: For population in homogeneous equilibrium,

 $\mathbb{E}\big[\big(\eta(\mathbf{x}) - \eta(\mathbf{y})\big)^2\big] = ?$

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where

 $\phi(\mathbf{x}, \mathbf{y}) = \mathsf{Prob.}(\mathsf{two individuals}, \mathsf{sampled at } \mathbf{x} \mathsf{ and at } \mathbf{y} \mathsf{ have same type}).$

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Assuming stationarity, we can estimate $\mathbb{E}[\eta(\mathbf{x})^2] = \mathbb{E}[\eta(\mathbf{0})^2]$ and $\mathbb{E}[\eta(\mathbf{x})] = \mathbb{E}[\eta(\mathbf{0})]$ from the data, for $\phi(\mathbf{x}, \mathbf{y})$ we use *Malécot's formula* (assuming, in particular, small mutation rates).

Malécot's formula

$$\phi(\mathbf{x}, \mathbf{y}) = \phi(\mathbf{x} - \mathbf{y}) \approx \frac{1}{N + \log(\sigma/\kappa\sqrt{2\mu})} K_0(\sqrt{2\mu}||\mathbf{x} - \mathbf{y}||/\sigma)$$

with μ = mutation rate, σ = (backward) 'dispersal distance',
 N = 'neighbourhood size', κ = 'local scale'
[and $K_0(r) = \int_0^\infty \exp(-r^2t - 1/(4t)) \frac{dt}{t}$ is the modified Bessel function of the second kind of order 0]

(Malécot 1948, cf also Barton, Depaulis, Etheridge 2002)

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with μ = mutation rate, σ = (backward) 'dispersal distance', N = 'neighbourhood size', κ = 'local scale' [and $\kappa_0(r) = \int_0^{\infty} \exp(-r^2t - 1/(4t)) \frac{dt}{t}$ is the modified Bessel function of the second kind of order 0] (Malécot 1948, cf also Barton, Depaulis, Etheridge 2002) Obtained from recursive decomposition ('follow two lineages backwards')

$$\begin{split} \phi(\mathbf{z}) &= (1-\mu)^2 \Big(\frac{1-\phi(\mathbf{0})}{\delta} \int_{\mathbb{R}^2} g(\mathbf{y}) g(\mathbf{z}-\mathbf{y}) \, d\mathbf{y} \\ &+ \int_{\mathbb{R}^2} \int_{\mathbb{R}^2} g(\mathbf{x}) g(\mathbf{x}') \phi(\mathbf{z}+\mathbf{x}-\mathbf{x}') \, d\mathbf{x} d\mathbf{x}' \Big) \end{split}$$

with $g(\cdot)$ an isotropic Gaussian density

[then solved e.g. via Fourier transform plus ad hoc assumption about behaviour near $\boldsymbol{z}=\boldsymbol{0}]$

M. Lamotte's grove snail data again



distance [km]

A successful fit??? $\overline{\phi(\mathbf{0})} \approx 0.22$, $\overline{\phi(\mathbf{0})^2} \approx 0.06$, applying Malécot's formula with $\mu = 10^{-8}$, $\kappa = 0.3$, N = 35, $\sigma = 10^{28}$

Colonies of *fixed* size N are arranged in a geographical space, say \mathbb{Z}^d



(d = 1 in this picture)

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For each child: Assign a random parent in same colony with probability $1-\nu,$ in a neighbouring colony with probability ν



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"Trivial" demographic structure, but paradigm model for evolution of *type distribution* in space

Stepping stone model: Ancestral lines



The stepping stone model (Kimura, 1953)

Fixed local population size N in each patch (arranged on \mathbb{Z}^d), patches connected by (random walk-type) migration

- Pros: + Stable population, no local extinction, nor unbounded growth
 - Ancestral lineages are (delayed) coalescing random walks (in particular, well defined),
 this makes detailed analysis feasible, yields via duality:

long-time behaviour of (neutral) type distribution

- Cons: An 'ad hoc' simplification, effects of local size fluctations not explicitly modelled
 - N is an 'effective' parameter, relation to 'real' population dynamics is unclear
 - Grid not so realistic for most populations

Remark: A problem with branching random walk

(Critical) branching random walks, where particles move and produce offspring independently, explicitly model fluctuations in local population size, but do not allow stable populations in $d \leq 2$: Branching random walk on Z(400Z)



(Felsenstein's "pain in the torus" 1975; Kallenberg 1977)

Branching random walk with local density-dependent feedback

- Possible and natural extension of the stepping stone model (and of branching random walks)
- Offspring distribution supercritical when there are few neighbours, subcritical when there are many neighbours

e.g. Bolker & Pacala (1997), Murrell & Law (2003), Etheridge (2004), Fournier & Méléard (2004), Hutzenthaler & Wakolbinger (2007) Blath, Etheridge & Meredith (2007), B. & Depperschmidt (2007), Pardoux & Wakolbinger (2011), Le, Pardoux & Wakolbinger (2013), ...

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Challenges:

- Mathematical analysis harder (population sizes are now a space-time random field; feedback mechanism makes different families dependent)
- Dynamics of ancestral lineages?

Logistic branching random walks

Particles 'live' in \mathbb{Z}^d in discrete generations, $\eta_n(x) = \#$ particles at $x \in \mathbb{Z}^d$ in generation n.

Given η_n ,

each particle at x has Poisson $((m - \sum_{z} \lambda_{z-x} \eta_n(z))^+)$ offspring, m > 1, $\lambda_z \ge 0$, $\lambda_0 > 0$, symmetric, finite range.

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$$\eta_{n+1}(y) \sim \operatorname{Poi}\Big(\sum_{x} p_{y-x}\eta_n(x) \big(m - \sum_{z} \lambda_{z-x}\eta_n(z)\big)^+\Big), \quad \text{independent}$$

Remarks

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- For $\lambda \equiv 0$, (η_n) is a branching random walk.
- (η_n) is a spatial population model with local density-dependent feedback:
 Offspring distribution supercritical when there are few neighbours, subcritical when there are many neighbours
- System is in general *not* attractive.
- Conditioning¹ on η_n(·) ≡ N for some N ∈ N ("effective local population size") yields a discrete version of the stepping stone model

¹and considering types and/or ancestral relationships

Remarks, 2

 Poisson offspring distribution is a somewhat artificial (though technically very convenient) choice, one could take any family ν(a) ∈ M₁(ℤ₊) parametrised by

$$a = \sum_k k
u_k(a)$$
 satisfying $\sum_k (k-a)^2
u_k(a) \leq ext{Const.} imes a$

- Logistic term x(1-x) could be replaced by another suitable function h(x), e.g. $h(x) = x \exp(a bx)$.
- We have little "explicit" information on the system, e.g. no closed formulas for means, variances/covariances, etc.
- Related continuous-mass models (Etheridge 2004, Blath et al 2007) can be obtained as scaling limit

Survival and complete convergence

Theorem (B. & Depperschmidt, 2007)

Assume $m \in (1,3)$, $0 < \lambda_0 \ll 1$, $\lambda_z \ll \lambda_0$ for $z \neq 0$.

 (η_n) survives for all time globally and locally with positive probability for any non-trivial initial condition η_0 . Given survival, η_n converges in distribution to its unique non-trivial equilibrium.

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Proof uses

corresponding deterministic system

$$\zeta_{n+1}(y) = \sum_{x} p_{y-x} \zeta_n(x) \left(m - \sum_{z} \lambda_{z-x} \zeta_n(z) \right)^+$$

has unique (and globally attracting) non-triv. fixed point

- $\bullet\,$ strong coupling properties of $\eta\,$
- coarse-graining and comparison with directed percolation

Restriction m < 3 is "inherited" from logistic iteration $w_{n+1} = mw_n(1 - w_n)$.

Coupling: An essential proof ingredient



 $m = 1.5, p = (1/3, 1/3, 1/3), \lambda = (0.01, 0.02, 0.01)$

Starting from any two initial conditions η_0 , η'_0 , copies (η_n) , (η'_n) can be coupled such that if both survive, $\eta_n(x) = \eta'_n(x)$ in a space-time cone.

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Dynamics of an ancestral line

Given stationary $(\eta_n^{\text{stat}}(x), n \in \mathbb{Z}, x \in \mathbb{Z}^d)$, cond. on $\eta_0^{\text{stat}}(\mathbf{0}) > 0$ (and "enrich" suitably to allow bookkeeping of genealogical relationships), sample an individual from space-time origin $(\mathbf{0}, 0)$ (uniformly) Let X_n = position of her ancestor n generations ago:

Given η^{stat} and $X_n = x$, $X_{n+1} = y$ w. prob.

$$\frac{p_{x-y}\eta_{-n-1}^{\text{stat}}(y)(m-\sum_{z}\lambda_{z-y}\eta_{-n-1}^{\text{stat}}(z))^{+}}{\sum_{y'}p_{x-y'}\eta_{-n-1}^{\text{stat}}(y')(m-\sum_{z}\lambda_{z-y'}\eta_{-n-1}^{\text{stat}}(z))^{+}}$$

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Question:

 (X_n) is a random walk in a – relatively complicated – random environment. Is it similar to an ordinary random walk when viewed over large enough space-time scales?

Dynamics of an ancestral line

$$\mathbb{P}(X_{n+1} = y \mid X_n = x, \eta^{\text{stat}}) \\ = \frac{p_{x-y}\eta_{-n-1}^{\text{stat}}(y)(m - \sum_{z} \lambda_{z-y}\eta_{-n-1}^{\text{stat}}(z))^+}{\sum_{y'} p_{x-y'}\eta_{-n-1}^{\text{stat}}(y')(m - \sum_{z} \lambda_{z-y'}\eta_{-n-1}^{\text{stat}}(z))^+}$$

Remarks

 Analysis of random walks in random environments (also in dynamic random environments) is today a major industry. Yet as far as we know, none of the general techniques developed so far in this context is applicable.

In particular: The natural "forwards" time direction for the walk is "backwards" time for the environment.

• Observation: (X_n) is close to ordinary rw in regions where relative variation of $\eta_{-n-1}(x)$ is small.

Large scale dynamics of an ancestral line

 X_n = position of ancestor *n* generations ago of an individual sampled today at origin in equilibrium

Theorem: LLN and (averaged) CLT If $m \in (1,3)$, $0 < \lambda_0 \ll 1$, $\lambda_z \ll \lambda_0$ for $z \neq 0$, $\mathbb{P}\left(\frac{1}{n}X_n \to 0 \mid \eta_0(0) \neq 0\right) = 1$ and $\mathbb{E}\left[f\left(\frac{1}{\sqrt{n}}X_n\right) \mid \eta_0(0) \neq 0\right] \underset{n \to \infty}{\longrightarrow} \mathbb{E}\left[f(Z)\right]$ for $f \in C_b(\mathbb{R}^d)$, where Z is a (non-degenerate) d-dimensional normal rv.

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for $f \in C_b(\mathbb{R}^d)$, where Z is a (non-degenerate) d-dimensional normal rv.

The proof uses a *regeneration* construction (and *coarse-graining* and *coupling*, in particular with directed percolation): Regeneration times $0 = T_0 < T_1 < T_2 < \cdots$, express $X_{T_k} = Y_1 + \cdots + Y_k$ with $Y_i := X_{T_i} - X_{T_{i-1}}$ and $(Y_i, T_i - T_{i-1})_{i \ge 1}$ 'almost i.i.d.'

Spatial population models (η_n) and ancestral lineages (X_k) : Abstract conditions

• Local Markov structure: $\eta_{n+1}(x)$ is a function of η_n in a finite window around x plus 'local randomness'

Given η , $(X_k)_{k=0,1,...}$ is a Markov chain, $\mathbb{P}(X_{k+1} = \cdot | \eta, X_k = x)$ depends on η_{-k} , η_{-k-1} in a finite window around x

[note reversal of time between η and X]

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Good configurations and coupling propagation for η on coarse-grained scale L_{space}Z^d × L_{time}Z: With high probability,
 'good' blocks have to make neighbours good in L_{time} steps and η's with two different good local initial conditions become locally identical after L_{time} steps

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 'good' blocks have to make neighbours good in L_{time} steps and η's with two different good local initial conditions become locally identical after L_{time} steps
- On good η blocks, the law of X is 'well behaved': e.g., close to a non-disorded symmetric finite range reference walk
- Symmetry in distribution

Idea for constructing regeneration times

Find time points along the path such that:

 a cone (with fixed suitable base diameter and slope) centred at the current space-time position of the walk covers the path

and everything it has explored so far (since the last regeneration)

- configuration $\eta^{\rm stat}$ at the base of the cone is "good"
- "strong" coupling for $\eta^{\rm stat}$ occurs inside the cone

Then, the conditional law of future path increments is completely determined by the configuration $\eta^{\rm stat}$ at the base of the cone (= a finite window around the current position)



Outlook

- Technique is robust (applies to many spatial population models in "high density" regime) but current result "conceptual" rather than practical
- We are hopeful that a "joint regeneration" construction can be implemented to analyse samples of size 2 (or even more) on large space-time scales.
- Meta-theorem: "Everything"² that is true for the neutral multi-type voter model is also true for the neutral multi-type spatial logistic model.
- Suitably controlled joint regeneration also allows to derive an a.s. version of the CLT, conditioned on a fixed realisation of $\eta^{\rm stat}$.

²with a suitable interpretation of "everything". Examples: Clustering of neutral types in d = 1, 2; multippe equilibria exist in $d \ge 3$, $\mathbb{P}(\text{two ind. sampled at distance } x \text{ have same type}) \sim C x^{2-d}$.

Outlook

- In fact, such a "joint regeneration" construction has been carried out for a simplified version of η^{stat}, the discrete time contact process. Then, (X_n) is a directed random walk on the "backbone" of an oriented percolation cluster.
- The diffusion rate σ² = σ²(p) = E[Y²_{1,1}]/E[T₁] ∈ (0,∞) is not very explicit (though in principle accessible by simulations), effective coalescence probability for two lineages still a "black box" (at least to me).

(Some) details can be found in

M. B., A. Depperschmidt, Ann. Appl. Probab. 17 (2007), 1777-1807

M. B., J. Černý, A. Depperschmidt, N. Gantert, Directed random walk on an oriented percolation cluster, Electron. J. Probab. 18 (2013), Article 80

M. B., J. Černý, A. Depperschmidt, Random walks in dynamic random environments and ancestry under local population regulation, arXiv:1505.02791 (2015)

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Thank you for your attention!