# Suzie Brown

2 November 2018

Genealogies of Sequential Monte Carlo Algorithms





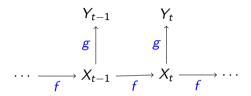


Adam Johansen



Paul Jenkins

#### Hidden Markov model



- $\blacktriangleright$  { $X_1, X_2, ...$ } hidden Markov states
- $\triangleright$   $Y_i$  noisy observation of  $X_i$
- ► Markov transition kernel f
- 'emission distribution' g

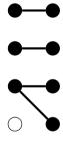
#### Inference on a HMM

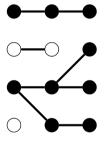
- filtering distribution  $p(x_T \mid y_{1:T})$
- ▶ **smoothing distribution**  $p(x_{1:T} | y_{1:T})$  'trajectory of all previous states'

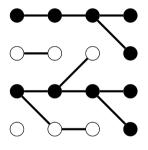
#### Sequential Monte Carlo

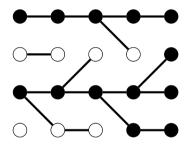
- ► Approximate these distributions using *N* particles
- Initialise, then iterate the steps:
  - 1. **propagate:** update positions of particles by applying the Markov kernel f
  - 2. **calculate weights:** weight the particles according to how well they agree with the observations
  - resample resample particles proportionally to their weights ('good' particles multiply, 'bad' particles die out)

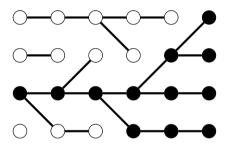
- ▶ Resampling step induces a genealogical (family tree) structure
- ► Ancestral degeneracy: genealogies of all current particles necessarily coalesce at some past time step
- ▶ Bad news for estimating smoothing distribution!











lacktriangle How many particles do I need to ensure n distinct lineages remain in generation T-t with probability greater than 1-lpha ?

- How many particles do I need to ensure n distinct lineages remain in generation T-t with probability greater than  $1-\alpha$  ?
- ► Easiest case (multinomial resampling) addressed in Koskela, Jere, et al. "Asymptotic genealogies of interacting particle systems with an application to sequential Monte Carlo." arXiv preprint arXiv:1804.01811 (2018).
- Next: relax assumptions, generalise to other resampling schemes and conditional SMC