

Estimating Mutation Parameters and Population History from Temporally-Spaced Genome Data

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Motivation

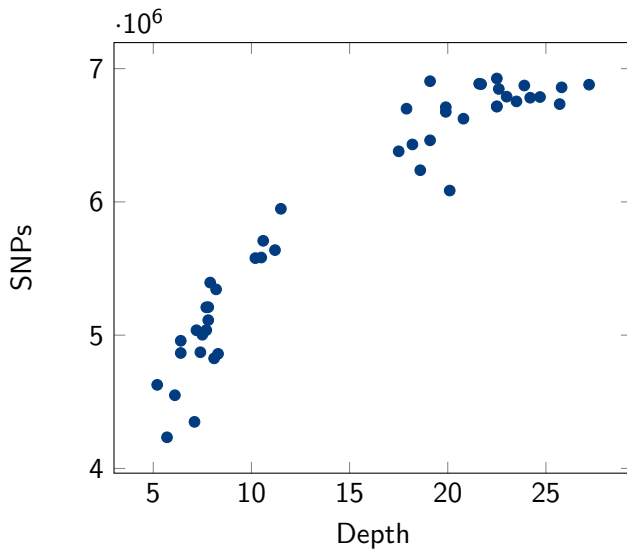
Data

- ▶ Really cool (but secret!) dataset
- ▶ Feasible to sequence entire genomes
- ▶ More recently, even possible to recover ancient genomes
- ▶ Temporally-spaced genome data
- ▶ Opportunity to do inference previously only possible for viruses
 - ▶ mutation rate
 - ▶ population size and changes through time

Challenges

- ▶ Difficult to phase diploid genomes
- ▶ Recombination
- ▶ Sequencing error, especially in ancient genomes
- ▶ Cannot use Bayesian phylogenetic methods

Sequencing Error



The Composite Likelihood

Definition (Cox and Reid, 2004)

Consider an n -dimensional vector random variable X with density

$$X \sim f(x | \theta)$$

Suppose that the full n -dimensional density is intractable, but

$$f_i(x_i | \theta) \text{ and } f_{ij}(x_i, x_j | \theta), i \neq j$$

are not. Letting

$$\ell_1(\theta; x) = \sum_i \log f_i(x_i | \theta)$$

$$\ell_2(\theta; x) = \sum_{i \neq j} \log f_{ij}(x_i, x_j | \theta) - an\ell_1(\theta; x)$$

then ℓ_2 is the **pairwise composite loglikelihood**.

The Composite Likelihood for Serially-Sampled Genomes

Assumptions

- ▶ Every site in the alignment has an independent phylogeny
 - ▶ No more concerns about recombination and phasing!
- ▶ Phylogenies are i.i.d. under the same coalescent process
- ▶ Substitution process is identical across sites
- ▶ Sites are i.i.d.
- ▶ A site is our n -dimensional vector X

The Composite Likelihood for Serially-Sampled Genomes

- ▶ $\theta = (\mu, \mathbf{N}_e, \epsilon)$, substitution parameters, effective population sizes, sequence error probabilities
- ▶ Computing $f(x | \theta)$ requires integrating out all phylogenies
- ▶ Instead, approximate with a pairwise composite likelihood
- ▶ $\ell_1(\theta; x)$ ignored because a single sequence not dependent on θ
- ▶ For a pair of genomes, integrate out their coalescence time

$$f_{ij}(x_i, x_j | \theta) = \int_0^\infty p(x_i, x_j | t, \mu, \epsilon) p(t | \mathbf{N}_e) dt$$

Why use composite likelihoods?

- ▶ Frequently used in genetics
- ▶ Well-studied in general so plenty of existing theory
- ▶ Make the intractable tractable

Theorem (Xu and Reid, 2011)

Under some assumptions, the maximum composite likelihood is consistent under the full model.

Probability for a Pair of Nucleotides

- ▶ Closed-form (but fairly complex) expression for f_{ij} under HKY and skyline coalescent
- ▶ Under Jukes-Cantor with a constant population size, we have

$$\begin{aligned} p(i, j \mid \mu, N_e) &= \int_0^\infty \frac{1}{4} p_{ij}((\tau + 2t)\mu) p(t \mid N_e) dt \\ &= \begin{cases} \frac{1}{4} \left(\frac{1}{4} + \frac{9 \exp(-\frac{4}{3}\mu\tau)}{64\mu N_e + 12} \right) & \text{if } i = j \\ \frac{1}{4} \left(\frac{1}{4} - \frac{3 \exp(-\frac{4}{3}\mu\tau)}{64\mu N_e + 12} \right) & \text{if } i \neq j \end{cases} \end{aligned}$$

- ▶ Sequencing error considered by integrating over uncertainties

The Complete Composite Loglikelihood

- ▶ Just a big summation over all sites and all pairs

$$\mathcal{L}(\boldsymbol{\theta}; \mathcal{A}) = \sum_{k=1}^m \sum_{i=1}^{n-1} \sum_{j=i+1}^n \log(f_{ij}(\mathcal{A}_{ik}, \mathcal{A}_{jk} \mid \boldsymbol{\theta}))$$

- ▶ To consider multiple categories of sites, substitution parameters $\boldsymbol{\mu}$ for each category are independent but \mathbf{N}_e and ϵ are linked

An Efficient Implementation

Data Structure

- ▶ Preprocessing is $O(mn^2)$, where m = number of sites
- ▶ For every pair of genomes, count every substitution $i \rightarrow j$
- ▶ Calculation per category is $O(n^2)$
- ▶ Preprocessing/calculation are parallelised

Maximum Likelihood Optimisation

- ▶ L-BFGS-B algorithm (quasi-Newton method)
- ▶ Uses automatically-calculated gradient
- ▶ Single tuning parameter affects number of iterations necessary before convergence

Assessing the Estimates

Confidence Intervals

- ▶ Distribution is much narrower than it should be
- ▶ Using non-parametric bootstrapping across sites
- ▶ Better to use block-bootstrap b/c of dependence across sites

Date-Randomisation Test

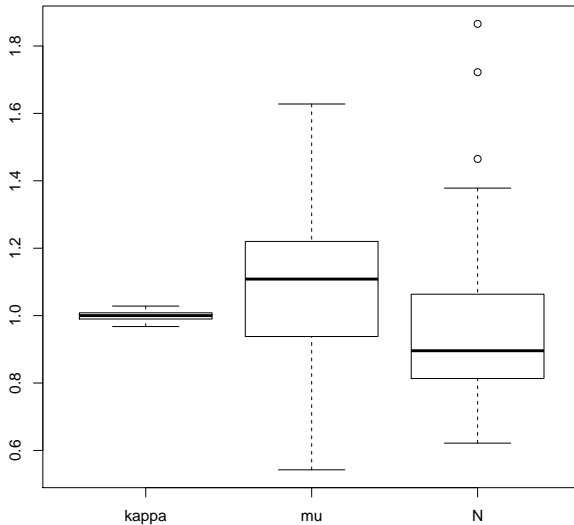
- ▶ Is there signal for the mutation rate in our data?
- ▶ Randomly reassign times to taxa and reestimate rate
- ▶ Verify that estimates fall outside of true confidence interval
- ▶ Even stronger: verify no overlap of intervals

Irreproducible Simulation Results

Set Up

- ▶ 46 diploid taxa, with 22 ancient individuals as old as 50k years
- ▶ Mutation rate is $\mu = 10^{-9}$
- ▶ HKY model with $kappa = 5$
- ▶ Constant-size population with $N_e = 3 \times 10^6$
- ▶ 10^6 independent phylogenies for 10^6 sites
- ▶ Attempt to estimate parameters from simulated data

Irreproducible Simulation Results



Concluding Remarks

Summary

- ▶ An efficient method for inference from serially-sampled genomes
- ▶ Applying to an exciting dataset
- ▶ Looks promising but needs more validation

Future Work

- ▶ Fix-up implementation and reign in numerical instability
- ▶ Successfully estimate all parameters
- ▶ Prepare some convincing simulation studies
- ▶ Consider structured population in model
- ▶ Find faster alternatives to bootstrapping
- ▶ Can we show consistency theoretically?

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References

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