# SOME MATHEMATICAL MODELS FROM POPULATION GENETICS 

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with thanks to numerous collaborators, especially Nick Barton, IST Austria

## Spatial models so far: subdivided populations

Kimura's stepping stone model Special case $N_{e}(i) \equiv N_{e}$
$d p_{i}=\sum_{j} m_{j i}\left(p_{j}-p_{i}\right) d t+\sqrt{\frac{1}{N_{e}} p_{i}\left(1-p_{i}\right)} d W_{i}$

$\left\{W_{i}\right\}_{i \in I}$ independent Brownian motions
System of W-F diffusions coupled through migration

The structured coalescent $\underline{n}$ :

- $\left\{\begin{array}{l}n_{i} \mapsto n_{i}-1 \\ n_{j} \mapsto n_{j}+1\end{array}\right.$ at rate $n_{i} m_{j i}$
- $n_{i} \mapsto n_{i}-1$ at rate $\frac{1}{2 N_{e}} n_{i}\left(n_{i}-1\right)$


## Isolation by distance

Malécot-Wright approximation for the stepping stone model


## The unreasonable effectiveness of the Kingman coalescent

Common to use Kingman coalescent even for natural populations Replace census population size by an effective population size

Sampling uniformly from the torus $\mathbb{T}(L) \subset \mathbb{Z}^{2}$ $T=$ time to MRCA two individuals sampled uniformly from $\mathbb{T}(L)$

- $T_{0}=$ time to first come into same deme

$$
\begin{aligned}
& T=T_{0}+t_{0} \\
& t_{0} \ll T_{0}
\end{aligned}
$$

- $t_{0}=$ time to coalesce started from same deme
On timescale $L^{2} \log L$ genealogy uniform sample from $\mathbb{T}(L) \rightarrow$ Kingman coalescent as $L \rightarrow \infty \quad$ Zähle, Cox, Durrett (2005)

Census population size grows with $L^{2}$ so this does not explain the timescale seen in real populations

## An obvious challenge




## Modelling a spatial continuum: the Wright-Malécot model

- Individuals are scattered across a two-dimensional space.
- In each generation, each individual produces a Poisson number of offspring (average one).
- Offspring are scattered in a Gaussian distribution around their parent.


Mitch Gooding Jerome Kelleher

## The pain in the torus (Felsenstein, 1975)

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In $d=1,2$ population exhibits clumping/extinction

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In 2D the diffusion limit fails over small scales ... and so does the obvious backwards model.

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> Demographic history of many species dominated by large scale extinction-recolonisation events


## Small neighbourhood size



In a spatial continuum, a single individual can be parent to a significant proportion of the local population.

## An individual based model

- Start with Poisson intensity $\lambda d x$. Events rate $d t \otimes d x \otimes \xi(d r, d u)$. Throw down ball $B(x, r)$.


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- New individuals born according to Poisson intensity $\lambda u \mathbf{1}_{B_{r}(x)}$.
Offspring inherit type of parent


## $\lambda \rightarrow \infty$ limit (no space)

Start from Poiss $(\lambda)$
If first reproduction event has 'impact' $u$

- Poiss $((1-u) \lambda)$ 'survivors';
- Poiss $(u \lambda)$ offspring.

As $\lambda \rightarrow \infty$ proportion $u$ of individuals die and are replaced by offspring of the type of the parent.

## The $\Lambda$-Fleming-Viot process

State $\left\{\rho(t, \cdot) \in \mathcal{M}_{1}(K), t \geq 0\right\}$. $K$ space of genetic types.

- Poisson Point Process $\Pi$ intensity $d t \otimes F(d u)$
- if $(t, u) \in \Pi$, individual sampled at random from population at time $t$ - (i.e. choose $k \sim \rho(t-)$ )
- proportion $u$ of population replaced by offspring of chosen individual

$$
\rho(t, \cdot)=(1-u) \rho(t-, \cdot)+u \delta_{k} .
$$

$F(d u)=\frac{\Lambda(d u)}{u^{2}}, \Lambda$ finite measure on $[0,1]$.
Donnelly \& Kurtz (1999)
('Generalised Fleming-Viot process', Bertoin \& Le Gall 2003)

## The $\Lambda$-Fleming-Viot process



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## $\Lambda$-coalescents

Donnelly \& Kurtz (1999), Pitman (1999), Sagitov (1999)
If there are currently $n$ ancestral lineages, each transition involving $j$ of them merging happens at rate

$$
\beta_{n, j}=\int_{0}^{1} u^{j}(1-u)^{n-j} \frac{\Lambda(d u)}{u^{2}}
$$

- $\Lambda$ a finite measure on $[0,1]$
- Kingman's coalescent, $\Lambda=\delta_{0}$


## The spatial $\Lambda$-Fleming-Viot process Barton - E - Véber and friends

State $\left\{\rho(t, x, \cdot) \in \mathcal{M}_{1}(K), x \in \mathbb{R}^{2}, t \geq 0\right\}$.

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For all $y \in B_{r}(x)$,

$$
\rho(t, y, \cdot)=(1-u) \rho(t-, y, \cdot)+u \delta_{k} .
$$



## Backwards in time

- A single ancestral lineage evolves in series of jumps with intensity

$$
d t \otimes \int_{(|x| / 2, \infty)} \int_{[0,1]} \frac{L_{r}(x)}{\pi r^{2}} u \xi(d r, d u) d x
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on $\mathbb{R}_{+} \times \mathbb{R}^{2}$ where $L_{r}(x)=\left|B_{r}(0) \cap B_{r}(x)\right|$.


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Note: If $\xi(d r, d u)=\mu(d r) \otimes \delta_{u}$, rate of jumps $\propto u$.


## Duality

Suppose $K=\{a, A\}$. Define $w(t, x)=\rho(t, x,\{a\})$ to be the proportion of the population at site $x$ at time $t$ that are of type $a$.

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- Sample $N_{0}$ individuals from locations $\left\{X_{i}(0)\right\}_{i=1}^{N_{0}}$ from the present day population;
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$$
\mathbb{E}\left[\prod_{i=1}^{N_{0}} w\left(t, X_{i}(0)\right)\right]=\mathbb{E}\left[\prod_{i=1}^{N_{t}} w\left(0, X_{i}(t)\right)\right] .
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Direct analogue of our duality in the stepping stone model

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(actually have to sample from random positions and integrate to circumvent issues with sets of Lebesgue measure zero)

Direct analogue of our duality in the stepping stone model

## A framework for modelling

- Different spaces,
- Different shapes of event,
- Non-uniform replacement,
- Non-constant density,
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Robust results? $\sim$ Scaling limits.

## Example: Wright and Malécot again

The effect of mixed events on $F(x, \mu)$. A mixture of rare large events and frequent small events
OXFORD

## Recap: The Wright-Fisher model with selection

Two types $a, A$, relative fitnesses | $a$ | $A$ |
| :---: | :---: |
| $1-s$ | 1 |

During reproduction, each individual produces large number of juveniles from which next generation sampled.

If proportion $A$-alleles in parental population is $q$, proportion in pool of juveniles is

$$
q^{*}=\frac{q}{1-s(1-q)} \approx q+s q(1-q)
$$

Population size $N$ (fixed).

## Establishment of a favourable allele (Fisher 1930)

While rare, No. offspring of a favoured individual
$\sim \operatorname{Binom}(N,(1+s) / N) \approx \operatorname{Poiss}(1+s)$.
Branching process approximation: probability extinction satisfies

$$
x=\exp (-(1+s)(1-x)),
$$

Survival probability, $y=1-x$,

$$
y=1-\exp (-(1+s) y)=(1+s) y-\frac{1}{2}(1+s)^{2} y^{2}+\mathcal{O}\left(y^{3}\right)
$$

Rearranging:

$$
\frac{1}{2}(1+s)^{2} y^{2}=s y \quad \Longrightarrow \quad y \approx 2 s
$$

## Does space matter?

Maryuama (1970),

- subdivided population, demes (large) constant size;
- selection acts independently in each deme;
- contribution of each deme to next generation proportional to size.
$\leadsto$ Fixation probability independent of population subdivision.


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Aim to investigate the interaction of natural selection and spatial structure in the framework of the spatial Lambda-Fleming-Viot process.

## Introducing selection to the SLFV

WARNING: There are lots of ways to do this.
Here we mimic what we did for the Wright-Fisher/Moran models in the first lecture.

## Introducing selection to the SLFV

$K=\{a, A\}, w(t, x)=\rho(t, x, a)$ proportion of type $a$

- (i) Two types, $a, A$. Weight type $a$ by $(1-s)$. If a reproduction event affects a region $B(x, r)$ in which current proportion of $a$-alleles is $\bar{w}$, then probability offspring are type $a$ is

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- (ii) Neutral events rate $\propto(1-s)$, selective events rate $\propto s$. At selective reproduction events, sample two potential parents. If types $a a$, then an $a$ reproduces, otherwise an $A$ does.


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c.f. what we did for Moran model


## (Spatial) Ancestral selection graph

Evolution of ancestry due to neutral events as before:

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A sampled individual is type $a$ iff all lineages in the corresponding ASG are type $a$ at any previous time.

## Zooming out: recovering classical models

The spread of a favoured allele is classically modelled through the (stochastic) Fisher-KPP equation:

$$
d u=\left(\frac{1}{2} \Delta u+s u(1-u)\right) d t+\mathbf{1}_{d=1} \epsilon \sqrt{u(1-u)} W(d t, d x) .
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Key tool: ancestral selection graph.
Stochastic Fisher-KPP is dual to branching and coalescing Brownian motion

## Branching Brownian motion and the Fisher-KPP equation

Binary branching BM

$$
\mathbf{X}_{t}=\left\{X_{t}^{1}, \ldots, X_{t}^{N_{t}}\right\}
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- Individuals follow independent Brownian motions
- Individual lifetime $\operatorname{Exp}(s)$
- Replaced (at location where die) by two offspring


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w(t, x)=\mathbb{E}_{x}\left[\prod_{i=1}^{N_{t}} w\left(0, X_{t}^{i}\right)\right], \quad \frac{\partial w}{\partial t}=\frac{1}{2} \Delta w+s\left(w^{2}-w\right)
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$$

$S \sim \operatorname{Exp}(s)=$ lifetime ancestor started at $x, h \ll 1$,

$$
\begin{aligned}
\mathbb{E}_{x}\left[\prod_{i=1}^{N_{t+h}} w\left(0, X_{t+h}^{i}\right)\right]= & \mathbb{E}_{x}\left[\prod_{i=1}^{N_{t+h}} w\left(0, X_{t+h}^{i}\right) \mid S<h\right] \mathbb{P}[S<h] \\
& +\mathbb{E}_{x}\left[\prod_{i=1}^{N_{t+h}} w\left(0, X_{t+h}^{i}\right) \mid S>h\right] \mathbb{P}[S>h]
\end{aligned}
$$

$$
\begin{array}{r}
\mathbb{E}_{x}\left[\prod_{i=1}^{N_{t+h}} w\left(0, X_{t+h}^{i}\right) \mid S<h\right] \mathbb{P}[S<h]=\operatorname{sh}\left(\mathbb{E}_{x}\left[\prod_{i=1}^{N_{t}} w\left(0, X_{t}^{i}\right)\right]\right)^{2} \\
+O\left(h^{2}\right)
\end{array}
$$

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& \mathbb{E}_{x}\left[\prod_{i=1}^{N_{t+h}} w\left(0, X_{t+h}^{i}\right) \mid S>h\right] \mathbb{P}[S>h] \\
& =(1-s h) E_{x}\left[\mathbb{E}_{B_{h}}\left[\prod_{i=1}^{N_{t}} w\left(0, X_{t}^{i}\right)\right]\right]+O\left(h^{2}\right)
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& \quad+s\left(w(t, x)^{2}-w(t, x)\right) \\
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u(t, x)=1-w(t, x) \text { solves } \frac{\partial u}{\partial t}=\frac{1}{2} \Delta u+s u(1-u)
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## Convergence of SLFV with selection

- SLFV dual to system of branching and coalescing random walks
- Fisher-KPP equation dual to binary branching Brownian motion


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Recall Wright-Fisher diffusion (genetic drift) dual to Kingman coalescent
In spatial setting, Wright-Fisher noise reflected in coalescence in dual - lineages coalesce at rate determined by local time they spend together, but only makes sense in $d=1$

To identify convergence to (stochastic) Fisher-KPP, show convergence of the dual processes

## Brief aside on random walk

Suppose $X$ is simple random walk on $\mathbb{Z}$.

Write $\tau$ for hitting time of $\{0, N\}$
Take $X_{0}=1$. Doob's Optional Stopping Theorem says $\mathbb{E}\left[X_{\tau}\right]=X_{0}$.

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In $d=2$, corresponding quantity has mean $\propto \log N$.

## Reminder: parameters in SLFV with selection

- Events driven by Poisson Point Process $\Pi$ that specifies
- centre and radius event
- impact event
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Dual lineages make jumps of length $O(r)$ at rate proportional to $u r^{d}$, and branch at rate proportional to $s u r^{d}$
lineages can only coalesce when at separation less than $4 r$

## Scaling limits I: High neighbourhood size

Set $u_{n}=u / n^{\gamma}, s_{n}=s / n^{\delta}, w^{(n)}(t, x)=w\left(n t, n^{\beta} x\right)$, Jump rate $n u_{n}$, jump size $1 / n^{\beta}$. Diffusive scaling: $2 \beta=1-\gamma$

- At 'branching' event, two lineages at separation $\mathcal{O}\left(1 / n^{\beta}\right)$.
- Probability separate to $\mathcal{O}(1)$ before come back together is $\mathcal{O}\left(1 / n^{\beta}\right),(d=1) ; \mathcal{O}(1 / \log n),(d=2) ; \mathcal{O}(1),(d \geq 3)$.
- If two lineages hit by same event, given one jumps, they coalesce with probability $\mathcal{O}\left(1 / n^{\gamma}\right)$.
$d \geq 2$ : Probability 'long' excursion before coalesce $\mathcal{O}(1)$;
$d=1$ : Number attempts to reach separation $\mathcal{O}(1)$
$\sim$ number of attempts to coalesce: $\beta=\gamma$;
Selection events rate $n u_{n} s_{n} \mathcal{O}(1): 1-\gamma-\delta=0$.

$$
\leadsto \beta=\gamma=1 / 3, \quad \delta=2 / 3
$$

## Scaling limits I: High neighbourhood size

Fixed impact $u$ and event radius $r$, selection coefficient $s$

- Set $u_{n}=u / n^{1 / 3}, s_{n}=s / n^{2 / 3}, w^{(n)}(t, x)=w\left(n t, n^{1 / 3} x\right)$,

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d w=\frac{1}{2} \Delta w d t+s w(1-w) d t+\mathbf{1}_{d=1} \epsilon \sqrt{w(1-w)} W(d t, d x)
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E. Véber, Yu.

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Here, $u_{n} \rightarrow 0$, corresponding to high neighbourhood size.
$\gamma>\beta$ (even bigger neighbourhood size) $\leadsto$ deterministic equation in all dimensions

