

# Some mathematical models from population genetics

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

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#### What we have so far: Wright-Fisher/Moran models

In time units of  $N_e$  generations,  $p = proportion \ a$ -alleles

 (Forwards time) The Wright-Fisher diffusion (with and without selection)

$$dp_t = -sp_t(1-p_t)dt + \sqrt{p_t(1-p_t)}dW_t;$$

Backwards time) The Kingman coalescent/ ASG

$$n_t \mapsto n_t - 1$$
 at rate  $\binom{n_t}{2}$ ,  $n_t \mapsto n_t + 1$  at rate  $sn_t$ ;

Sampling probabilities

$$\mathbb{E}[p(t)^{n(0)}] = \mathbb{E}[p(0)^{n(t)}]$$

Stronger result holds. Kingman coalescent really describes genealogy of random sample from (neutral) population.

## Adding spatial structure: subdivided populations

Population subdivided into demes = islands = colonies

- Vertices of graph,  $i \in I$ ;
- $i \sim j$  if i, j neighbours
- $N_i =$  population size in deme i

#### Structured Wright-Fisher model

Reproduction in discrete generations

- neutral Wright-Fisher within each deme
- proportion  $m_{ij}$  of individuals in deme *i* migrate to deme *j*

$$N_i \sum_{j \sim i} m_{ij} = \sum_{j \sim i} N_j m_{ji}$$

#### Genealogy of structured Wright-Fisher model

1. Two lineages sampled from deme i

$$\mathbb{P}\left[\text{coalesce in } j \neq i \text{ in previous generation}\right] = \frac{\binom{m_{ji}N_j}{2}}{\binom{N_i}{2}} \frac{1}{N_j}$$
$$\mathbb{P}\left[\text{coalesce in } i \text{ in previous generation}\right] = \frac{\binom{N_i - \sum_{j \sim i} m_{ji}N_j}{2}}{\binom{N_i}{2}} \frac{1}{N_i}$$

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2. Two lineages sampled from demes  $i \neq j$ 

 $\mathbb{P}\left[\text{coalesce in } k \notin \{i, j\} \text{ in previous generation}\right] = \frac{m_{ki}N_k}{N_i} \frac{m_{kj}N_k}{N_j} \frac{1}{N_k}$  $\mathbb{P}\left[\text{coalesce in } j \text{ in previous generation}\right] = \frac{m_{ji}N_j}{N_i} \frac{\left(N_j - \sum_{l \sim j} m_{lj}N_l\right)}{N_j} \frac{1}{N_j}$ 

▶  $N_i = O(N)$  (large)

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 $\mathbb{P}\big[\text{simultaneous or multiple mergers}\big] = O(1/N^2)$ 

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The structured coalescent  $\underline{n} = (n_i)_{i \in I}$ :

$$\left\{ \begin{array}{l} n_i \mapsto n_i - 1\\ n_j \mapsto n_j + 1 \end{array} \text{ at rate } n_i \frac{N_e(j)}{N_e(i)} m_{ji} \\ n_i \mapsto n_i - 1 \text{ at rate } \frac{1}{2N_e(i)} n_i (n_i - 1) \end{array} \right.$$

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Ancestral lineages drawn into more populous demes

$$N_i \sum_{j \sim i} m_{ij} = \sum_{j \sim i} m_{ji} N_j, \ m_{ij} = O(1/N)$$

$$\mathbb{E}[\Delta p_i] = \frac{1}{N_i} \Big( \Big(1 - \sum_{j \sim i} m_{ij}\Big) N_i p_i + \sum_{j \sim i} m_{ji} N_j p_j \Big) - p_i$$
$$= \sum_{j \sim i} m_{ji} \frac{N_j}{N_i} p_j - \frac{1}{N_i} \sum_{j \sim i} m_{ij} N_i p_i$$

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Alleles a, A.  $p_i(t) =$  proportion of type a in deme i at time t $\Delta p_i$  change across single generation

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 $\mathbb{E}\left[(\Delta p_i)^2\right] = \frac{1}{N_i} \left(p_i(1-p_i) + O(1/N)\right) \qquad \operatorname{Cov}\left(\Delta p_i, \Delta p_j\right) = O(1/N^2)$ 

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As  $N \to \infty$  recover a system of diffusions coupled through migration

#### Kimura's stepping stone model

 $\sum_{j} N_e(i)m_{ij} = \sum_{j} N_e(j)m_{ji}$ 

$$dp_{i} = \sum_{j} \frac{N_{e}(j)}{N_{e}(i)} m_{ji}(p_{j} - p_{i}) dt + \sqrt{\frac{1}{N_{e}(i)} p_{i}(1 - p_{i})} dW_{i} \overset{\text{optimal}}{\longrightarrow} 0 + \frac{1}{N_{e}(i)} dW_{i} \overset{\text$$

 $\{W_i\}_{i \in I}$  independent Brownian motions

System of W-F diffusions coupled through migration

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# for simplicity $N_i \equiv N_e$

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 $\frac{d}{du}\mathbb{E}[\underline{p}_{\underline{u}}^{\underline{n}_{t-u}}] = 0$ 

 $\mathbb{E}\left[\underline{p}_{t}^{\underline{n}_{0}}\right] = \mathbb{E}\left[\underline{p}_{0}^{\underline{n}_{t}}\right].$ 

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 $\underline{n} \mapsto \underline{n} + \underline{e}_j - \underline{e}_i$  at rate  $n_i m_{ji}$ 

 $\underline{n} \mapsto \underline{n} - \underline{e}_i$  at rate  $\frac{1}{N_e} \binom{n_i}{2}$ 

#### Interpretation

$$\mathbb{E}\left[\underline{\underline{p}}_{t}^{\underline{n}_{0}}\right] = \mathbb{E}\left[\underline{\underline{p}}_{0}^{\underline{n}_{t}}\right].$$

- Sample  $n_i(0)$  individuals from deme *i*,  $\sum_i n_i(0) < \infty$ ,
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**Example** Suppose  $I = \mathbb{Z}^2$ For any finite sample, eventually  $\underline{n}_t$  is a singleton, so all individuals in the sample are of the same type.

Need to account for mutation in our model

## Adding mutation

Simplest example:

- Infinitely many alleles model of mutation: each individual in each generation, independently, with small probability  $\mu$  mutates to a type never before seen in the population
- Probability of identity by descent of two individuals, F,
   = probability no mutation since most recent common ancestor (MRCA)
- Equivalently  $F = (1 2\mu)^T \approx \exp(-2\mu T)$  is the Laplace transform of the distribution of the time to the MRCA.

The neutral mutation rate dictates the timescales over which we can reconstruct information about genealogies.

In a population in which individuals typically migrate to geographically close subpopulations, and new mutations continuously accumulate,  $\mathbb{P}[\text{two individuals in same allelic state}]$  declines with increasing separation.

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In  $\mathbb{Z}$  with nearest neighbour migration there is an explicit expression for the probability of identity. It declines exponentially with distance. But the exact formula is very special.

## Probability of identity in subdivided population

Population on  $\mathbb{Z}^2,\,N$  individuals per deme, discrete generations

- Reproduction according to Wright-Fisher model in each deme;
- Proportion  $g_1(x-y)$  of offspring in deme x migrate to deme y.
- $T{=}\ensuremath{\mathsf{time}}$  to MRCA of sample of size two

$$F(x) = \mathbb{E}_x[(1-2\mu)^T]$$

(x vector in  $\mathbb{Z}^2$ )

$$\psi_t(x) = \mathbb{P}_x[T = t],$$
  
$$\psi_1(x) = \frac{G_1(x)}{N}, \quad G_1(x) = \int g_1(x, z)g_1(0, z)dz.$$

If t > 1, partition over location immediate ancestors

$$\psi_t(x) = \sum_y G_1(x-y)\psi_{t-1}(y) - \frac{1}{N}G_1(x)\psi_{t-1}(0).$$

Then

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$$\psi_t(x) = \frac{1}{N} \left( G_t(x) - \sum_{\tau=1}^{t-1} G_{t-\tau}(x) \psi_{\tau}(0) \right)$$

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Write  $\phi(z,x) = \mathbb{E}_x[z^T]$ , (†)  $\phi(z,x) = \frac{1}{N}\widetilde{G}(z,x)\Big(1-\phi(z,0)\Big)$ 

(convolution  $\rightarrow$  product under LT)

$$\phi(z, x) = \mathbb{E}_x[z^T],$$
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Set  $x = 0$  in (†),
$$\widetilde{G}(z, 0) = \frac{1}{N}\widetilde{G}(z, 0)\left(1 - \phi(z, 0)\right) = \widetilde{G}(z, 0)$$

$$\phi(z,0) = \frac{1}{N}\widetilde{G}(z,0)\left(1 - \phi(z,0)\right) \rightsquigarrow \quad \phi(z,0) = \frac{\widetilde{G}(z,0)}{N + \widetilde{G}(z,0)}$$

$$\begin{split} \phi(z,x) &= \mathbb{E}_x[z^T], \\ (\dagger) \quad \phi(z,x) &= \frac{1}{N}\widetilde{G}(z,x)\Big(1-\phi(z,0)\Big) \\ \text{Set } x &= 0 \text{ in } (\dagger), \\ \phi(z,0) &= \frac{1}{N}\widetilde{G}(z,0)\big(1-\phi(z,0)\big) \rightsquigarrow \quad \phi(z,0) &= \frac{\widetilde{G}(z,0)}{N+\widetilde{G}(z,0)} \\ \text{Substitute back in } (\dagger) \end{split}$$

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$$\phi(z,x) = \frac{\widetilde{G}(z,x)}{N + \widetilde{G}(z,0)}$$

If  $g_1$  approximately Gaussian

$$\frac{1}{N}\widetilde{G}(z,0) = \frac{1}{2\mathcal{N}}\log\left(\frac{1}{\sqrt{1-z}}\right); \quad \frac{1}{N}\widetilde{G}(z,x) = \frac{1}{\mathcal{N}}K_0\left(\frac{|x|}{\sigma}\sqrt{1-z}\right)$$

 $\mathcal{N} = 2N\pi\sigma^2$  is Wright's neighbourhood size,  $K_0$  modified Bessel function of second kind of degree zero.

Have shown

$$\phi(z,x) \approx \frac{K_0\left(\frac{|x|}{\sigma}\sqrt{1-z}\right)}{\mathcal{N} - \log(\sqrt{1-z})}$$

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## Calculating F(x)

Have shown

$$\phi(z,x) \approx \frac{K_0\left(\frac{|x|}{\sigma}\sqrt{1-z}\right)}{\mathcal{N} - \log(\sqrt{1-z})} \quad \text{DIVERGES as } x \to 0$$

Assume solution constant over small scale  $\kappa$ , use  $K_0(y) \approx -\log y$ as  $y \downarrow 0$ , set  $z = 1 - 2\mu \approx \exp(-2\mu)$  and substitute:

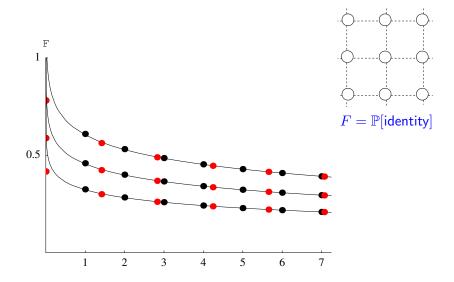
(\*) 
$$F(x) = \mathbb{E}_x[e^{-2\mu T}] \approx \frac{K_0(|x|/l_{\mu})}{\mathcal{N} + \log(l_{\mu}/\kappa)} \qquad |x| > \kappa$$

where  $l_{\mu} = \sigma/2\mu$ ,

$$\mathbb{E}_0[e^{-2\mu T}] \approx \frac{\log(l_\mu/\kappa)}{\mathcal{N} + \log(l_\mu/\kappa)}.$$

(\*) is known as the Wright-Malécot formula.

# Malécot-Wright approximation for the stepping stone model



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

 $N_e$  = number of individuals needed in an idealised population for specified quantity of interest (eg rate of change of genetic diversity) to be the same as in the real population.

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For Buri's data we saw  $N_e = N/\sigma^2$  where  $\sigma^2$  was variance in number of offspring of a single fly.

Typically,  $N_e < N$ , possibly  $\ll N$ .

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Why does it work?

- T =time to MRCA two individuals sampled uniformly from  $\mathbb{T}(L)$ 
  - $T_0$  = time to first come into same deme
  - ► t<sub>0</sub> = time to coalesce started from same deme

 $T = T_0 + t_0$ 

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- $T_0 = \text{time to first come into same deme}$
- ► t<sub>0</sub> = time to coalesce started from same deme

 $X_t = \text{distance between two lineages (for convenience continuous time r.w.)}$  Uniform stationary distribution  $\mathbb{P}_{\pi}[X_t = 0] = 1/L^2$ 

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 $\mathbb{E}_{\pi}\Big[\text{time up to }L^2 \text{ lineages in same colony}\Big] = \int_0^{L^2} \mathbb{P}_{\pi}[X_t = 0] dt = 1$ 

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 $X_t = \text{distance between two lineages (for convenience continuous time r.w.)}$  Uniform stationary distribution  $\mathbb{P}_{\pi}[X_t = 0] = 1/L^2$ 

$$\mathbb{E}_{\pi} \Big[ \text{time up to } L^2 \text{ lineages in same colony} \Big] = \int_0^{L^2} \mathbb{P}_{\pi} [X_t = 0] dt = 1$$
  
If  $X_0 = 0$ , local CLT  $\implies \mathbb{P}_0[X_t = 0] \approx 1/(4\pi\sigma^2 t)$   
 $\mathbb{E}_0 \Big[ \text{time up to } L^2 \text{ lineages in same colony} \Big] = \int_0^{L^2} \mathbb{P}_0[X_t = 0] dt$   
 $\approx \frac{\log(L^2)}{4\pi\sigma^2}$ 

$$1 = \int_0^{L^2} \mathbb{P}_{\pi}[X_t = 0] dt = \int_0^{L^2} \mathbb{P}_{\pi}[T_0 = s] \int_0^{L^2 - s} \mathbb{P}_0[X_t = 0] dt ds$$
  

$$\approx \mathbb{P}_{\pi}[T_0 \le L^2] \frac{\log(L^2)}{4\pi\sigma^2}$$
  
So  $\mathbb{P}_{\pi}[T_0 \le L^2] \approx \frac{2\pi\sigma^2}{\log L}$   $\rightsquigarrow T_0 = O(L^2 \log L)$ 

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Random walk to equilibriates over  $\mathbb{T}(L)$ in  $o(L^2 \log L)$  Cox & Durrett (2002)

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$$\begin{split} \tau &:= T_0/(L^2 \log L), & \qquad \begin{array}{l} \text{Random walk to equilibriates over } \mathbb{T}(L) \\ &\text{in } o(L^2 \log L) & \quad \begin{array}{l} \text{Cox \& Durrett (2002)} \\ \mathbb{P}[\tau > s + t | \tau > s] = \mathbb{P}[\tau > t] & \quad \text{as } L \to \infty \\ &\text{i.e (asymptotically) } \tau \text{ has exponential distribution} \end{split}$$

$$\mathbb{P}_{\pi}\Big[T_0 > \frac{L^2 \log L}{2\pi\sigma^2}t\Big] \to e^{-t}$$

$$\mathbb{P}_0[\text{lineages coalesce before jump apart}] = \frac{\frac{1}{N}}{\frac{1}{N} + 2m}$$

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 $R_0 =$ return time

$$\mathbb{E}_0[t_0] = N + \left(\frac{\frac{1}{N} + 2m}{\frac{1}{N}} - 1\right) \mathbb{E}[R_0]$$

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• Unless N grows with L,  $T_0$  dominates



Sample of size k: when first pair of lineages coalesces, positions remaining lineages uncorrelated with their starting points.

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