The Coalescent: Inference using trees of individuals



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Kingman's coalescent



 $P(G|\Theta) = \prod_{j=0}^{T} e^{-u_j \frac{k_j (k_j - 1)}{\Theta}} \frac{2}{\Theta}$ $\Theta = 4N_e \mu$

calculate the probability that we wait the time interval u until a coalescent
calculate the probability of the particular coalescent event

multiply these probabilities for all time intervals











Population growth (two parameters), fluctuations, bottlenecks

Migration among populations (potentially thousands, parameters)

Population splitting (many parameters)

Effect of assumption violation

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This leaves a signature in the data. We can exploit this and estimate the population growth rate g jointly with the current population size Θ .

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Populations are rarely completely stable through time, and attempts have been made to model population growth or shrinkage using linear, exponential or more general approaches. For example exponential growth could be modeled as

 $\frac{dN}{dt} = rN$ $N_t = N_0 e^{-rt}$ $N_0 = 80$ r = 0.02

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Past Present

For constant population size we found

$$p(G|\Theta) = \prod_{j} e^{-u_{j} \frac{k(k-1)}{\Theta}} \frac{2}{\Theta}$$

Relaxing the constant size to exponential growth and using $g = r/\mu$ leads to

$$p(G|\Theta_0, g) = \prod_{j} e^{-(t_j - t_{j-1})\frac{k(k-1)}{\Theta_0 e^{-gt}}} \frac{2}{\Theta_0 e^{-gt}}$$



Past

Problems with the exponential model: Even with moderately shrinking populations, it is possible that the sample lineages do not coalesce. With growing populations this problem does not occur. This discrepancy leads to an upwards biased estimate of the growth rate for a single locus. Multiple locus estimates improve the results.

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Grow-A-Frog



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Grow-A-Frog



Permafrost during last glad

Past

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Random fluctuations of the population size are most often ignored. BEAST (and to some extent MIGRATE) can handle such scenarios. BEAST is using a full parametric approach (skyride, skyline) whereas MIGRATE uses a non-parametric approach for its skyline plots that has the tendency to smooth the fluctuations too much, compared to BEAST.







BEAST





Accommodating more events



An analogy







The single population coalescence rate is

$$\frac{k(k-1)}{4N}$$

Changes for two populations to

$$\frac{k_1(k_1-1)}{\Theta_1} + \frac{k_2(k_2-1)}{\Theta_2} + k_1M_{2,1} + k_2M_{1,2}$$



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Structured populations













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Hotz et al (2013). Balancing a cline by influx of migrants: ... Journal of Heredity, 104(1):57–71, 2013.







Obvious migration pattern



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 $p(\mathcal{M}|D)$

scaled migration rate



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IM: isolation with migration; co-estimation of divergence parameters, population sizes and migration rates. Not all datasets can separate migration from divergence, and multiple loci are helpful.



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if we consider only a single individual that is today in population A. We also know that its ancestor was a member of population B then it will be only a matter of time to change the population label, but when?



(Beerli P., Ashki H., Mashayekhi S., and Palczewski M. 2022. Population divergence time estimation using individual lineage label switching. G3 Genes – Genomes – Genetics, 12(4),URL https://doi.org/10.1093/g3journal/jkac040.)

Looking backwards in time we could think about the risk of A turning into B which becomes larger and larger the further back in time the lineage goes. In the coalescence framework we are well accustomed to that thinking: we use the risk of a coalescent or the risk of a migration event. This risk can be expressed using the hazard function (or failure rate). Here we use the hazard function of the Normal distribution.

Today



(Beerli P., Ashki H., Mashayekhi S., and Palczewski M. 2022. Population divergence time estimation using individual lineage label switching. G3 Genes - Genomes - Genetics, 12(4),URL https://doi.org/10.1093/g3journal/jkac040.)

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One lineage is easy, but what about the genealogy? Each lineage is at risk of being in the ancestral population, thus we need to consider coalescences, migration events, and population label changing events. This results in genealogies that are realizations of migration and population splitting events.



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Comparison of estimated versus simulated divergence times for different number of loci





Comparison of estimated versus simulated divergence times for different number of loci

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Comparison of estimated versus simulated divergence times for different number of loci

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(Beerli P., Ashki H., Mashayekhi S., and Palczewski M. 2022. Population divergence time estimation using individ



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Phylogenetics of pygmy rattle snakes







Estimation of splitting dates of 6 subspecies of pygmy rattle snakes using MIGRATE (data from Kubatko et al. 2011)





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Offspring number is a random variable



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Offspring number is a random variable



Offspring number is a random variable

The habitat affects the potential of producing offspring and the quality differences are unpredictable. This will lead to a higher variance of the number of offspring: the Canning model allows arbitrary fixed variance of offspring number. We can treat this variance as a random variable.

Extensions of Coalescence theory



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Different α : model comparison with real data



Model selection using relative marginal likelihoods of DNA sequence from the flu (H1N1), Malaria parasites, Humpback whales.

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Robustness of the coalescence



Required samples (small samples/ deep coalescence)

- Average over long time
- Recombination









- The time to the most recent common ancestor is robust to different sample sizes.
- Simulated sequence data from a single population have shown that after 8 individuals you should better add another locus than more individuals.



Required number of samples is small



Average of parameters over long time

Researchers from the frequency-based camp claim that the coalescence-based methods are working on an evolutionary time-scale and therefore are not really usable in a conservation genetics or management context.

There is some truth to this claim because the time scale for the genealogies is in generations and with large populations such genealogies are deep, but ...



Average of parameters over long time

— True value **MIGRATE** estimate Support interval

Harmonic mean



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-Time

${\sim}500$ simulated datasets



Averages with 95% credibility intervals of runs with different mutation-scaled recombination rates $R = C/\mu$. The dotted lines mark the 'true' values.

Ignoring recombination

${\sim}500$ simulated datasets



Averages with 95% credibility intervals of runs with different mutation-scaled recombination rates $R = C/\mu$. The dotted lines mark the 'true' values.

 ${\sim}500$ simulated datasets



Averages with 95% credibility intervals of runs with different mutation-scaled 626 philos fraction rates $R = C/\mu$. The dotted lines mark the 'true' values.

 ${\sim}500$ simulated datasets



Averages with 95% credibility intervals of runs with different mutation-scaled 6360 mbination rates $R = C/\mu$. The dotted lines mark the 'true' values.

Outlook

► We will have a lab later this week where you will learn about Bayesian model selection with MIGRATE using a lab where we differentiate between 8 simple population models that include "speciation" (or population splitting) with and without migration using a data set of complete genomes of Zika viruses.

