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Estimating the evolution history of species from genome sequences

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CIMI, Semestre Mathématiques et Informatique pour les
sciences du vivant

20 septembre 2017

- Inference of evolutionary history over short time scale, typically **within species** (in contrast to phylogeny).
- Typical questions (humans): “out of Africa” hypothesis, Neandertal introgression within modern humans . . .
- Typical questions (breeding species): domestication process, impact of intensive selection since the 50's . . .

- 1 Data and objectives
- 2 Single population model
- 3 Estimation of population size from single locus data
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- n DNA sequences of length L from the same species.
- Mostly similar, but at some positions different **alleles** exist (genetic polymorphism).

A-A-C-G-**G**-G-T-A-**T**-C-G-

A-A-C-G-**G**-G-T-A-**A**-C-G-

A-A-C-G-**C**-G-T-A-**T**-C-G-

Single Nucleotide Polymorphism (SNP)

- Only one nucleotide is changed.
- Very common on the genome.
- Result from a single mutation event during evolution
→ only two distinct alleles, one **ancestral** (denoted 0) and one **derived** (denoted 1).

A-A-C-G-**G**-G-T-A-**T**-C-G-

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Single Nucleotide Polymorphism (SNP)

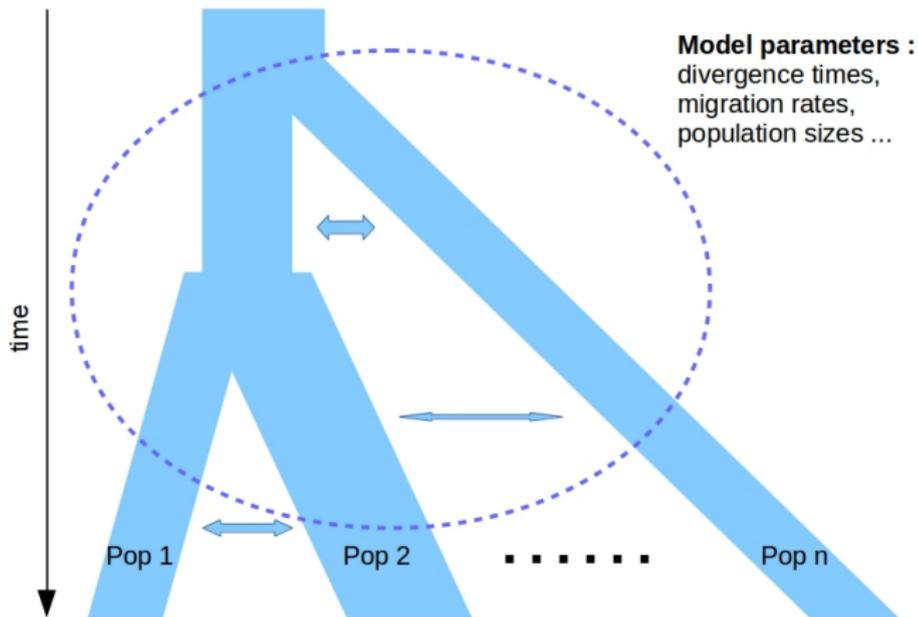
- Only one nucleotide is changed.
- Very common on the genome.
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0-0-0-0-**1**-0-0-0-0-0-0-

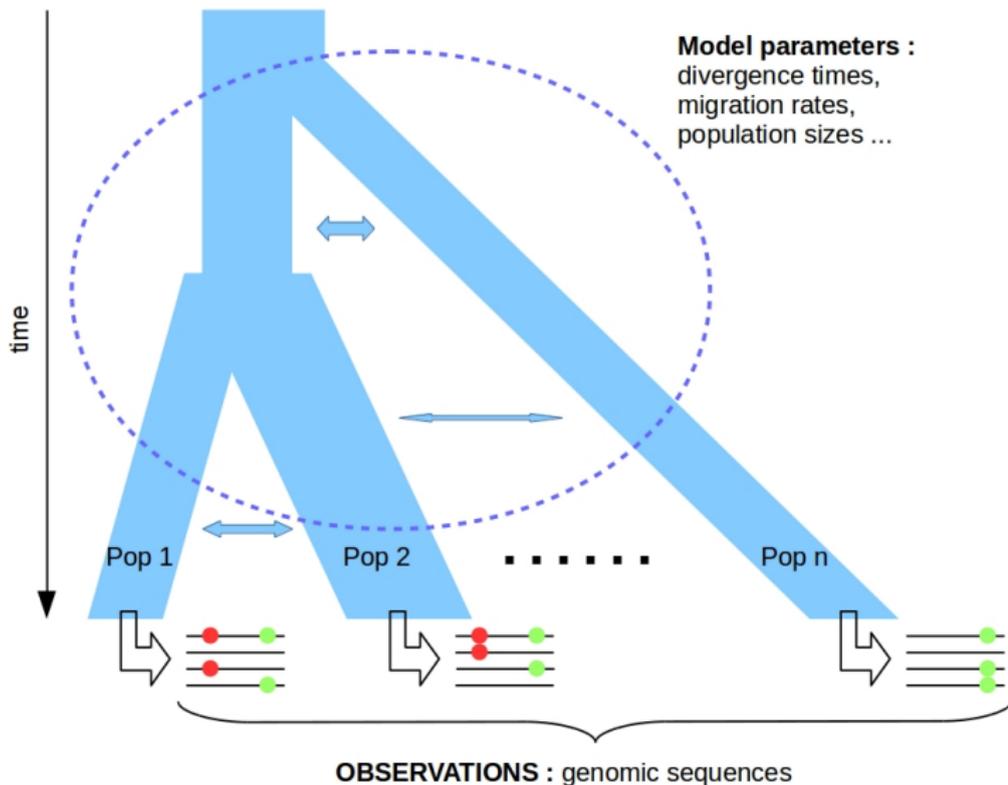
0-0-0-0-**1**-0-0-0-**1**-0-0-

0-0-0-0-**0**-0-0-0-0-0-0-

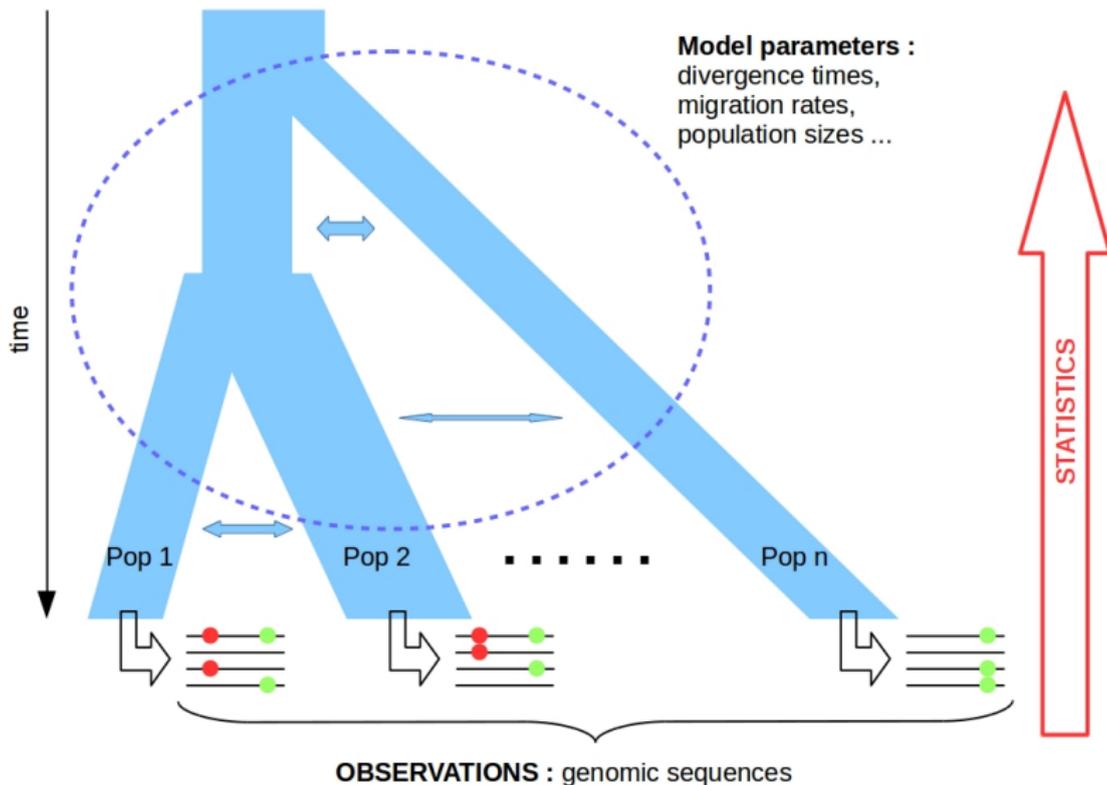
General evolution model



General evolution model

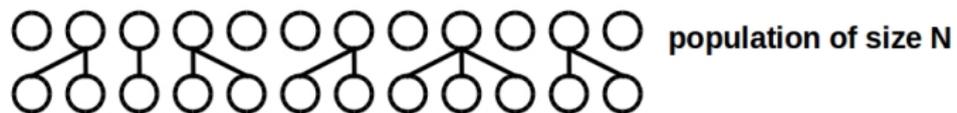


General evolution model

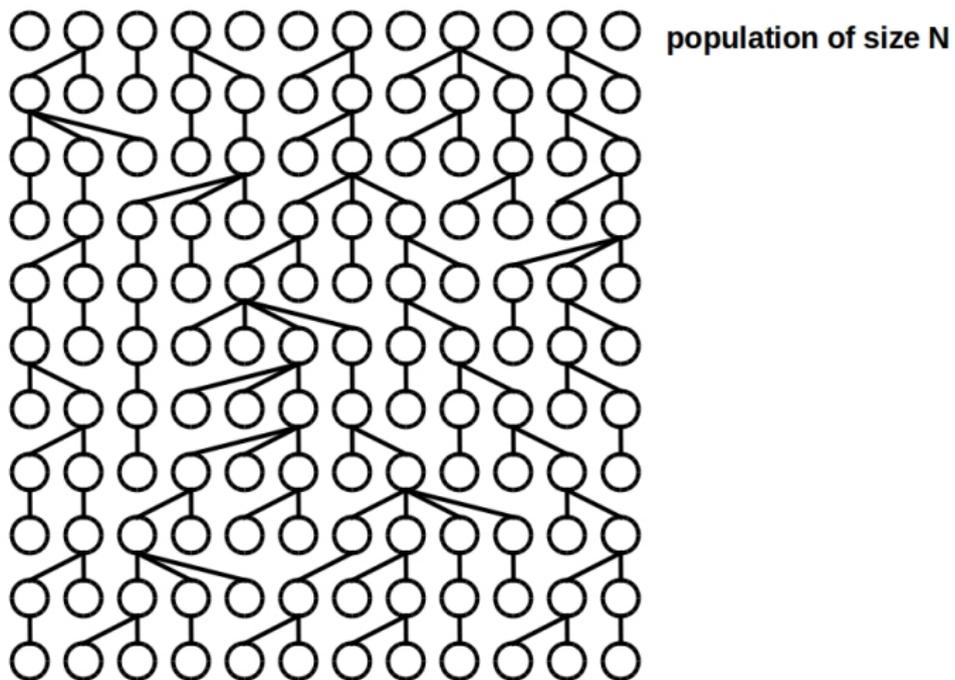


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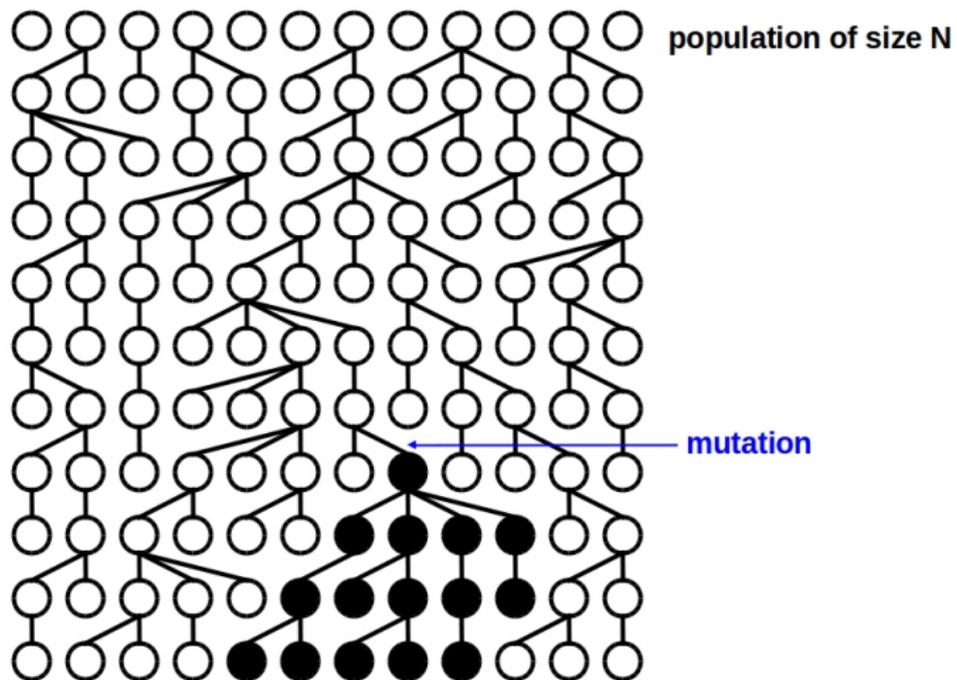
the Wright-Fisher process



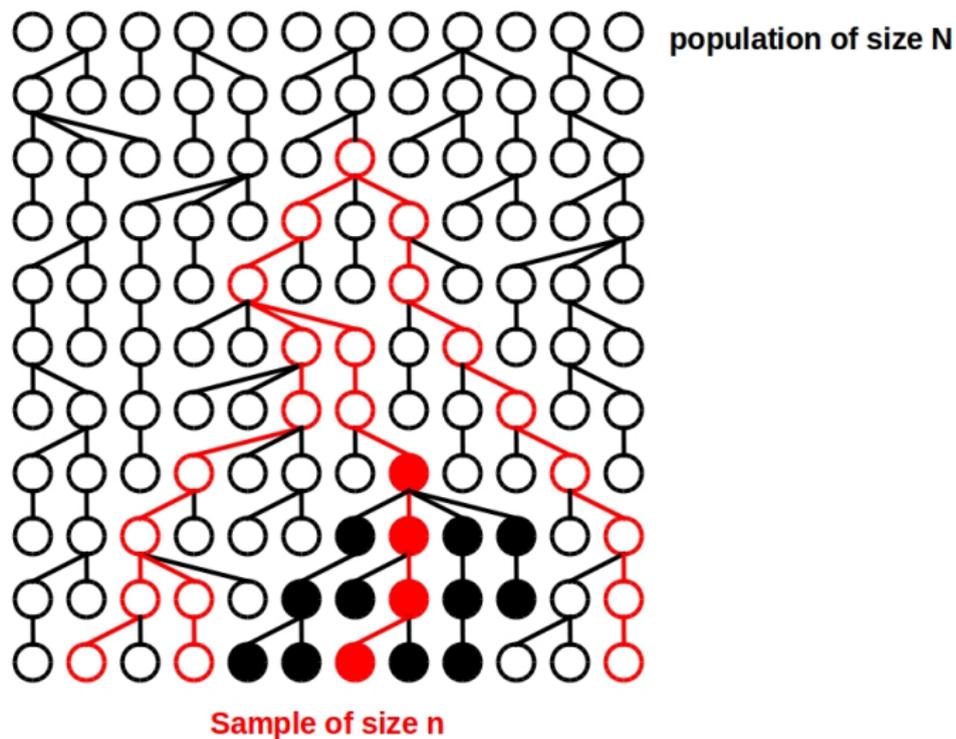
the Wright-Fisher process



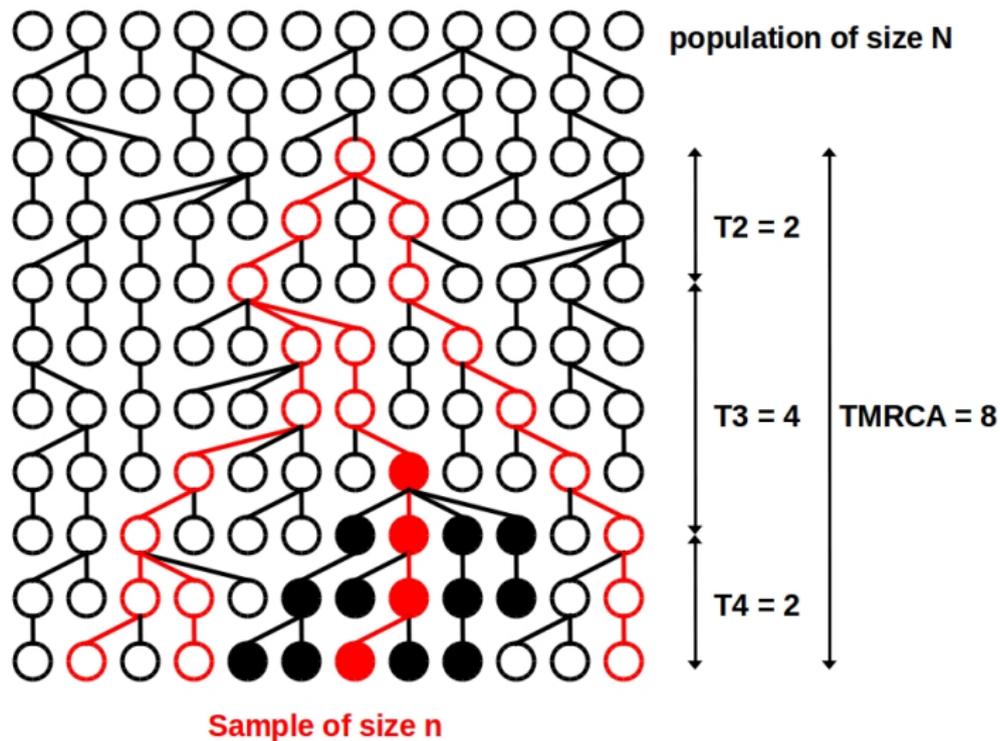
the Wright-Fisher process



The coalescent process



The coalescent process



- At each generation, **probability** that **no coalescence** occurs is

$$q^N(n) = \prod_{i=1}^{n-1} \left(1 - \frac{i}{N}\right) = 1 - \frac{n(n-1)}{2N} + O\left(\frac{1}{N^2}\right)$$

- Coalescence time T_k^N ($2 \leq k \leq n$) has geometric distribution

$$\mathbb{P}(T_k^N > t) = (q^N(k))^t$$

- All lineages coalesce at the same rate.
- Number of mutations on a branch of length t is Binomial $\mathcal{B}(t, \mu)$, μ mutation rate per meiosis and per nucleotide (biologically known).

Kingman's coalescent (1982)

- $N \rightarrow +\infty$, rescaled time $\tau = \frac{t}{N}$
- Coalescence time T_k^N tends to T_k , with exponential distribution

$$\mathbb{P}(T_k > \tau) = e^{-\frac{k(k-1)}{2}\tau}$$

- **Coalescence** events imply **one single pair of lineages**.
- Number of mutations on a branch of length τ is Poisson $\mathcal{P}(\frac{\theta}{2}\tau)$, with $\theta = 2N\mu$ (population scaled mutation rate).

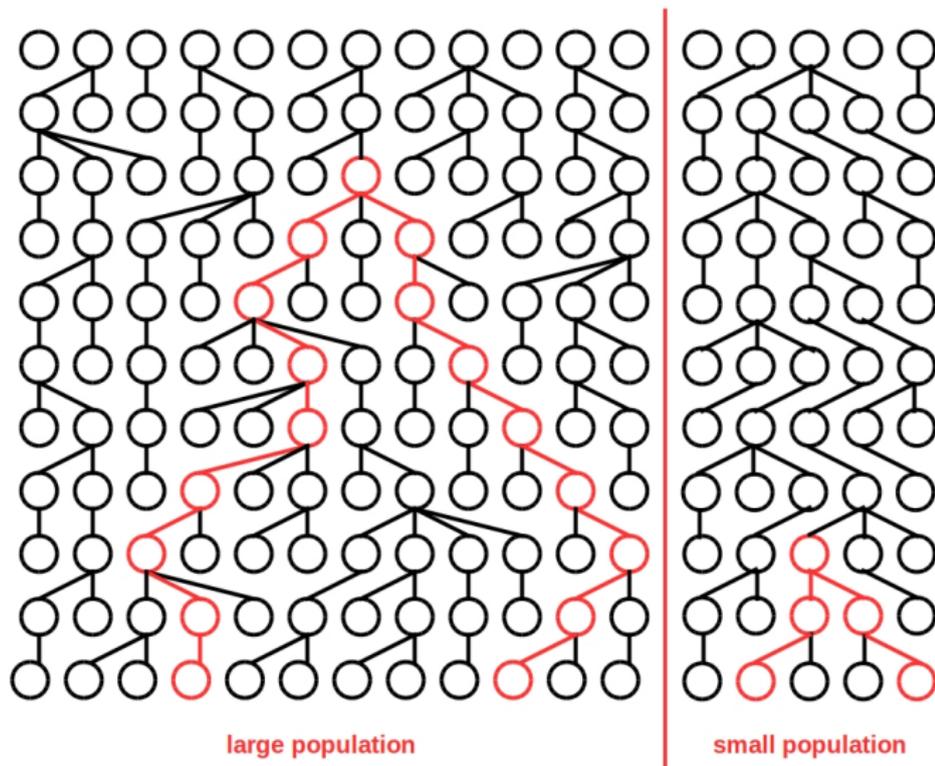
Advantages of the coalescent approach

- Very efficient way to **simulate genetic data**.
- Easily extended to **more complex models** (variable population sizes, structured populations ...).
- Used to **express the likelihood** of observed genetic data.
- Provides **conceptual framework** to understand the influence of some evolutionary parameters on observed genetic data.

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Constant population size : intuition

larger N \rightarrow longer coalescence times \rightarrow more mutations.



Constant population size : the Watterson estimator

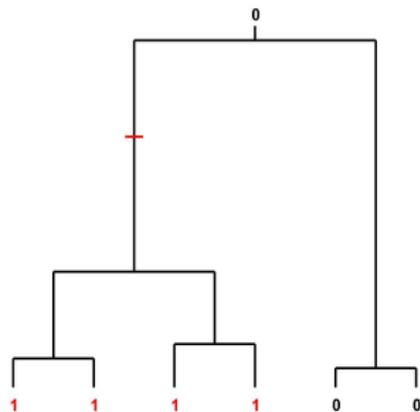
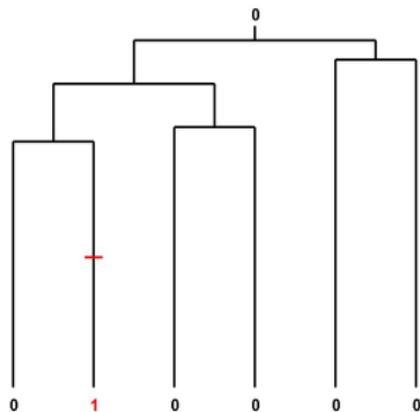
- S_n number of polymorphic sites in a sample of n DNA sequences of length L .

$$\theta_W = \frac{1}{L} S_n \left(\sum_{k=1}^{n-1} \frac{1}{k} \right)^{-1}$$

- $\mathbb{E}[\theta_W] = \theta = 2N\mu$.
- As μ is known, this provides an **unbiased estimator of N** .
- $\text{Var}(\theta_W) = \left(\theta^2 \sum_{k=1}^{n-1} \frac{1}{k^2} + \frac{\theta}{L} \sum_{k=1}^{n-1} \frac{1}{k} \right) \left(\sum_{k=1}^{n-1} \frac{1}{k} \right)^{-2}$

Variable population size : intuition

- Population **expansion** → larger coalescence times in the recent past → higher proportion of **derived alleles at low frequency**.
- Population **decline** → larger coalescence times in the distant past → higher proportion of **derived alleles at intermediate frequency**.



- **Likelihood:**

$$\mathbb{P}(\mathcal{D} | N()) = \sum_{\mathcal{T}} \mathbb{P}(\mathcal{D} | \mathcal{T}) \mathbb{P}(\mathcal{T} | N())$$

\mathcal{D} observed sequences, $N()$ population size history, \mathcal{T} coalescence tree.

- **No analytical expression**

$$\mathbb{P}(\mathcal{D} | N()) \approx \sum_{i=1}^I \mathbb{P}(\mathcal{D} | \mathcal{T}_i)$$

\mathcal{T}_i simulated from $\mathbb{P}(\mathcal{T} | N())$.

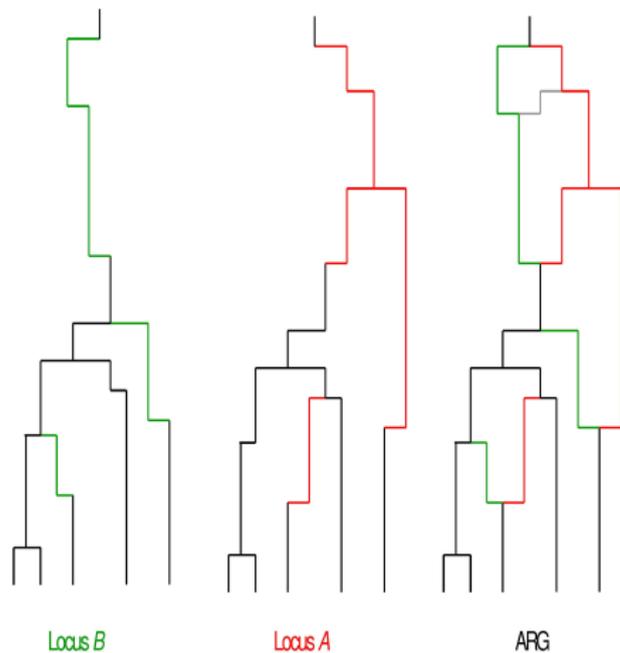
- **High dimension** of \mathcal{T}

→ explore using **Markov Chain Monte Carlo** (MCMC) or **Importance Sampling** (IS) algorithms (Beaumont, 1999; Drummond et Rambaut, 2007; Hobolt et al, 2008).

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- In diploid species (e.g. humans), recombination during meiosis → each gamete is a **mixture of two sequences**, one inherited from the mother and one from the father.
- Negligible at short distance (single locus), but important when studying whole-genome sequences.
- The **genealogy** of n DNA sequences becomes a **graph**.

The Ancestral Recombination Graph (ARG)



Consequences for inference

- Coalescence trees at two distinct loci are neither similar nor independent.
- **Complex correlation structure.**
- Dimension of the space of genealogies explodes, **previous MCMC or IS approaches no longer possible.**
- Open and active research area.

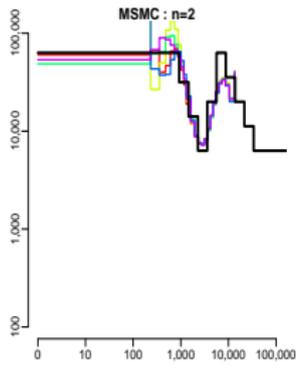
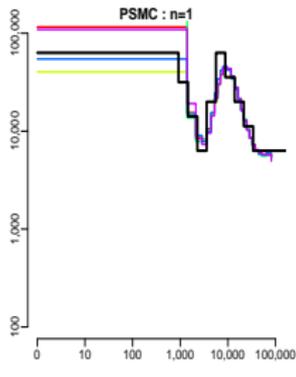
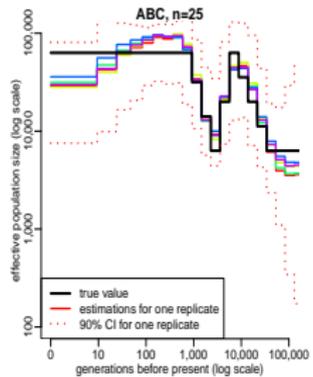
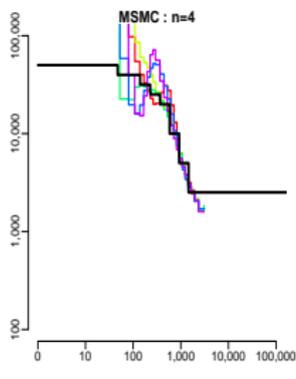
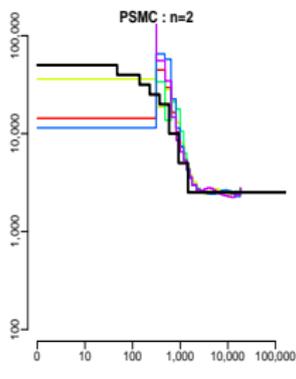
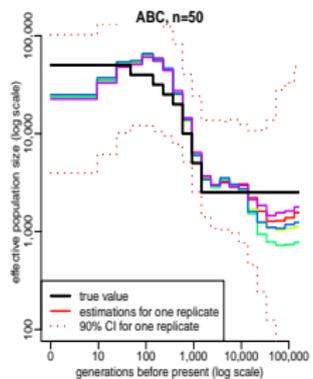
The Approximate Bayesian Computation (ABC) approach

- First proposed by Beaumont (2002), allows estimating parameters θ of a model when likelihood cannot be evaluated.
- Approximate the posterior $\mathbb{P}(\theta|\mathcal{D})$ by the posterior $\mathbb{P}(\theta|\mathcal{S})$, for a set \mathcal{S} of (meaningfull!) **summary statistics**.
- Estimate $\mathbb{P}(\theta|\mathcal{S})$ using **intensive simulations**:
 - 1 Compute $\mathcal{S} = f(\mathcal{D})$
 - 2 For i from 1 to l :
 - 1 Sample parameter θ_i from a prior distribution.
 - 2 Simulate dataset \mathcal{D}_i from the model with parameter θ_i .
 - 3 Compute $\mathcal{S}_i = f(\mathcal{D}_i)$.
 - 4 Select the simulation if $\text{dist}(\mathcal{S}_i, \mathcal{S}) < \epsilon$.
 - 3 Estimate the posterior distribution of θ from the empirical distribution of selected θ_i values.

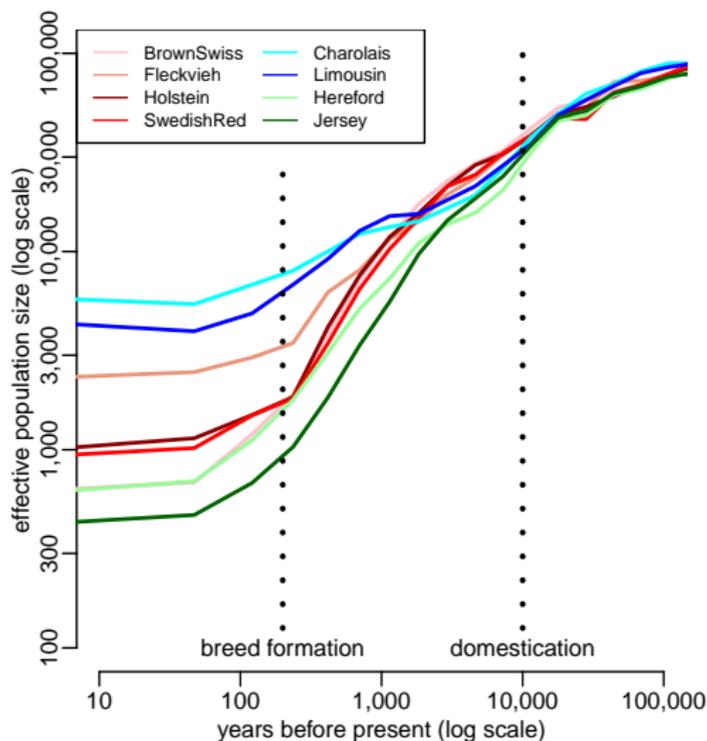
Application to population sizes (Boitard *et al*, 2016)

- **Panmictic population** with population size history $N()$.
- **Large sample of whole-genome sequences** from this population.
- Approximates $\mathbb{P}(N()|\mathcal{S})$ using ABC.
- Set of ≈ 50 summary statistics, describing (among others) the **distribution of allele frequencies**.

Simulation results



Analysis of cattle genomes



- **Common trajectory before domestication.**
- Continuous decline since domestication.
- Ranking of recent sizes consistent with current knowledge of these breeds.

Influence of population structure

- In real life, **populations not isolated**.
- Relationship between populations **affect population size estimations**.
 - **Identifiability issue**: can we distinguish population size changes and population structure from genetic data?
- Mazet *et al* (2016): **not from two genomes**, because population size change models can reproduce every possible distribution of T_2 .
- Important conclusion, because one popular estimation method (Li and Durbin, 2011) is based on this distribution.
- Distinction would be in theory possible from the joint distribution of (T_2, T_3) (Grusea *et al*, in prep.).

- **Genetic data informative** about species history.
- **Population genetics:** a very active field of research, interface between biology and applied mathematics.
- Contributes to answer **fundamental questions** about human (and other species) history.
- Many **theoretical and computational issues** to be solved.
- **Massive amount of data** to be analyzed.

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