

Recent Progress in Genealogies of Sequential Monte Carlo Algorithms

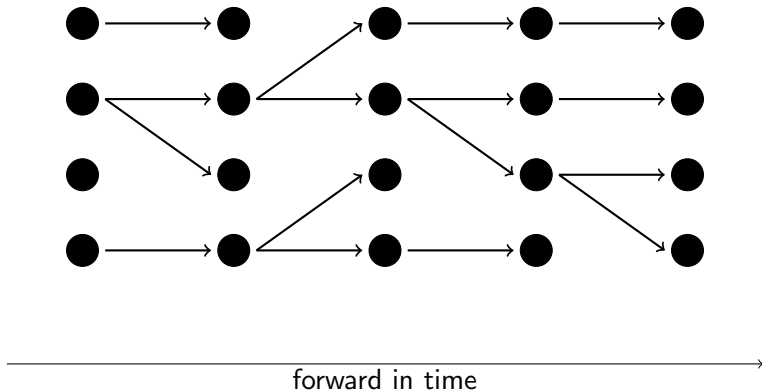
Suzie Brown

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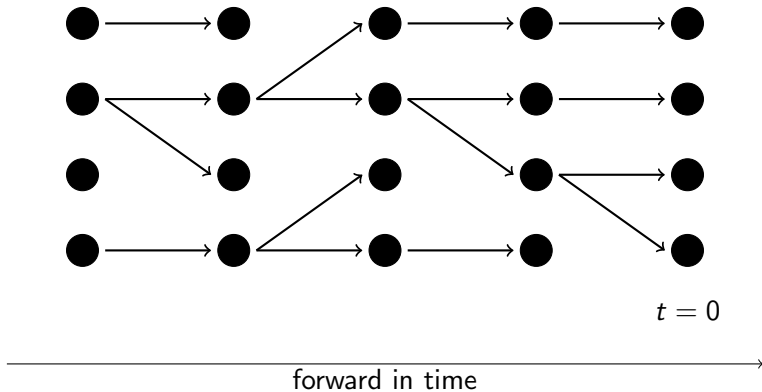
with Paul Jenkins, Adam Johansen & Jere Koskela

15 December 2019

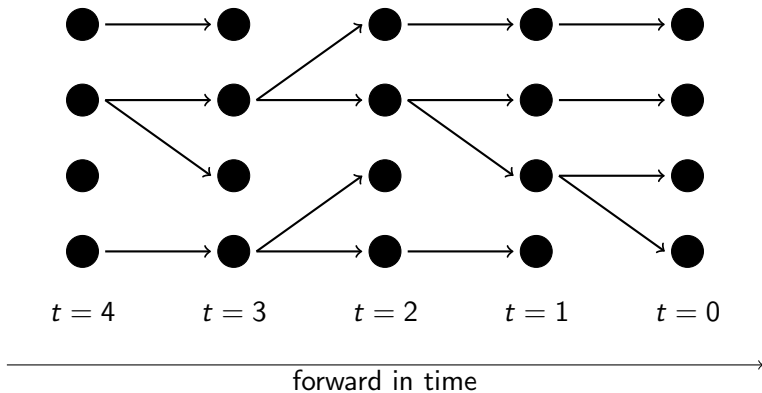
Sequential Monte Carlo



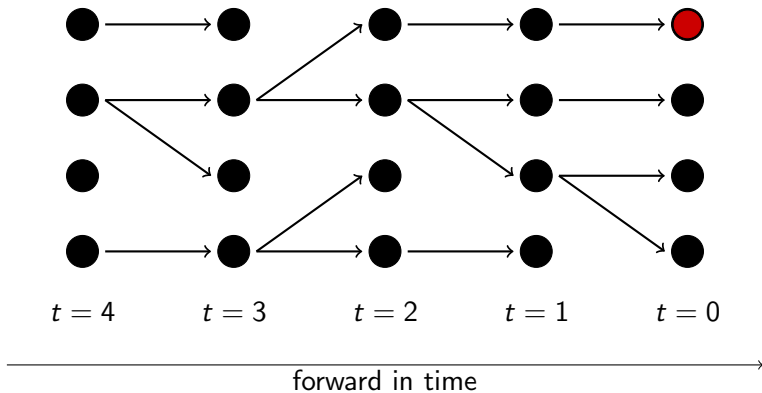
Sequential Monte Carlo



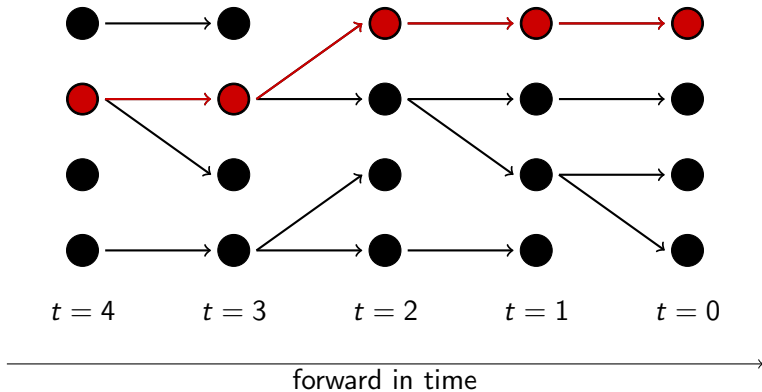
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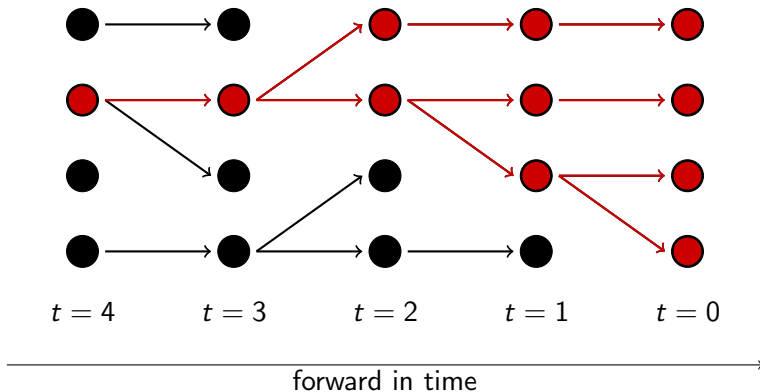
Sequential Monte Carlo



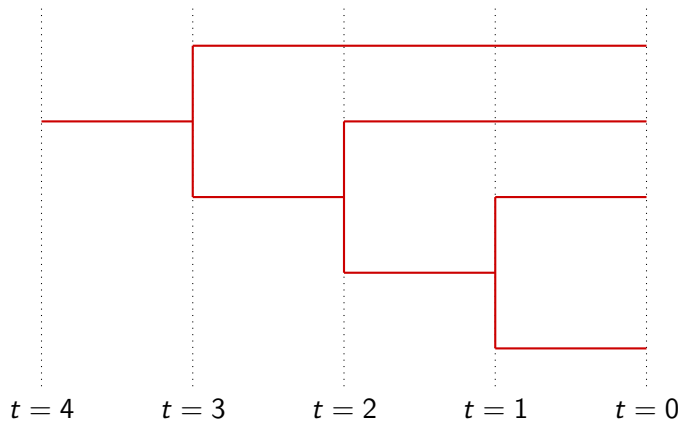
Sequential Monte Carlo



Sequential Monte Carlo



Induced genealogy



Mathematical formulation

- ▶ Population of N particles
- ▶ Sample $n \leq N$ terminal particles

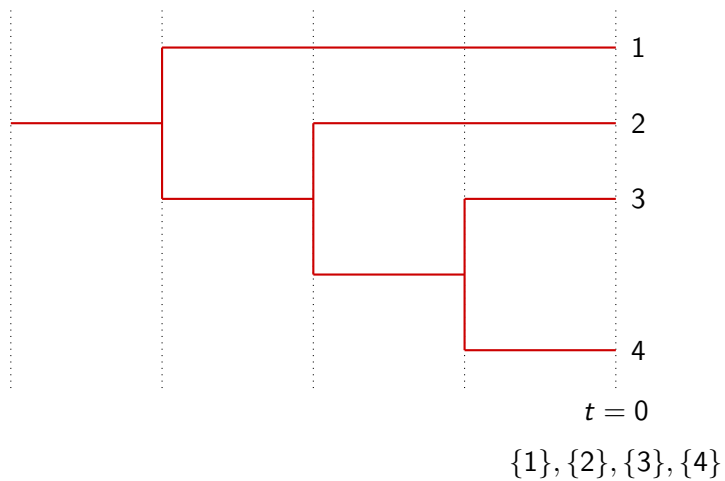
Mathematical formulation

- ▶ Population of N particles
- ▶ Sample $n \leq N$ terminal particles
- ▶ Describe genealogy by a partition-valued stochastic process $(G_t^{(n,N)})_{t \in \mathbb{N}_0}$
- ▶ Elements i, j are in the same block of the partition $G_t^{(n,N)}$ iff particles i and j share a common ancestor at time t

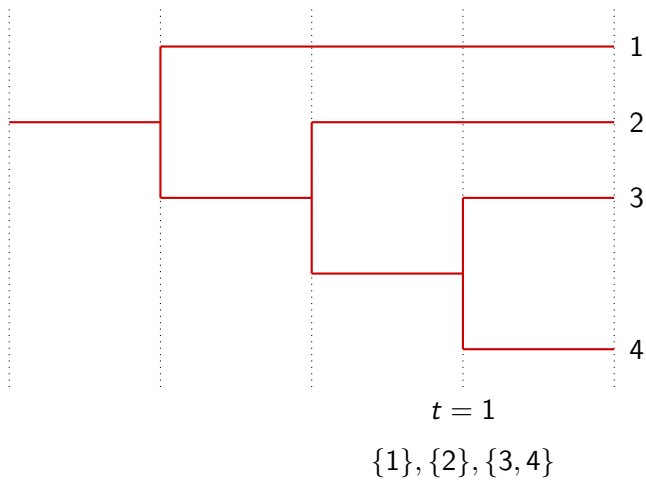
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- ▶ At time 0, the partition of $\{1, \dots, n\}$ consisting of singletons: $G_0^{(n,N)} = \{\{1\}, \dots, \{n\}\}$
- ▶ The only possible non-identity transitions are those that merge blocks

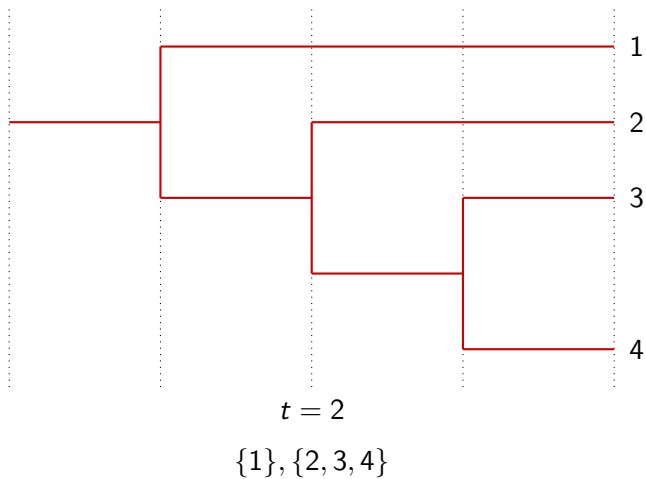
Example



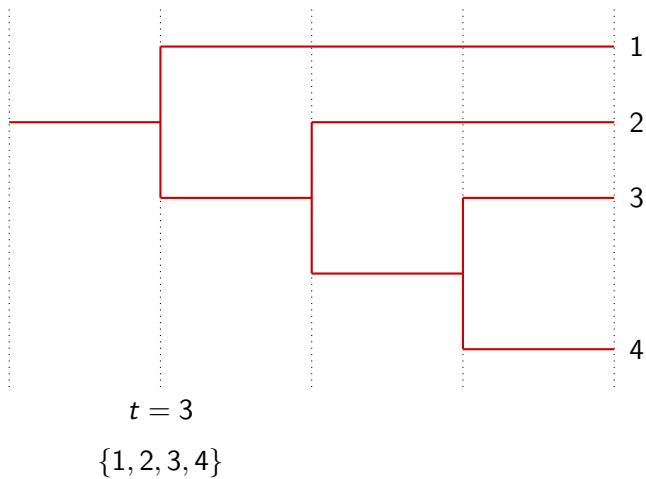
Example



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Kingman's n -coalescent

Kingman's n -coalescent

- ▶ n terminal particles
- ▶ Continuous time
- ▶ Each pair of lineages coalesces at rate 1
- ▶ No other ($>$ pair) mergers allowed

Notation

- ▶ $w_t^{(i)}$ = weight of particle i in generation t
- ▶ family size $v_t^{(i)}$ = number of offspring of particle i in generation t

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- ▶ time scale $\tau_N(t) = \text{inverse of } c_N(t)$

A convergence theorem¹

Suppose:

$$\begin{aligned}\mathbb{E}[c_N(t)] &\rightarrow 0 \\ \mathbb{E} \left[\sum_{r=\tau_N(s)+1}^{\tau_N(t)} D_N(r) \right] &\rightarrow 0 \\ \mathbb{E} \left[\sum_{r=\tau_N(s)+1}^{\tau_N(t)} c_N(r)^2 \right] &\rightarrow 0 \\ \mathbb{E}[\tau_N(t) - \tau_N(s)] &\leq C_{t,s} N\end{aligned}$$

Then the rescaled genealogical process $(G_{\tau_N(t)}^{(n,N)})_{t \geq 0}$ converges to Kingman's coalescent in the sense of finite-dimensional distributions as $N \rightarrow \infty$.

¹Koskela, Jenkins, Johansen, Spanò. *Ann Stat*, to appear.

A simplified statement

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Suppose there exists a deterministic sequence $(b_N)_{N \in \mathbb{N}}$ uniform in $t \geq 1$ such that $b_N \rightarrow 0$.

$$\frac{1}{N(N-1)(N-2)} \sum_{i=1}^N \mathbb{E}_t[v_t^{(i)}(v_t^{(i)} - 1)(v_t^{(i)} - 2)] \leq b_N \frac{1}{N(N-1)} \sum_{i=1}^N \mathbb{E}_t[v_t^{(i)}(v_t^{(i)} - 1)]$$

Then the rescaled genealogical process $(G_{\tau_N(t)}^{(n,N)})_{t \geq 0}$ converges to Kingman's coalescent in the sense of finite-dimensional distributions as $N \rightarrow \infty$.

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- ▶ We replace four conditions with one
- ▶ We remove condition 4, which we know is not a necessary condition
- ▶ We remove conditions 2 and 3, which contain awkward mixed moments
- ▶ We can verify the new condition in more complicated cases...

Resampling schemes

Problem : (stochastically) map weights $(w_t^{(1)}, \dots, w_t^{(N)})$ to family sizes $(v_t^{(1)}, \dots, v_t^{(N)})$.

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Desirable properties:

- ▶ Number of particles constant $\sum_{i=1}^N v_t^{(i)} = N$
- ▶ Equal weights after resampling $w_{t+}^{(i)} = 1/N$
- ▶ Unbiased $\mathbb{E}[v_t^{(i)} | w_t^{(i)}] = N w_t^{(i)}$

Corollary: multinomial resampling

Consider an SMC algorithm with potential g and transition density q , satisfying

$$\frac{1}{a} \leq g_t(x, x') \leq a$$
$$\varepsilon h(x') \leq q_t(x, x') \leq \frac{1}{\varepsilon} h(x')$$

for constants $0 < \varepsilon \leq 1 \leq a < \infty$, and probability distribution $h(\cdot)$.

Under multinomial resampling, the rescaled genealogies converge to Kingman's coalescent.

Stochastic roundings

Stochastic roundings

Let $X \geq 0$.

$Y : \mathbb{R}_+ \rightarrow \mathbb{N}$ is a *stochastic rounding* of X if Y takes the values

$$Y \mid X = \begin{cases} \lfloor X \rfloor & \text{with probability } 1 - X + \lfloor X \rfloor \\ \lfloor X \rfloor + 1 & \text{with probability } X - \lfloor X \rfloor \end{cases}$$

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Can generalise to multivariate case, with marginals $Y_i \mid X_i$ as above.

Stochastic roundings

- ▶ $X_i = Nw_t^{(i)}$
- ▶ $v_t^{(i)} = Y_i$
- ▶ Constraint $Y_1 + \dots + Y_N = N$

²Gerber, Whiteley, Chopin. *Ann Stat*, 2019.

Stochastic roundings

- ▶ $X_i = Nw_t^{(i)}$
- ▶ $v_t^{(i)} = Y_i$
- ▶ Constraint $Y_1 + \dots + Y_N = N$
- ▶ Examples: systematic resampling, residual-stratified resampling, SSP resampling²,...

²Gerber, Whiteley, Chopin. *Ann Stat*, 2019.

Corollary: stochastic rounding -based resampling

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Under stochastic rounding -based resampling, the rescaled genealogies converge to Kingman's coalescent.

Conditional SMC

- ▶ Used for SMC updates in particle MCMC³
- ▶ Given a fixed “immortal trajectory”, conditioned to survive all transition and resampling steps

³Andrieu, Doucet, Holenstein. *JRSSB*, 2010.

Corollary: conditional SMC

Consider a conditional SMC algorithm with potential g and transition density q , satisfying

$$\frac{1}{a} \leq g_t(x, x') \leq a$$
$$\varepsilon h(x') \leq q_t(x, x') \leq \frac{1}{\varepsilon} h(x')$$

for constants $0 < \varepsilon \leq 1 \leq a < \infty$, and probability distribution $h(\cdot)$.

Under multinomial resampling, the rescaled genealogies converge to Kingman's coalescent.

What about finite N ?

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- ▶ As $N \rightarrow \infty$ but sample size n fixed, probability of sampling immortal line vanishes, so its effect isn't seen in the limit
- ▶ For finite N we have more interesting behaviour
- ▶ Depends how “typical” the immortal trajectory is

Summary

- ▶ Genealogies can provide insight into performance of SMC algorithms
- ▶ We provide simple conditions for asymptotically Kingman genealogies
- ▶ Satisfied by stochastic rounding -based resampling
- ▶ Satisfied by conditional SMC with multinomial resampling...
- ▶ ... but this hides some interesting pre-limiting behaviour